UNIVERSIDADE FEDERAL DO RIO GRANDE DO SUL
ESCOLA DE ADMINISTRAÇÃO
DEPARTAMENTO DE CIÊNCIAS ADMINISTRATIVAS
PROGRAMA DE PÓS-GRADUAÇÃO EM ADMINISTRAÇÃO

RODRIGO HELDT

PhD DISSERTATION

BOTTOM-UP APPROACH TO MANAGE CUSTOMERS, PRODUCT CATEGORIES, AND BRANDS SIMULTANEOUSLY

Porto Alegre
2020

RODRIGO HELDT

PhD DISSERTATION

BOTTOM-UP APPROACH TO MANAGE CUSTOMERS, BRANDS, AND PRODUCT CATEGORIES SIMULTANEOUSLY

PhD dissertation presented to the graduate business administration program at Universidade Federal do Rio Grande do Sul as a final requirement to obtain the title of PhD in Business Administration.

Advisor: Professor Fernando Bins Luce

Porto Alegre
2020

CIP - Catalogação na Publicação

Heldt, Rodrigo
Bottom-up approach to manage customers, product categories, and brands simultaneously / Rodrigo Heldt. -- 2020.
150 f.
Orientadora: Fernando Bins Luce.

Tese (Doutorado) -- Universidade Federal do Rio Grande do Sul, Escola de Administração, Programa de Pós-Graduação em Administração, Porto Alegre, BR-RS, 2020.

1. customer relationship management. 2. customer equity. 3. customer lifetime value. 4. brand management. 5. product management. I. Bins Luce, Fernando, orient. II. Título.

Elaborada pelo Sistema de Geração Automática de Ficha Catalográfica da UFRGS com os dados fornecidos pelo(a) autor(a).

RODRIGO HELDT

BOTTOM-UP APPROACH TO MANAGE CUSTOMERS, BRANDS, AND PRODUCT CATEGORIES SIMULTANEOUSLY

PhD dissertation presented to the graduate business administration program at Universidade Federal do Rio Grande do Sul as a final requirement to obtain the title of PhD in Business Administration.

Advisor: Professor Fernando Bins Luce

PhD dissertation presented and approved on the 16th of July of 2020.

Examination board:

Professor Fernando Bins Luce, PhD
Advisor - Universidade Federal do Rio Grande do Sul - Brazil

Professor João Luiz Becker, PhD
Fundação Getúlio Vargas – Brazil

Professor José Afonso Mazzon, PhD
Universidade de São Paulo – Brazil

Professor Sarang Sunder, PhD
Texas Christian University - USA

ACKNOWLEDGEMENTS

The gap in marketing literature and practice, which motivated the main objective of this dissertation, was identified based on the various activities conducted by the marketing analytics research group at the Universidade Federal do Rio Grande do Sul (UFRGS). My colleagues (Prof. Fernando Bins Luce, Prof. João Luiz Becker, Prof. Cleo Schmitt Silveira, Guilherme Brandelli Bucco, and João Batista Gonçalves de Brito) and I have worked with companies from several industries over the years to develop and apply customer-centric predictive algorithms to large customer bases aiming to enhance customer services and increase companies' profitability. I am very glad to have the opportunity to work with such smart and friendly professionals and I would like to thank very much all of them for all the discussions and great ideas provided as well as the partnership built over the years.

I am very thankful to my advisor, Prof. Fernando Bins Luce, for all the support and great contributions to this project. It has been a very pleasant and productive partnership since I was an undergrad student. I am very fortunate to have the opportunity to learn so much with him along all these years.

I would also like to thank very much Prof. Sarang Sunder, who have been extremely kind to me since the very first time we met. During my time as visiting scholar at Texas Christian University (TCU) and our online meetings, his very smart contributions and his partnership were of great relevance for the development of this dissertation.

Last but definitely not least, I would like to thank my mother, my father, and my brothers, who have always supported me and incentivized me in my decisions and activities. I am very happy to have all of you in my life.

ABSTRACT

One of the most relevant marketing objectives is to create value for both to and from customer (Kumar & Reinartz, 2016). In order to create value for customers, marketers develop and manage product categories and brands to deliver the intended value proposition. In turn, customer-centric practices aim to extract value from customers in the form of customer lifetime value (Kumar & Reinartz, 2016). Although these levels of decision-making – customer, product category, and brand – are clearly intertwined, extant marketing research has mostly addressed them separately. In this PhD dissertation, a collection of three papers is presented with the main objective of proposing and empirically applying a framework to manage customers, product categories, and brands simultaneously. The first paper is a conceptual paper in which a customer, product category, and brand (CPB) bottom-up approach is proposed to unify the performance assessment of these three perspectives and managerial implications of applying it are provided. In the second paper, methods based on the traditional recency, frequency, and monetary value (RFM) method (Fader, Hardie, & Lee, 2005b; Fader, Hardie, & Shang, 2010) are proposed to estimate customer values per product category (RFM/P). Using these methods, the CPB bottom-up approach was partially addressed, considering only customer and product category perspectives, and empirically applied using data from a financial services company and a supermarket. The results show a better predictive accuracy of the proposed RFM/P methods over traditional RFM ones and novel managerial analyses are provided. Finally, in the third paper, the method used in the second paper is extended to additionally incorporate brand in the CPB bottom-up approach. It is applied to data from a traditionally product-centric company, a large consumer-packaged goods (CPG) distributor. Again, the predictive accuracy was found to be better than the traditional RFM method. Besides this, the relevance of the proposed CPB bottom-up approach to product-centric companies was highlighted and, through various analyses, key managerial insights that would not be possible using extant methods are provided to drive marketing efforts and increase profitability.

Keywords: customer equity, customer lifetime value, customer relationship management, brand management, product management, RFM method

RESUMO

Um dos mais relevantes objetivos do marketing é criar valor tanto a partir do cliente quanto para o cliente (Kumar & Reinartz, 2016). Para criar valor para o cliente, profissionais de marketing desenvolvem e gerem categorias de produtos e marcas para entregar a proposição de valor pretendida. Por outro lado, práticas centradas no cliente objetivam extrair valor dos clientes sob a forma de *customer lifetime value*. Embora esses níveis de tomada de decisão – clientes, categorias de produtos e marcas – sejam claramente interligados, pesquisas anteriores têm, na maioria dos casos, endereçado essas perceptivas separadamente. Nesta dissertação, uma coleção de três artigos é apresentada com o objetivo principal de propor e aplicar empiricamente uma abordagem para gerir simultaneamente clientes, categorias de produtos e marcas. O primeiro artigo é um artigo teórico no qual uma abordagem de gestão de baixo para cima de clientes, categorias de produtos e marcas é proposta para unificar a mensuração de performance dessas três perspectivas e implicações gerenciais a partir da adoção dessa abordagem são providas. No segundo artigo, métodos baseados no tradicional método de recência, frequência e valor monetário (RFM) (Fader Hardie, & Lee, 2005b; Fader, Hardie, & Shang, 2010) são propostos para estimar o valor dos clientes por categoria de produto (RFM/P). Usando esses métodos, a abordagem de gestão de baixo para cima de clientes, categorias de produtos e marcas foi parcialmente endereçada, considerando apenas clientes e categorias de produtos, e aplicada empiricamente usando dados de uma empresa de serviços financeiros e de um supermercado. Os resultados evidenciam uma melhor acurácia preditiva dos métodos RFM/P propostos sobre os tradicionais métodos RFM e novas análises gerenciais são apresentadas. Finalmente, no terceiro artigo, um dos modelos usados no segundo artigo é estendido para adicionalmente incorporar a marca na abordagem de gestão de baixo para cima de clientes, categorias de produtos e marcas. Esse método é aplicado usando os dados de uma empresa tradicionalmente centrada em produtos, uma grande distribuidora de bens de consumo embalados. Novamente, a performance preditiva obtida foi maior do que aquela do tradicional método RFM. Além disso, a relevância da abordagem de gestão de baixo para cima de clientes, categorias de produtos e marcas foi destacada e, por meio de diversas análises, implicações gerenciais chave que não seriam possíveis utilizando métodos tradicionais foram desenvolvidas para direcionar os esforços de marketing e aumentar a lucratividade.

Palavras-chave: *customer equity*; *customer lifetime value*; gestão do relacionamento com clientes; gestão de marcas; gestão de produtos; método RFM.

FIGURES

TABLES

TABLE OF CONTENTS

1. INTRODUCTION

The availability of disaggregate databases, including customer level transaction data, has helped marketing managers to increase marketing accountability. Companies have more and more precise data on who their customers are, which products and brands they purchase, what their preferences are, when they visit the e-commerce or the brick-and-mortar stores, and so on. Additionally, "the routine capture of digital information via online and mobile applications produces vast data-streams on how consumers feel, behave and interact around products and services, and how they respond to marketing efforts" (Wedel & Kannan, 2016, p. 2). This availability of data allowed marketing researchers and practitioners to propose forward-looking metrics that not only indicate the performance of the marketing department, but also support marketing decisions. (Fader et al., 2005b; Kumar & Shah, 2009; Fader et al., 2010; Sunder, Kumar, & Zhao, 2016). It has certainly contributed to the emergence of the concept of customer centricity.

Customer-centric companies should bring the customer to the top of the list of issues they must focus on for growth, pursuing marketing strategies to obtain the maximum value from customer relationships (Kumar & Shah, 2009). To accomplish this, there is a growing amount of customer relationship management (CRM) methods developed to drive acquisition, retention and satisfaction of customers to improve their lifetime value to the firm (Wedel & Kannan, 2016). Thus, marketing scholars have recommended firms to adopt customer centricity, rearranging their organizational structures around customers (Kumar & Shah, 2009; Lee, Kozlenkova, & Palmatier, 2015) and aiming to acquire and retain the most valuable ones (Blattberg & Deighton, 1996). Even though this should indeed be pursued by managers, the customer-centric concept focuses mainly on decision-making at the strategic level and customer level. Thus, forward-looking measures (e.g.

customer lifetime value) proposed to assess performance and help implementing strategies to retain current customers and grow their value are aggregated only at the customer level.

Marketing managers, however, also make relevant decisions at the product category and brand levels. They also need to assess performance of products (Wu, Ming, Wang, & Wang, 2014; Joo & Choi, 2015; Ma, Fildes, & Huang, 2016) and brands (Ailawadi, Lehmann, & Neslin, 2003; Keller, 2013; Lehmann & Srinivasan, 2014). Products and brands are means for a firm to create value propositions for customers and, consequently, they allow companies to extract value from these customers after they decide to purchase such offers. Thus, firms' decision makers need to dynamically manage resources spent on customers, products, and brands simultaneously to generate value both to and from customers (Kumar & Reinartz, 2016).

In spite of this, the CLV literature has largely focused on predicting lifetime value neither accounting for decision-making at both product category and brand levels nor considering the expected contribution of a customer for each product category and brand that a firm offers (e.g. Kumar, 2010; Kim, Ko, Xu, & Han, 2012; Lin et al., 2017). Therefore, either in marketing academia and practice, decision-making at the product category and brand levels is not fully integrated to decision-making at the customer level. Additionally, the assessment of the expected value of each of these perspectives are generally addressed separately, resulting in individual performance metrics, preventing managers to link the expected cash flows generated by customers, product categories, and brands, leading to the use of disconnected measures to drive marketing efforts. According to Ding et al. (2020), there is a need to develop performance metrics that properly re-aggregate the contributions of different marketing silos. Thus, there is a need to unify these three perspectives to provide a unified metric to help managers to deal with them together, increasing profitability and being able to adopt customer centricity without losing sight over the performance of product category and brand decisions.

As a result of this, the main objective of this PhD dissertation is to propose and empirically apply a framework to unify customer, product category, and brand expected performance assessment, providing novel managerial insights for decision-making that would not be possible using traditional methods. In order to accomplish it, the dissertation comprehends three papers that contribute to achieve this main objective. The major highlights of these papers are presented in Table 1.

Table 1. Highlights of the papers of the PhD dissertation

Paper ID	**Title**		
1	UNIFYING CUSTOMER, PRODUCT CATEGORY, AND BRAND PERFORMANCE MANAGEMENT Co-authors: Fernando Bins Luce and Cleo Schmitt Silveira		
	Main Objetive	**Publication**	**Award**
	- Propose the CPB bottom-up approach by providing the conceptual foundation for unifying customer, product categories, and brand management to drive more efficient marketing efforts and allow companies to adopt customer centricity without losing sight over its product categories and brands.	- Conference proceedings: Encontro Nacional da ANPAD (EnANPAD) 2018	-
2	PREDICTING CUSTOMER VALUE PER PRODUCT: FROM RFM TO RFM/P Co-authors: Cleo Schmitt Silveira and Fernando Bins Luce		
	Main Objetive	**Publication**	**Award**
	- Propose an RFM per product (RFM/P) method to estimate customer values per product, which allows unifying customer and product category perspectives. - Empirically apply the RFM/P method for a financial services company and a supermarket.	- Conference proceedings: Business Association of Latin American Studies (BALAS) Conference 2017 - Journal publication: Journal of Business Research DOI: https://doi.org/10.1016/j.jbusres.2019.05.001	Luiz Sanz Best Student Paper Award: Business Association of Latin American Studies (BALAS) Conference 2017

3	CUSTOMER CENTRICITY IN A PRODUCT-CENTRIC MARKETPLACE: BOTTOM-UP APPROACH TO MANAGE CUSTOMERS, BRANDS, AND PRODUCT CATEGORIES SIMULTANEOUSLY Co-authors: Fernando Bins Luce and Sarang Sunder	
Main Objetive	**Publication**	**Award**
- Propose an RFM per product and brand (RFM/PB) method to estimate customer values per product and brand, which allows unifying customer, product category, and brand perspectives. - Empirically apply the RFM/PB method to a consumer-packaged goods (CPG) distributor, which operates in a traditionally product-centric marketplace.	- Conference proceedings: Business Association of Latin American Studies (BALAS) Conference 2020	Lourdes S. Casanova Best Applied Paper Award: Business Association of Latin American Studies (BALAS) Conference 2020

The first paper is a conceptual paper. The theoretical foundation of the proposed customer, product category, and brand bottom-up approach (CPB bottom-up approach) is built. The CPB bottom-up approach involves estimating the present value of expected cash flows for every existing intersection among customers, product categories and brands. It provides the basis for unifying these three perspectives and allow companies to adopt customer centricity while also being able to manage product categories and brands. The CPB bottom-up approach allows analyzing the performance of any level of aggregation among customers, product categories, and brands, which may be calculated through bottom-up summations. Additionally, several managerial implications of adopting it are provided. The main portion of the CPB bottom-up approach, developed in the first paper, is represented in Figure 1. Based on the proposed approach, if customer 1, for instance, is expected to purchase products from category 1 and brand A, the expected cash flows among customer 1, product category 1, and brand A should be estimated. Hence, similar cash flow predictions should be conducted to all of the other existing intersections represented in Figure 1.

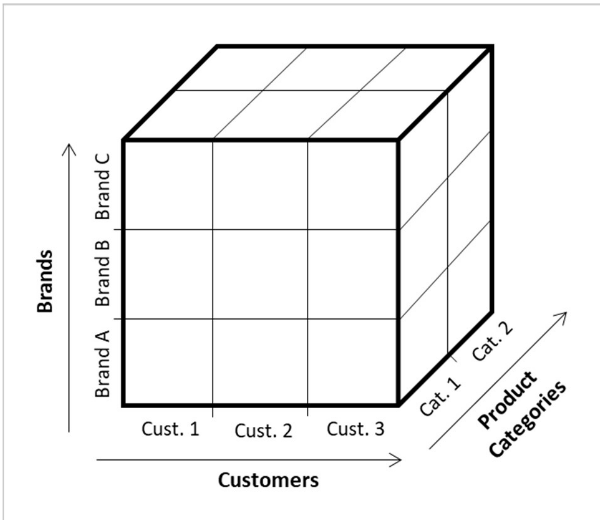

Figure 1. CPB bottom-up approach developed in the first paper

In the second paper, two methods are proposed and empirically applied to estimate the expected cash flows only for the relationship between customers and product categories, represented by the highlighted area in Figure 2. Traditional recency, frequency, and monetary value (RFM) methods (Fader, Hardie, & Lee, 2005a; Fader et al., 2005b; Fader et al., 2010) are adapted to allow the estimation of customer lifetime values per product categories. Empirical applications for a financial services company and a supermarket demonstrate that the proposed methods bring the possibility to combine customer and product category perspectives.

Finally, as it is represented by the highlighted area in Figure 3, in the third paper, one of the RFM methods proposed in the second paper is extended to allow the estimation of customer lifetime values per product categories and brands. Thus, the expected cash flows of every existing intersection among customers, product categories, and brands are empirically estimated for the case of a large consumer packaged-goods (CPG) distributor. Once a CPG distributor is a type of

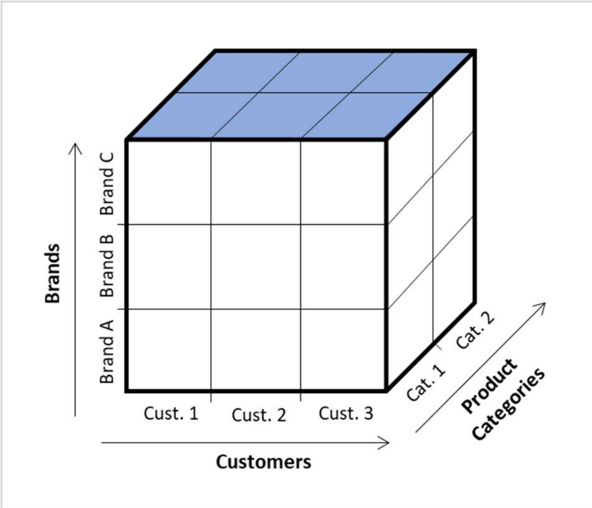

Figure 2. Portion of the CPB bottom-up approach addressed in the second paper

company that is traditionally product-centric, it is also emphasized the relevance of the proposed CPB bottom-up approach to these companies. Decision-making at the product category and brand level is essential for companies operating in traditional product-centric marketplaces (such as consumer packaged goods, consumer durable goods, and clothing). Given this, unifying customer, product category, and brand perspectives is important to facilitate such companies to adopt customer centricity. Additionally, in the third paper, key managerial insights that would not be possible using extant methods are provided to drive marketing efforts and increase profitability.

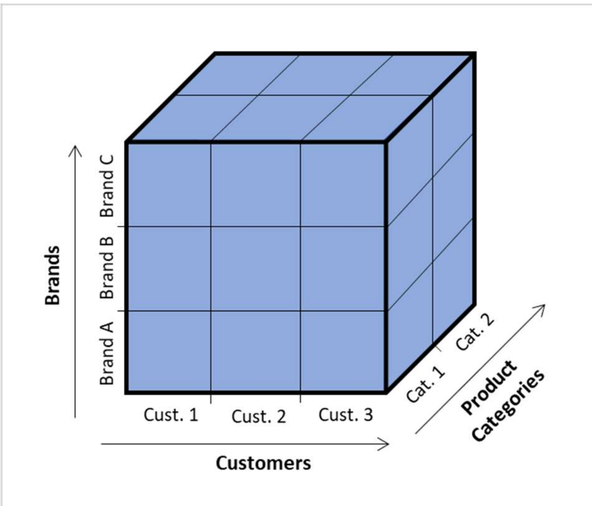

Figure 3. Portion of the CPB bottom-up approach addressed in the third paper

The empirical applications in the second and third papers were implemented using programs coded in R, containing a set of functions to generate each result presented along the papers. The use of R also facilitates the replicability of the methods to other datasets. Once the datasets needed are organized as it is required to be inputted into the programs, all the analyses may be consistently replicated.

2. OVERALL CONCLUSION

In this section, conclusions regarding the findings of all papers as well as the limitations and future research opportunities are presented. The benefits of adopting customer centricity are undeniable. However, past research on customer-centric metrics and activities has mainly addressed the customer-level of decision-making, while leaving aside the product category and brand level as well as the potential to enhance marketing efforts by unifying the three perspectives. Recently, for instance, Ma, Zhang, and Wang (2020) have showed that product managers in hospitality industry should target customers with higher purchase recency, frequency, and monetary value in purchases from hotels. It indicates that to achieve better results in product recommendations, customer value, measured by RFM methods, should be taken into account.

In the first paper of this PhD dissertation, a conceptual framework is proposed to allow marketers to unify customer, product category, and brand performance management. Nowadays, measuring the expected value of such perspectives simultaneously has become feasible given the availability of disaggregated data on every interaction that a company has with its customers as well as data about competitors' sales to their customers.

The managerial implications of adopting the proposed framework involve enhanced customer acquisitions and retention efforts, more precise guidance for new product launches and brand extensions strategies as well as the definition of which product should be removed from the portfolio without threatening the company's relationship with its best customers. Besides this, marketers may also conduct more informed product recommendations based not only on the probability of the customer to purchase a given product but also on the value that this product purchased will add to the customer's lifetime value. Regarding salesforce goals, the framework allows managers to define goals based on equity value per product category and brand added by each salesperson to the customer portfolio he/she manages. In this way, by using a unified metric, managers can assess the expected performance of the salespeople in terms of customers, product categories, and brands. Finally, when data about competition is available, the framework applied at the market level provides forward-looking information about competitors' performance within the market. Additionally, it opens the possibility of estimating the potential lifetime value of the customers in the market, as the expected value of a given customer may be estimated based on its purchases from every player operating in the market.

Given the conceptual CPB bottom-up approach proposed in the first paper, the second paper addresses the proposition of a method to empirically apply the framework to predict the expected values of customers and product categories. The two models used to apply the recency, frequency, and monetary value method per product category (RFM/P) showed the feasibility of applying the CPB bottom-up approach, even though in this paper the brand perspective was not addressed. The results showed that RFM/P prediction accuracy was found to be equivalent to or better than traditional RFM methods. Finally, the unified customer and product category performance assessment enables managers to get an integrated strategic view of their product and customer portfolios. It provides, for instance, the identification of which products are relevant to the most valuable customers and which customers buy the most profitable products.

Lastly, in the third paper an extension of the RFM/P method was proposed to incorporate the brand perspective and allow all the disaggregated cash flows estimations that compose the CPB bottom-up approach presented in the first paper. Again, the unified performance assessment enables managers to get an integrated strategic view of the product, brand, and customer portfolios. Besides this, several analyses were conducted to highlight the predictive accuracy improvements of the proposed approach and develop key managerial insights that would not be possible using extant methods. In terms of prediction accuracy, not using the proposed method can lead to a 11.1 % under estimation in customer equity. We also have showed that the Pareto ratio for the distribution of customer expected values is different depending on the brand and product category considered. Finally, we have identified up to 20 % misclassification on who are the most/least valuable customers at the brand level as well as up to 18 % misclassification at the product category level. Such results are not available when traditional methods are used, because only aggregated customer values are observed. Then, these discordances were used to suggest product recommendations which have potential to increase company's profitability.

Given this, the proposed CPB bottom-up approach creates the possibility to considerably contribute to marketing literature by unifying essential marketing perspectives which are most of the times addressed separately in extant research. Besides this, it also provides a solution for managers to, at the same time, adopt customer centricity, so important in todays' businesses, and keep track of the performance of their decisions at the product category and brand levels. Finally, the framework leads to the several positive managerial implications already highlighted.

Even though the framework proposed and the empirical applications conducted in the dissertation bring relevant contributions to theory and practice, there are also limitations in the studies that must be mentioned. Firstly, as it is highlighted in the second and third papers, the methods proposed in these papers to apply the CPB bottom-up approach do not take into account the correlations among expected cash flows of customers, products categories and brands. Although the method used does not take them into account, the results show that the model was able to accurately predict the number of future transactions and contribution margin per each combination analyzed, resulting in a higher accuracy at the customer level than the traditional RFM methods used to estimated customer value. Besides these positive results, we encourage future studies to develop methods to account for the correlations among the cash flows of different customer, product category, and brand combinations.

Finally, in the first paper we have indicated the possibility to extend the CPB bottom-up approach to include several players operating in the market. In the dissertation, we could not have access to data involving customer purchases from different players. Thus, it was not possible to empirically apply the CPB bottom-up approach for the entire market. Given that such datasets are available from companies such as Nielsen, IRI, and Neogrid, we also encourage researchers to apply the proposed framework for the entire market and also estimate the potential customer lifetime value indicated in the first paper of this dissertation.

REFERENCES

Ailawadi, K. L., Lehmann, D. R., & Neslin, S. A. (2003). Revenue premium as an outcome measure of brand equity. *Journal of Marketing*, *67*, 1-17.

Blattberg, R. C., & Deighton, J. (1996). Manage marketing by the customer equity test. *Harvard Business Review*, *74*(4), 136.

Ding, Y., DeSarbo, W. S., Hanssens, D. M., Jedidi, K., Lynch, J. G. Jr., & Lehmann, D. R. (2020). The past, present, and future of measurement and methods in marketing analysis. *Marketing Letters*. June.

Fader, P. S., Hardie, B. G., & Lee, K. L. (2005a). RFM and CLV: Using iso-value curves for customer base analysis. *Journal of Marketing Research*, 42, 415–430.

Fader, P. S., Hardie, B. G., & Lee, K. L. (2005b). Counting your customers the easy way: an alternative to the Pareto/NBD model. *Marketing Science*, *24*(2), 275-284.

Fader, P. S., Hardie, B. G., & Shang, J. (2010). Customer-base analysis in a discrete-time noncontractual setting. *Marketing Science*, *29*(6), 1086-1108.

Joo, S., & Choi, H. P. (2015). Assessing comparative production efficiencies for product line management. *International Journal of Production Research*, *53*(17), 5241-5250.

Keller, K. L. (2013). *Strategic brand management: building, measuring and managing brand equity*. 4ed. Edinburgh: Pearson Education.

Kim, K. H., Ko, E., Xu, B., & Han, Y. (2012). Increasing customer equity of luxury fashion brands through nurturing consumer attitude. *Journal of Business Research*, *65*(10), 1495–1499.

Kumar, V., & Shah, D. (2009). Expanding the Role of Marketing: From Customer Equity to Market Capitalization. *Journal of Marketing*, *73*(6), 119-136.

Kumar, V. (2010). A Customer Lifetime Value-Based Approach to Marketing in the Multichannel, Multimedia Retailing Environment. *Journal of Interactive Marketing*, *24*(2), 71–85.

Kumar, V., & Reinartz, W. (2016). Creating Enduring Customer Value. *Journal of Marketing*. *80*(6), 36-68.

Lee, J.-Y., Kozlenkova, I. V., & Palmatier, R. W. (2015). Structural marketing: Using organizational structure to achieve marketing objectives. *Journal of the Academy of Marketing Science*, *43*(1), 73–99.

Lehmann, D. R., & Srinivasan, S. (2014). Assessing Brand Equity Through Add-on Sales. *Customer Needs and Solutions, 1*(1), 68–76.

Lin, H.-H., Li, H.-T., Wang, Y.-S., Tseng, T. H., Kao, Y.-L., & Wu, M.-Y. (2017). Predicting Customer Lifetime Value for Hypermarket Private Label Products. *Journal of Business Economics and Management*, *18*(4), 619–635.

Ma, S., Fildes, R., & Huang, T. (2016). Demand forecasting with high dimensional data: the case of SKU retail sales forecasting with intra-and inter-category promotional information. *European Journal of Operational Research*, *249*(1), 245-257.

Ma, S., Zhang, C., & Wang, Y. (2020). From service engagement to product purchase: cross-buying behavior in hospitality contexts. International Journal of Contemporary Hospitality Management. Ahead-of-print.

Sunder, S., Kumar, V., & Zhao, Y. (2016). Measuring the Lifetime Value of a Customer in the Consumer Packaged Goods Industry. *Journal of Marketing Research*, *53*(6), 901-921.

Wedel, M.; Kannan, P. K. (2016). Marketing analytics for data-rich environments. *Journal of Marketing*, *80*(6), 97–121.

Wu, Z.Y., Ming, X.G., Wang, Y.L., & Wang, L. (2014). Technology solutions for product lifecycle knowledge management: framework and a case study. *International Journal of Production Research*, *52*(21), 6314-633.

UNIVERSIDADE FEDERAL DO RIO GRANDE DO SUL
ESCOLA DE ADMINISTRAÇÃO
DEPARTAMENTO DE CIÊNCIAS ADMINISTRATIVAS
PROGRAMA DE PÓS-GRADUAÇÃO EM ADMINISTRAÇÃO

RODRIGO HELDT

PhD DISSERTATION

BOTTOM-UP APPROACH TO MANAGE CUSTOMERS, PRODUCT CATEGORIES, AND BRANDS SIMULTANEOUSLY

PAPER 1:

UNIFYING CUSTOMER, PRODUCT CATEGORY, AND BRAND PERFORMANCE MANAGEMENT[1][2]

Porto Alegre
2020

[1] Paper initially published in the Encontro Nacional da ANPAD (EnANPAD) Conference Proceedings 2017.

[2] Co-authors: Fernando Bins Luce and Cleo Schmitt Silveira

ABSTRACT

Customer, product category, and brand management constitute relevant levels of decision-making that marketers should manage to drive business success. Even though they are inextricably linked perspectives, they are generally treated separately in extant research under the competing viewpoints of product orientation and customer orientation. It leads to a disconnected assessment and management of customers versus product categories and brands, preventing managers to take advantage of the positive implications of managing them simultaneously. Based on the rationale that customers, product categories, and brands are, in fact, different sides of the same problem - how marketing creates value -, a framework to unify these perspectives is proposed: the customer, product category, and brand (CPB) bottom-up approach. It would allow predicting and managing the expected values of these three intertwined perspectives together, providing a unified forward-looking metric to drive marketing efforts. It may be applied to the scope of one company only or it may consider other players competing in the same industry, allowing broader analyses concerning the whole market.

Keywords: customer equity; customer lifetime value; brand equity; product management.

RESUMO

Clientes, marcas e categorias de produtos constituem relevantes níveis de tomada de decisão que profissionais de marketing devem gerenciar para direcionar o sucesso do negócio. Apesar de elas serem perspectivas conectadas, elas são geralmente tratadas separadamente na literatura sob os pontos de vista opostos de orientação para o cliente e orientação para o produto. Isso leva a uma mensuração e gestão desconectadas clientes versus marcas e categorias de produtos, impedindo os gestores de tirar proveito das implicações positivas de gerenciá-las simultaneamente. Com base na lógica de que clientes, categorias de produtos e marcas são, de fato, lados diferentes do mesmo problema - como o marketing cria valor -, propõe-se uma abordagem para unificar essas perspectivas: a abordagem de baixo para cima de clientes, categorias de produtos e marcas. A adoção dessa abordagem permitiria prever e gerir os valores esperados dessas três perspectivas entrelaçadas de forma conjunta, provendo uma métrica unificada para direcionar os esforços de marketing. Essa abordagem pode ser aplicada para o escopo de uma empresa apenas ou pode considerar outros competidores, permitindo alcançar análises mais amplas sobre todo o mercado.

Palavras-chave: *customer equity*; *customer lifetime value*; *brand equity*; gestão de produto.

FIGURES

TABLES

TABLE OF CONTENTS

1. INTRODUCTION

Customer, product (or product categories), and brand management have guided a great deal of research in the literature. Supporting a customer-centric orientation, researchers have developed methods to estimate how valuable the customers of a given company are and to develop marketing programs around them (e.g. Gupta, Lehmann, & Stuart, 2004; Fader, Hardie, & Lee, 2005; Kumar & Reinartz, 2016). At the same time, supporting the relevance of managing brands to drive the firm's long-term success, a product-oriented concept, other researchers have also developed methods to estimate how valuable the brands of a given company are and to potentiate marketing programs (e.g. Aaker 1991, 1996; Ailawadi, Lehmann & Neslin, 2003; Keller, 2013; Lehmann & Srinivasan, 2014). Meanwhile, companies and researchers have not abandoned the importance of accessing the future value of each product category a given company sells, of developing products based on the customers' needs and wants, and of monitoring product lifecycle (e.g. Papinniemi, Hannola & Maletz, 2014; Wu, Ming, Wang, & Wang, 2014; Joo & Choi, 2015; Ma, Fildes & Huang, 2016).

However, when these three perspectives are addressed, they are usually treated separately. Moreover, in terms of product versus customer orientation discussions, often researchers establish a trade-off between both perspectives, suggesting that managers should decide which one they will follow. For instance, Rust, Lemon, and Zeithaml (2004) suggest that "customers and customer equity are more central to many firms than brands and brand equity", and Blattberg and Deighton (1996) and Blattberg, Getz, and Thomas (2001) stated that the product-oriented concept of brand equity has been challenged by the customer-oriented concept of customer equity. On the other hand, authors such as Kapferer (2008) suggest that brands are more likely to generate long-term competitive advantage than customer related tools, because the latter may become standard practice in the market once everyone adopts them.

Over the years, however, customer centricity has gained the central stage empowered by the availability of disaggregated databases, which allow analyses and decision-making at the customer-level (Lee, Kozlenkova & Palmatier, 2015; Kumar & Reinartz, 2016). Although extant research has recommended the adoption of customer centricity based on solid evidences that support its relevance for company's success, managers still need to make decisions and assess performance at the product category and brand levels. After all, they need products to satisfy their customers and these products carry a brand with them. Thus, marketing researchers and practitioners should recognize that customer, product category, and brand perspectives are complementary and not mutually exclusive.

Unfortunately, the inability to unify these perspectives cause marketing managers to end-up having to deal with different metrics to assess customer, product category, and brand performance. It is common to observe product category and brand performance being managed through traditional aggregate metrics such as market-share or revenue (Sunder, Kumar & Zhao, 2016). On the other hand, customer performance is assessed at the customer level through forward-looking measures such as customer lifetime value (e.g. Kumar & Shah, 2009; Zhang, Bradlow & Small, 2015). Since these metrics are not fully connected to each other, decision-making at the customer level does not take into account the expected value of products categories or brands, whereas decision-making at the product category and brand levels does take into account the expected value of each customer.

Marketing managers decisions involve these three perspectives, because they are different sides of the same problem: how marketing creates value. As a result, the overall cash flow generate by these perspectives is actually the same. Therefore, it is relevant for companies to more effectively manage its customers, product categories, and brands using only one unified framework to predict the future values of these intertwined perspectives and drive marketing efforts to increase company's profitability. Given this, in order to bridge such gap both in the literature and in practice, we have proposed a framework to manage customer, product category, and brand performance together and presented managerial implications of adopting it. Given data availability, it may be applied to the scope of one focal company only or include the different players competing in the same market.

In the following, first the literature about customer centricity is presented. Second, the literature about brand equity and product management is presented. After, a discussion about why the three perspectives are related and should be managed simultaneously is conducted. Finally, we present the theoretical foundations of the proposed framework and provide managerial implications of using it.

2. CUSTOMER CENTRICITY

Marketing literature has started decreasing its emphasis on short-term transactions and increasing its focus on long-term customer relationships (Rust et al., 2004). Even though brand asset also contributes to long-term firm performance, it was the customer, managed as a company's asset through the concept originally defined by John Deighton as customer equity (CE), who received central focus ever since (Blattberg et al., 2001). Thus, customers have become the main focus of marketing efforts (Gupta et al., 2004). Kumar and Shah (2009) state that customer-centric firms are increasingly aligning their organizations around customers. CE basic premise is straightforward: the customer is a financial asset that companies and organizations should measure, manage, and maximize just like any other asset (Blattberg et al., 2001). In order to accomplish it, the cornerstone of a successful marketing program is to acquire and retain the most valuable customers (Blattberg & Deighton, 1996).

The concept of CE is by definition related to the concept of customer lifetime value (CLV). CLV is the present value of the sum of the estimated cash flows that are expected to be provided by a customer or a customer segment during the time it is expected to maintain relationship with a given company (Villanueva & Hanssens, 2007). Once the concept of CLV is understood, the comprehension of the definition of CE is straightforward. For Kumar and Shah (2009) the sum of lifetime values of all customers of the firm represents the CE of the firm. Therefore, CLV is a disaggregate measure of customer profitability, and CE is an aggregate measure (Kumar & Shah, 2009).

The estimation of CLV usually involves estimating customer retention rate or customer purchase probability and combining them with the contribution margin expected to be spent by the customer in the future. Some models may also consider the marketing costs spent by the company (Berger & Nasr, 1998; Kumar & Shah, 2009). Based on this view, maximizing CE is all about retaining or acquiring customers that are more likely to realize more purchases with higher contribution margins from the firm in the future.

While the concepts of CLV and CE and the basic variables usually involved in its estimation are relatively simple to understand, the complexity of it relies on the challenge of accurately predicting those basic variables and, therefore, CLV and CE. Variables such as contribution margin, and retention rate or purchase probability may vary across customers and over time. Therefore, more robust methods are needed to provide the prediction of such variables. To cope with it, several methods have been proposed in the literature. In order to better understand how CLV and CE have been measured, a summary of extant research on the topic is presented in Table 1 to provide a spectrum of which methods have been used. The reviewed studies were classified based on (1) the data used to conduct the empirical study; (2) whether the CLV model

Table 1. Models to measure Customer Lifetime Value and Customer Equity

Authors	Data used	Level of analysis	Method
Gupta et al. (2004)	Data from companies' annual reports	Customer base level	S-shape function
Schmittlein and Peterson (1994)	Sales data from a company which sells office supplies to other companies	Individual customer level	Probability mixture model: Pareto/Negative Binomial Distribution (NBD)
Fader et al. (2005)	- Simulated purchasing data - Sales data from the company CDNOW	Individual customer level	Probability mixture model: Beta-Geometric (BG)/ Negative Binomial Distribution (NBD)
Fader, Hardie, and Shang (2010)	- Donations dataset from a nonprofit organization	Individual customer level	Probability mixture model: Beta Geometric (BG)/Beta Binomial (BB)
Zhang et al. (2015)	Sales and visits data from: - a large North American retailer; - CDNOW; - Mecoxlane; - Hulu; - YouTube; - Amazon; - eBay	Individual customer level	- Probability mixture model: Beta Geometric (BG)/Beta Binomial (BB) - Clumpiness metric
Pfeifer and Carraway (2000)	Only numerical a example provided	Customer segment level	Markov Chain
Libai, Narayandas, and Humby (2002)	Data from a large European retailer	Customer segment level	Markov Chain
Rust et al. (2004)	- Survey with customer samples - Secondary census data - Data from companies' annual reports	- Customer base level - Individual customer level (restricted to the customers surveyed)	- Choice model - Markov chain
Kumar, Venkatesan, Bohling, and Beckmann (2008)	Data from B2B company	Individual customer level	- Bayesian hierarchical seemingly unrelated regressions
Kumar and Shah (2009)	Data from large B2B and B2C companies	Individual customer level	- **Bayesian** hierarchical seemingly unrelated regressions
Rust, Kumar, and Venkatesan (2011)	High-technology services company	Individual customer level	Monte Carlo simulation algorithm
McCarthy, Fader, and Hardie (2016)	Data form an omnichannel retailer	Individual customer level	- Probability mixture model: Beta Geometric (BG)/Beta Binomial (BB)

measure the value at the individual customer level, customer segment level, or customer base level; and (3) the method used to predict CLV.

Gupta et al. (2004) use a S-shaped function to predict the growth in number of customers and estimate the average CLV of a company. Pfeifer and Carraway (2000) and Libai et al. (2002) use markov chain model for modelling customer relationships over time and estimate CLV at the segment level. Likewise, Rust et al. (2004) also use markov chain model to estimate CLV considering the competitors in a given industry and modelling the probability of a customer to switch from one competitor to another. In turn, Rust et al. (2011) adopted a Monte Carlo simulation algorithm to predict customer purchase propensity, profit, and firm marketing actions. The results obtained indicated better prediction accuracy compared to simpler models in extant literature.

Other researchers adopted the Recency, Frequency, and Monetary value (RFM) method to estimate CLV: (1) Schmittlein and Peterson (1994) use the traditional Pareto/Negative Binomial Distribution method to estimate customer expected amount of transactions which may be used to predicted CLV; (2) Fader et al. (2005) use Beta Geometric/Negative Binomial Distribution as an alternative to the traditional Pareto/Negative Binomial Distribution; and (3) Fader et al. (2010), McCarthy et al. (2016), and Zhang et al. (2015) use a Beta Geometric/Beta Binomial model to predict the number of future transactions for cases in which there is no information about how many transactions a customer made in a given period, but only a binary (it bought or it did not buy) historical information is available. Finally, Kumar et al. (2008) and Kumar and Shah (2009) adopted Seemingly Unrelated Regressions method to estimate customer probability of purchase, contribution margin, and marketing costs, which were the variables used to calculate CLV.

According to Kumar and Reinartz (2016), once CLVs have been estimated, the firm can develop strategies such as optimally allocating its limited resources and balancing acquisition and retention efforts to achieve maximum return. The vast literature around CE and CLV reinforces the relevance of customer-centric marketing metrics, which are aligned with customer orientation, so important in today's dynamic environment. Therefore, marketing managers are oriented to organize their efforts around customers and not around products (Kumar & Shah, 2009; Kumar & Reinartz, 2016). Even the organizational structures should be rearranged around customers (Lee et al., 2015). In this sense, the old concept of product orientation, also related to brand equity, should be replaced by customer centricity, based on metrics such as CE and CLV (Hogan, Lemon & Rust, 2002). This metrics, however, are managed only at the customer level, not accounting for the expected value of each customer related to each product category and brand offered.

3. BRAND EQUITY

Despite the rise of customer-centric practices, marketing managers are still making decisions at the brand level and managing the performance of such strategies remains of great relevance for many companies. Given this, the concept of brand equity and the methods to measure it have been extensively developed in marketing literature. In this section, in order to show the importance that brands still have for firms and to define the appropriate approach to measure brand performance in the framework proposed in the present study, we have provided a summary of the literature about brand equity and the different approaches used to measure it.

A brand signals to the customer the source of the product and protects both the customer and producer from competitors who would attempt to provide products that appear to be identical (Aaker, 1991). Consequently, there is growing recognition that brands are valuable (Shankar, Azar & Fuller, 2008). Thus, there is also growing interest in the valuation of one of the most important marketing assets: brand equity.

The concept of brand equity is important because it links financial and marketing management concerns in understanding how a brand can command margins and loyalty beyond that which would be obtained from the mere functional value of the product or service offered (Leuthesser, 1988). Given such relevance, brand equity has become a key marketing asset (Buil, De Chernatony & Martínez, 2013), which can nurture long-term buying behavior (Christodoulides & De Chernatony, 2010). Strong, favorable, and unique brand associations are essential as sources of brand equity to drive customer behavior. And it results in advantages such as improved perceptions of product performance; greater loyalty; less vulnerability to competitive marketing actions and crises; larger margins; more elastic (inelastic) customer responses to price decreases (increases); increased marketing communication effectiveness; expanded growth opportunities from brand extensions; and longevity and reduced risk through more persistent and less volatile cash flows (Leone et al., 2006). Additionally, an established and successful brand name is one of the best mechanisms for providing this long-term performance. While sales that are not associated with a strong brand are relatively vulnerable to competitors, to innovation, and to price wars, a strong relationship between the brand and its consumers is not so easily disrupted (Haigh, 1999).

Although there have been several alternative definitions of brand equity proposed in the literature, most researchers agree that brand equity consists of the marketing effects uniquely attributable to a brand. That is, brand equity explains why different outcomes result from comparing the marketing of a branded product or service to the case in which the same product or service was not branded (Keller, 2013; Ailawadi et al., 2003).

Given the advantages that result from a brand with high equity, effective brand management requires careful measuring and monitoring of its equity over time (Sriram, Balachander & Kalwani, 2007). Researchers have proposed many different approaches to measure brand equity (Shankar et al., 2008). Extant research on the topic has looked at the issue from the perspective of either the consumer or the firm (financial viewpoint) (Christodoulides & De Chernatony, 2010). The use of the consumer perspective originates the approaches termed consumer-based brand equity (CBBE), whereas the use of the firm (or financial) perspective originates the approaches termed firm-based brand equity (FBBE). CBBE may be divided into direct and indirect approaches to measure it. In turn, the FBBE may be divided into product market and financial market approaches to measure it. Finally, some authors have recently proposed what we have called holistic approach to measure brand equity, once it combines CBBE and FBBE. In Figure 1, we represent these five brand equity measurement approaches used in extant research and a brief review of studies under each of these categories is presented afterwards.

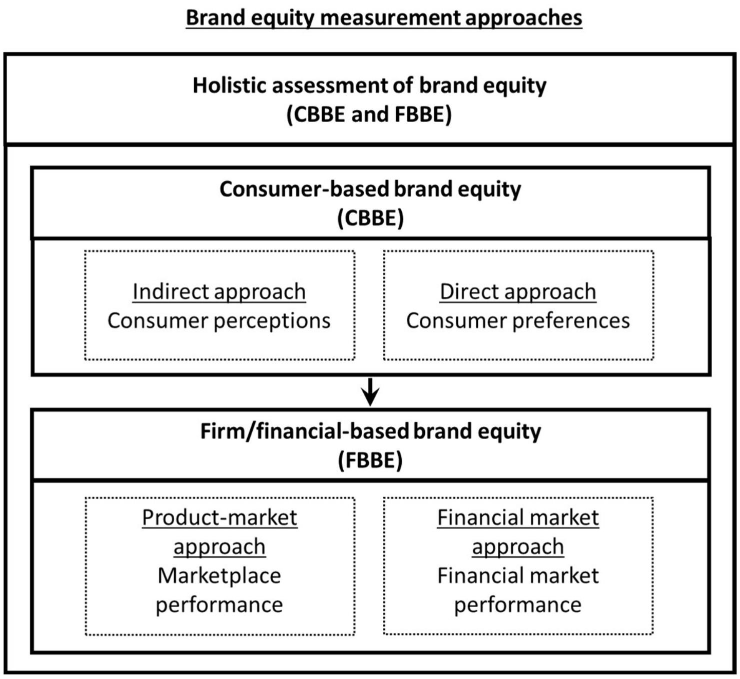

Figure 1. Brand equity measurement approaches

CBBE focuses on the conceptualization and measurement of brand equity from the consumers' perspective (Leone et al., 2006). CBBE is based on the value consumers derive from the brand name (Sriram et al., 2007). It involves the set of memory-based associations to a particular brand that exist in the minds of consumers (Keller, 2013). According to Keller (2013), there is both an indirect and a direct approach to measure CBBE. The indirect approach tries to identify potential sources of such equity (Yoo & Donthu, 2001), whereas the direct approach focuses on consumer responses to different elements of the firm's marketing program such as brand preferences and utilities (Park & Srinivasan, 1994; Kamakura & Russell, 1993).

Indirect CBBE approach: Since brand equity is a multidimensional concept and a complex phenomenon, the indirect CBBE measurement approach usually involves collecting data on mindset measures of brand equity from the consumer through surveys or experiments, and using the data to assess the sources of brand equity, which are CBBE dimensions such as perceptions, feelings, attitudes, positive impressions, awareness, associations, and loyalty towards the brand (Aaker, 1991, 1996; Ailawadi et al., 2003; Kartono & Rao, 2005; Atilgan, Akinci, Aksoy, & Kaynak, 2009; Keller, 2013). Given this multitude of consumer-level dimensions proposed in extant research, unfortunately, there is no general agreement in current marketing literature concerning the nature and content of CBBE dimensions (Netemeyer et al., 2004, Atilgan et al., 2009, Oliveira, Silveira, & Luce, 2015). However, as stated by Tong and Hawley (2009), the dimensions proposed by Aaker (1991, 1996) remain as the most commonly adopted: brand awareness, brand associations, perceived brand quality, and brand loyalty.

Direct CBBE approach: The direct CBBE approach is based on the value consumers derive from the brand name. However, instead of collecting data on consumer mindset measures of brand equity through surveys to assess brand equity dimensions, the direct approach focuses on consumers' responses to different elements of the firm's marketing program such as brand preferences and utilities, it is about capturing consumers' choices toward brands given their performance (Park & Srinivasan, 1994; Kamakura & Russell, 1993; Christodoulides & De Chernatony, 2010; Keller, 2013), without attributing a monetary value to these brands. The studies of Kamakura and Russel (1993) and Park and Srinivasan (1994) are examples of the direct approach to measure brand equity. The method used by these authors consists of using actual consumer choice data to estimate the implied utility assigned by consumers to a brand in a given product category through choice models, assuming that brand choice always involves an attempt to maximize utility.

On the other hand, FBBE focuses on a brand's financial performance and on the value of a brand to the firm. It is about measuring the added value in terms of cash flows, price, revenue, market share, or similar financial or market-outcome measures at the firm-level (Sriram et al., 2007). Brand equity research from a firm's perspective generally involves the use of observed market data to assess the brand's financial value to the firm. The market in question could be a geographic or physical product market, where performance measures such as market share or profit can be used, or it could be a financial market, where performance measures such as the firm's stock price or other financial variables may be used to assess the brand's value (Kartono & Rao, 2005). Under this perspective, according to Haigh (1999), equity in the context of brands is essentially a financial concept, once it is the bottom line, the specific dollar worth of a product or service, beyond its physical and delivery costs, that is realized because of the impact of its branding. Farquhar (1989), aligned with this perspective, states that "from the firm's perspective, brand equity can be measured by the incremental cash flow from associating the brand with the product". As presented in Figure 1, two main approaches to measure FBBE are observed in extant research: (1) product market and (2) financial market.

Product market FBBE approach: The product market approach to measure FBBE generally involves the use of observed market data to assess the brand's financial value to the firm (Kartono & Rao, 2005). Past research following the product market FBBE approach includes measures of brand equity such as (1) revenue premium to calculate the difference between the revenue of a branded product and that of a corresponding private label (Ailawadi et al., 2003; Lehmann & Srinivasan, 2014); (2) price premium (Holbrook, 1992; Bello & Holbrook, 1995, Randall, Ulrich, & Reibstein, 1998; Lehmann & Srinivasan, 2014); (3) incremental cash flow from associating the brand with the product (Farquhar, 1989; ISO, 2010); (4) total cash flow from associating the brand with the product (Oliveira et al., 2015); and (5) CLV attributable to a brand (Trent & Mohr, 2017).

Financial market FBBE approach: the financial market approach considers brand performance measures in the financial market. From this point of view, "brands are assets that, like plant and equipment, can and frequently are bought and sold" (Keller & Lehmann, 2006, p. 745). It is about, for instance, valuing FBBE as a stock price premium that investors grant to a firm, based on its portfolio of brand assets (Anderson, 2011) or the proportion of the transaction value that may be attributed to the brand in mergers and acquisitions (M&As) (Bahadir, Bharadwaj, & Srivastava, 2008). Extant research following the financial market FBBE approach includes measures of brand equity such as (1) use of intangible assets information to calculate brand equity as a percentage of the firm's assets replacement value (the intangible value) (Simon & Sullivan, 1993) and (2) the dollar value of the acquired firm's brand portfolio that acquirer firms reported in the U.S. Securities and Exchange Commission (SEC) fillings related to their mergers and acquisitions (M&A).

Finally, in the fifth approach to measure brand equity, the holistic approach, researchers have recognized that CBBE models do not provide a monetary estimation of brand equity, whereas FBBE models do not take consumer perceptions into account. Therefore, some authors have suggested that instead of choosing one approach, marketing researchers could combine both in the same brand equity measurement model, capturing consumer perceptions about the brand as well as delivering a monetary estimation of the brand value (Kartono & Rao, 2005; Burmann, Jost-Benz, & Riley, 2009; Oliveira et al., 2015). The model proposed by Oliveira et al. (2015) exemplify how this approach is applied. These authors surveyed telecon consumers in order to measure the CBBE dimensions. These measures were used to estimate each brands' utility, which allows the managers to verify the impact of investments in each of the CBBE dimensions on the monetary value of the FBBE. The FBBE, in turn, based on the product market approach, was estimated through the expected future cash flows for each customer based on the average customer spending per brand in the market.

In summary, the literature related to brand equity is way more diverse than the literature related to customer equity. There is no consensus about how brand equity should be measured. However, since the objective of this research is to unify customer, product category, and brand performance assessment in the same framework, the product-market approach to measure FBBE is the most suitable for this purpose, because, through this approach, it is possible to measure the outcomes of the companies' investments to build brand equity using a monetary estimation based on the present value of the expected cash flows generated by the brand. The adoption of expected cash flows to measure FBBE allows linking brand performance assessment to customer and product category performance assessment, which may also be measured based on expected cash flows at the customer level and product category level respectively.

Finally, it is noteworthy that most of the authors who have developed models to measure FBBE do not aim to disaggregate the monetary value of the brand per each customer the firm has. It indicates that in brand equity literature there has not been much effort to combine brand valuation to the expected value of each customer.

4. PRODUCT MANAGEMENT

Product is defined as any company's offer designed to satisfy consumer's needs and desires. Therefore, it may be a tangible product, such as consumer packaged-good, or a service, such as fixed income, investment funds or shares in the financial services industry. Our main focus is to assess expected product performance at the category level.

According to Kapferer (2008), a brand asset only exists if products and services also exist. How do we contrast a brand and a product? Keller (2013) answered this question defining a product as anything we can offer to a market for attention, acquisition, use or consumption that might satisfy a need or want. Given such product definition, Keller (2013) states that a brand is more than a product because it can have dimensions that differentiate it in some way from other products designed to satisfy the same need. These differences may be rational and tangible, related to the product performance of the brand, or more symbolic, related to what the brand represents.

Consequently, considering the possibility of using brand extension strategies, managers may use the same brand to label different products in a given product category or across product categories. For example, PepsiCo's Pepsi brand is used to label colas (one product category), whereas Unilever's Dove brand is used to label soaps, shampoos and deodorants (several product categories). Furthermore, even though some companies may have only one brand to manage, it usually offers different product categories. For instance, an insurance company having only its institutional brand usually has a portfolio of products that includes categories such as life insurance, car insurance, and house insurance which have to be managed. Based on such product and brand management possibilities, marketers need to manage not only brands but also the products categories offered.

Product management research involves subjects such as deciding which products should be offered (Carrol & Grimes, 1995), forecasting product demand on stock keeping unit (SKU) level or product category level (Carrol & Grimes, 1995; Ma et al., 2016), analyzing product performance (Joo & Choi, 2015), managing product lifecycle (Grieves, 2006; Wu et al., 2014), managing customer requirements to product lifecycle management (Papinniemi et al., 2014), providing product customization for each customer (Forza & Salvador, 2008), and developing new products (Akbar & Tzokas, 2013; Figueiredo, Travassos, & Loiola, 2015).

Nowadays, product management is also about designing products to satisfy customers' needs and wants and monitor whether it is still able to deliver it over its product lifecycle. Moreover, modern companies are also adopting co-creation practices in which the final value of a product to a given customer is to some extent dependent on the participation of this customer in its production, delivery, or use (Vargo & Lusch, 2004). Consequently, it is expected that the customer will reward the company by purchasing and recommending its products. In this way, one of the main alternatives to assess and manage product category is based on the estimation of the present value of cash flows it is expected to generate in the future (Carrol & Grimes, 1995; Joo & Choi, 2015; Ma et al., 2016). However, as it is also the case in the brand equity literature, usually studies related to product category management have not aimed to combine the expected value of product categories to the expected value of each customer.

5. UNIFYING CUSTOMER, PRODUCT, AND BRAND PERSPECTIVES

Kapferer (2008) states that all business managers are supposed to be interested in customer relationship management, customer equity, CLV, customer database management, and so on, and all these new tools criticize the old brand concept and focus on the most efficient techniques to serve the most profitable customers. Rust et al. (2004), for instance, reinforce that brand equity, a product-centric concept, has been challenged by the customer-centric concept of customer equity. However, for Kapferer (2008), it is surprising to see how brand management continues to stimulate managers' interests. Even though brand equity is a product-centric concept, brands, through all their functions, end up creating value for customers, generating loyalty and stable cash flows, facilitating effective word-of-mouth, and so on. Decision-making at the brand level aims to build brands to reverberate in the customers' minds engaging them and supporting customer-centric marketing programs. Given this rationale, concerning the relationship between brand equity and customer equity, Kapferer (2008) questions: What is customer equity without brand equity? Although customer-centricity has been proven to be relevant to drive firm performance (Kumar & Shah, 2009; Kumar & Reinartz, 2016), Kapferer's (2008) argument remains valid once brand management is still relevant for companies' success.

Ambler et al. (2002) while also criticizing the brand equity concept, stated that it is traditionally organized around products, therefore it does not account for the financial contribution of the customer to each brand. Reacting to this argument, another question may be asked: Why cannot brand equity account for the financial contribution of the customer to each brand, especially in today's world in which we have more and more individual level data available? FBBE may be assessed based on brand level estimations of expected cash flows. Therefore, it is possible to estimate the portion of a given brand value that is attributable to a given customer. It could unify brand and customer perspectives and drive more efficient marketing efforts.

Regarding the relationship between product and customers, we also verify that, amid all the lights that are shed over customer equity and brand equity, product management problems such as product performance management (Joo & Choi, 2015), product demand forecast (Ma et al., 2016), and product development (Akbar & Tzokas, 2013) are still very relevant in academic research, even though sometimes it is more frequently addressed not by marketing scholars but by scholars from other disciplines such as operations research.

In the marketing literature, it is well documented that there has been an old era of product orientation that has been overcome by the marketing concept, related to the focus on customers, since the emergence of the marketing management school in the 1950s (Shaw & Jones, 2005). However, the referred era of product orientation characterizes an old time in which firms, competing in abundant markets, were able to prosper only by producing massive quantities of standardized products without need to meet a diverse range of customers' desires. By stating that product management is still relevant, it does not mean at all going back to that time. Once we need products to satisfy our customers, what makes today's product management relevant is the fact that it is aligned with customer orientation. Thus, it is about creating value for customers by developing and improving products based on what meets customer's needs and desires, even considering including the customers in this process through co-creation (Vargo & Lusch, 2004).

It is well-known that nowadays the customer centricity paradigm, aligned with the marketing concept, has long been documented as one of the most important pillars of effective marketing and that, with the advent of technology and customer relationship management, there is an explosion of disaggregate and granular customer level data available to firms and it provides even more relevance for customer management (Sunder et al., 2016). Nevertheless, customer-centricity is not isolated from today's evolved way of doing product management. Therefore, concerning relationship between products and customer equity, and following Kapferer's (2008) rationale about brands, one could also correctly question: What is customer equity without products? The answer to such question suggests that product management is also still relevant for companies' success.

Finally, concerning the relationship between products and brands, as aforementioned, it is understood that brand asset only exists if products and services also exist (Kapferer, 2008). So, in order to build a brand asset that is valuable, a firm needs to develop and improve products that will be labeled with its brand and are able to create customer value.

Consequently, when we analyze customers, products, and brands, we are actually dealing with different perspectives of the same problem: how marketing creates value. Kumar and Reinartz (2016) affirm that business is about creating value and the purpose of a sustainable business is, first, to create value for customers and, second, to extract some of this value in the form of profit, thereby creating value for the firm. In this sense, in order to be successful, first, firms have to create or co-create (Vargo & Lusch, 2004) perceived value for/with customers through developing products and brands. Second, customers provide value (customer lifetime value) for the organization (Kumar & Reinartz, 2016). Gupta and Lehmann (2006) also understand that customer value has two sides: the value that the firm generates to its customers and the value its customers generate to the firm. Thus, a firm, in allocating its resources, needs to consider both sides. For the firms' decision makers, the challenge is to dynamically align resources spent on customers, products, and brands in order to simultaneously generate value both to and from customers (Kumar & Reinartz, 2016).

An increase in perceived value from customers is expected to be observed if this task is successfully accomplished. It, in turn, is the driving force to deliver customer, product category, and brand performance, which are represented by the expected cash flows at each existing intersection among these three perspectives. The perceived value created generates customer favorable behavior toward the brands and products. Then, customers are expected to try the branded products and are likely to repurchase them in the future. Therefore, not only customers' expected cash flows increase, but also expected cash flows of products categories and brands increase.

In fact, even though the cash flows may be analyzed from the customer, product category or brand levels of aggregation, the overall cash flow is actually only one. In extant research, however, these three perspectives are usually addressed separately. Only few studies in the literature address more than one of them together. Ambler et al. (2002) developed discussions about the theoretical link between customer equity and brand equity. Rust et al. (2004) proposed a model to measure customer equity taking competitors into account and considering customer-based brand equity as one of the drivers of customer equity, however it does not consider the possibility of a customer purchasing from two or more brands at the same time, neither it considers the different product categories purchased by each customer. Leone et al. (2006) conceptually suggested the estimation of brand value for the retailer and, in order to accomplish it, the retailer is supposed to estimate the value of its customers by product categories and by brands. Shankar et al. (2008) built a model to measure multi-category brand equity, accounting for brand's spillover effects from one product category to another; (5) Stahl, Heitmann, Lehmann, and Neslin (2012) analyzed the relationship between brand equity and customer acquisition, retention, and profit margin – key components of CLV. Finally, Sunder et al. (2016) proposed a model to measure customers lifetime values for different brands in a given product category, however their proposed model becomes unfeasible to be estimated for a higher number of categories and brands as well as it is dependent on the availability of data from competitors.

Some of these studies provide relevant discussions about the relationship between brand equity and customer equity and also suggestions of what are interesting future research directions on the subject. Even though product management sometimes seems to be forgotten in such discussions, this subject is closely related to the brand equity perspective and, therefore, it is somehow present when brand equity is addressed.

Stahl et al. (2012) found that brand equity has a predictable and meaningful impact on customer acquisition, retention, and profitability. It only reinforces the existence of relationship between brand and customer assets. Kumar, Lemon, and Parasuraman (2006), while addressing future research directions, also suggest the relevance of conducting research in order to better understand the relationship between brand equity and customer equity and to answer whether it is possible to link the value of individual brands to CLV. They also mentioned that answering such questions will help firms to optimize investments in branding and in customers, enabling managers to deal with brands and customers simultaneously to grow the long-term value of the firm. Kumar et al. (2006) suggestions reflect an alternative viewpoint to the traditional conflict between brand and customer perspectives in the literature. They emphasize that marketers should better understand the relationship between brand equity and customer equity as well as how to manage them together.

In turn, Ambler et al. (2002) suggest that an exclusive focus on brand or customer alone is not as likely to be successful as a focus on both. “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" (Ambler et al., 2002, p. 21). The authors state that firms may expand their focus to include both brand and customer perspectives. Therefore, they would need to manage both brand and customer portfolios. Likewise, Ding et al. (2020) urge future research in marketing to define how brand equity and customer equity relate to each other as well as how they contribute to the overall value created by the marketing department.

Finally, aligned with Ambler et al. (2002), Leone et al. (2006) suggested that one way to reconcile brand and customer perspectives is to think of a matrix, as in Figure 2, where all the brands from a given company are on the rows and all the different customer segments or individual customers that purchase those brands are on the columns. For them, an effective brand and customer management would necessarily take into account both the rows and the columns to arrive at optimal marketing solutions.

Figure 2. Brand and Customer Management
Source: Leone et al. (2006)

6. CUSTOMER, PRODUCT CATEGORY, AND BRAND (CPB) BOTTOM-UP APPROACH

Even though there is a clear link among customer, product category, and brand perspectives, they have most of the times been addressed separately in the literature. Likewise, practitioners also fall short of combining forward-looking measures to assess these perspectives inside companies. Moving toward a method to accomplish it is needed. They all affect the firm’s capacity to perform and, ultimately, generate future cash flows. According to Ding et al. (2020, p. 10) without performance metrics that properly re-aggregate the contributions of different silos inside the marketing department, the CMO will continue to face a familiar problem: “If I add up all the reported returns produced by the different marketing groups in my organization, I end up with a company that is three times the size of its current operations”.

In summary, once cash flows are actually only one, which is the monetary value expected to be received from customers purchases of branded products, customer, product category, and brand performance may be assessed by the estimation of the respective expected cash flows of each of these perspectives. Given this, as aforementioned, Ambler et al. (2002) stated that firms should think of brand and customer assets as two sides of the same coin and, therefore, they should expand their focus to manage both brand and customer portfolios. Additionally, in the literature, it is also understood that brand asset only exists if products also exist (Kapferer, 2008), and, even though a customer-centric orientation is relevant, we still need products to satisfy our customers. Consequently, the statement of Ambler et al. (2002) could have an even wider sense if it were updated to state that firms should think of customers, product categories, and brands as three faces of the same cube and, therefore, they should expand their focus to simultaneously manage these three portfolios. It represents a disaggregated estimation of the present value of expected cash flows for each existing intersection among these three perspectives. This originates the customer, product category, and brand (CPB) bottom-up approach proposed in this study. Such rationale is explained in detail in the following sections. Firstly, the framework is built for the scope of only one focal company. Then, it is expanded to also encompass competitors, allowing an assessment of these three perspectives at the market level.

6.1. CPB BOTTOM-UP APPROACH CONSIDERING A FOCAL COMPANY ONLY

In this section each part of the proposed framework is explained considering the scope of only one focal company. In order to exemplify how the proposed framework works, a hypothetical company called Beta is used.

Brands and product categories. Regarding the relationship between brands and product categories, some brands may be used only in one product category and others in several product categories. In our example, we have assumed that there are only two different product categories (1 and 2) and three brands (A, B, and C). In Figure 3 and in the other following figures, each black dot represents the intersections with present values of expected cash flows greater than 0. In Figure 3, it is shown that brand A is used to label only products in category 1, brand B is used to label both category 1 and 2, and the brand C is used to label only category 2. Each branded product sold contributes to the overall cash flow of Beta. Given the matrix in Figure 3, the brand equity of brand B is divided into two product categories: category 1 and category 2, whereas all of the brand equity of brand A is only in category 1 and all of the brand equity of brand C is only in category 2.

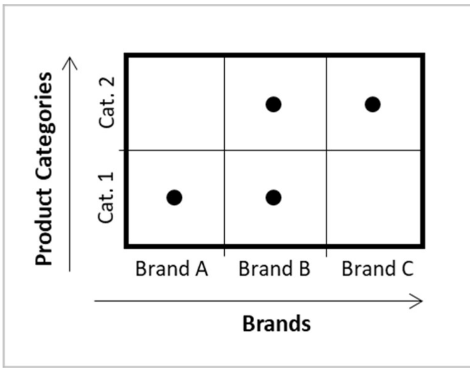

Figure 3. Product Categories x Brands
Note. The black dots represent intersections with present values of expected cash flows greater than zero.

Customers and product categories. Regarding the relationship between customers and product categories, a given company may offer specific product categories to specific customers or it may offer all product categories to all customers. We have assumed that Beta has only three customers. From its transactions database, Beta has found out that even though it offers all product categories to all customers, some of them are expected to purchase only one of the product categories. It may happen because some customers do not perceive the same value that others do. Figure 4 shows that all of the customers are expected to buy category 1 in the future, whereas only customer 3 is expected to purchase products from category 2. Given Figure 4, we understand from which customers the cash flows provided by each product category are coming from. It may also contribute to validate the performance of product personalization practices the firms use to better satisfy each customer. Only a fraction of the lifetime value of customer 3 contributes to the performance of category 2, whereas the lifetime values of customers 1 and 2 and a fraction of the lifetime value of customer 3 contribute to the performance of category 1. Consequently, from Figure 4, it is suggested that it is managerially relevant to analyze the CLVs divided by product category.

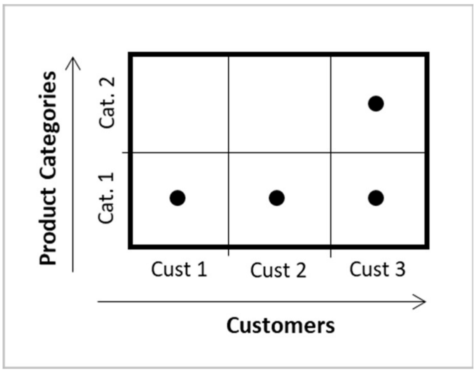

Figure 4. Product Categories x Customers
Note. The black dots represent intersections with present values of expected cash flows greater than zero.

Customers and brands. Finally, concerning the relationship between customers and brands, a given company may offer specific brands to specific customers or it may offer all brands to all customers. Because of the value perceived by each customer toward each brand, Beta has also found out that even though it offers all brands to all customers, they are not expected to purchase every brand. In Figure 5, similar to what was proposed by Leone et al. (2006), there is a brand by customer portfolio which shows that Customer 1 is expected to buy only brand A in the future, whereas Customer 2 is expected to buy only brand B in the future and Customer 3 is expected to buy brand B and brand C. Figure 5 shows from which customers the cash flows provided by each brand is coming. Only the lifetime value of customer 1 contributes to the brand equity of brand A and only a fraction of the lifetime value of Customer 3 contributes to the brand equity of brand C, whereas the lifetime value of Customer 2 and a fraction of the lifetime value of Customer 3 contribute to the brand equity of brand B. Consequently, from Figure 5, it is suggested that it is also managerially relevant to analyze the CLVs divided by brand.

Based on the analyses of Figures 3, 4, and 5, the final step is to unify those three viewpoints into only one framework. Given that customers, product categories, and brands are interconnected around the same business objective - value creation -, firms should understand that the value created is in fact the result of managing them simultaneously. Therefore, such portfolios should be measured and monitored as shown in the CPB bottom-up approach that should be applied when there is data available from only one company (Figure 6).

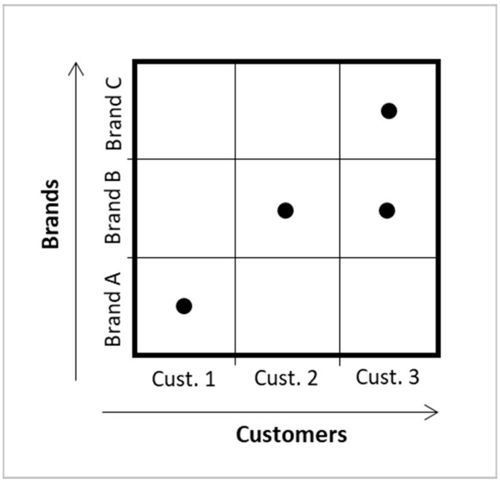

Figure 5. Brands x Customers
Note. The black dots represent intersections with present values of expected cash flows greater than zero.

Given the availability of historical transactional data for each customer toward each brand and product category, the expected present value of future cash flows for each intersection among these three perspectives may be estimated. From this result, the performance of any level of aggregation among customers, product categories, and brands may be calculated through bottom-up summations.

Finally, Figure 6 also indicates the possibility of estimating the present value of potential customer acquisitions that are expected to be made by the company. For the sake of simplification, only one column of potential acquisitions is represented on the right side of Figure 6, however, it could contain several columns, each of them representing the expected present value of potential acquisitions for a given customer segment. According to Ambler et al. (2002) strong brands positively influence firm's ability to extend into new product areas and to acquire new customers. Furthermore, strong brands provide advantages such as reduced risk through more persistent and less volatile cash flows (Leone et al., 2006), implying that they impact positively on customer loyalty and, thus, on the retention of new customers. Given this rationale, the proposed framework may also represent the present value of the expected cash flows for segment(s) of customers that are expected to be acquired by the firm for each product category and brand. For this, the acquisition rate may be defined based on the acquisition goals set by marketing managers and potentiated by the investments planned to be spent on the acquisition efforts (Kumar & Shah, 2009) or predicted based on the number of past acquisitions that the firm has obtained.

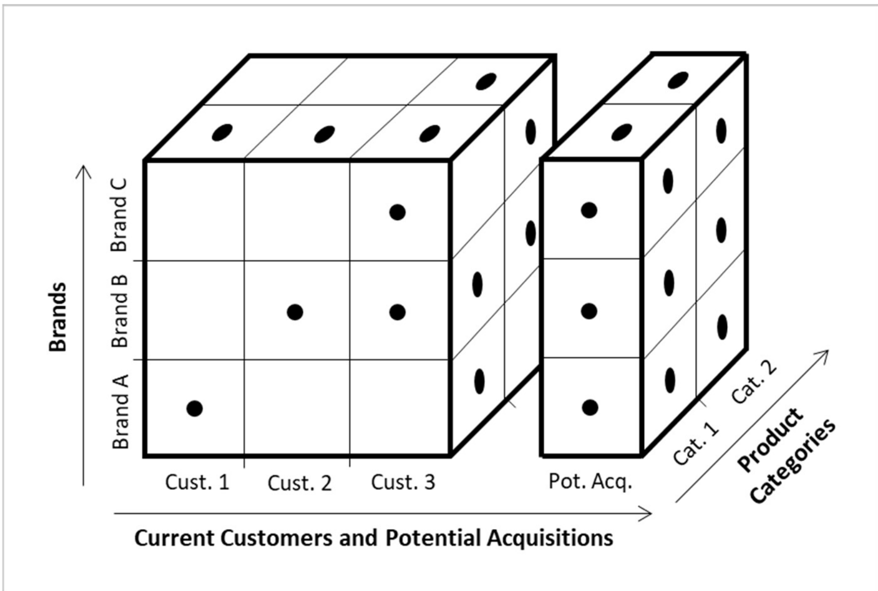

Figure 6. CBP bottom-up approach considering a focal company only
Note. The black dots represent intersections with present values of expected cash flows greater than zero.

6.2. CPB BOTTOM-UP APPROACH CONSIDERING THE ENTIRE MARKET

The proposed framework until this point is considering only the analysis of customer, product category, and brand portfolios from one focal company, so it is not taking competitors into account. By including competitors, it will take the use of the CPB bottom-up approach to a broader and higher level in terms of analysis, once it will allow conclusions about all the considered players in the industry. For it to be possible, data containing customer transactions from different competitors within the same market should be available. One of the main sources of such data is third party scanning panel data provided by companies such as Neogrid, Nielsen, and IRI, whose data has already been used in past research in marketing (Liu, Pancras & Houltz, 2015; Sunder et al., 2016). It contains precise information about customer purchases from different players.

In order to exemplify how the CPB bottom-up approach is enhanced if competitors are also considered, for the sake of simplification, it is assumed that the same market in which company Beta competes has only one more competitor: another hypothetical company called Alfa. It is also assumed that Alfa has only two brands: brand D (in category 1) and brand E (in category 2). Beta and Alfa compete for five customers that represent the whole market and they could be aggregated in customer segments based on their transactional or demographic (firmographic) characteristics (see Figure 7). When the entire market is considered, the expected value of potential acquisitions from a given company standpoint is directly obtained by the estimation of the expected cash flows of potential customers with product categories and brands from competitors.

7. MANAGERIAL IMPLICATIONS

Given the adoption of the proposed framework, in this section, we explore managerial implications that arise when customers, product categories, and brands expected values are linked. Managing these perspectives simultaneously allows companies to organize their efforts around customers and take advantage of the same benefits well documented in extant research on customer centricity, while also being able to manage the performance of product categories and brands in a forward-looking way.

Customer acquisitions and retention efforts. Once the expected value of all existing intersections among these three perspectives are known, there is forward-looking information on

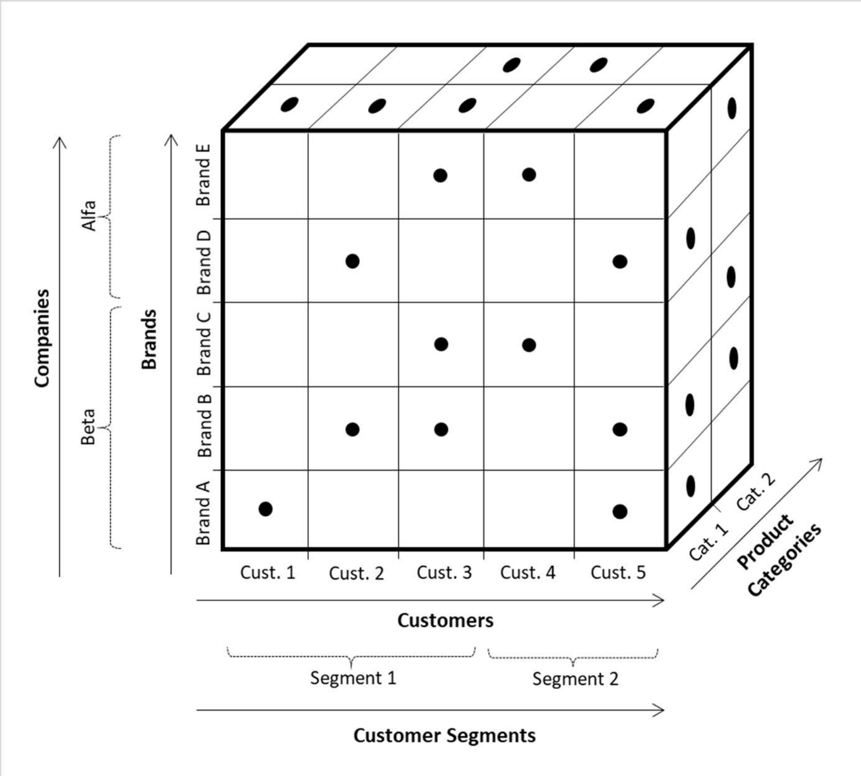

Figure 7. CBP bottom-up approach considering the entire market
Note. The black dots represent intersections with present values of expected cash flows greater than zero.

who are going to be the most valuable customers for each brand and product category. Such result may be used to drive more precise customer acquisition efforts since managers are able to define the profile of the best customers to each brand and category to guide salespeople searching for prospects and planning the product mix that should be offered to them. Likewise, retention efforts may be improved. If a customer is not likely to purchase a given brand or category in the future as it has purchased it in the past, managers or automized customer relationship tools may precisely target this customer with the correct categories or brands when trying to avoid the customer to have a lower value in the future or even defect. Empirically testing the effectiveness of such strategies to generate higher profitability would be relevant for marketing practice.

New product launches and brand extensions. The CPB bottom-up approach also provides forward-looking information on which brands and product categories are the most important ones for the most valuable customers. It may be used to drive brand and product portfolio management. New product launches and brand extensions may be offered firstly for customers who are more likely to purchase that specific product category or brand. Observing the impact on profitability and on the customer's share-of-wallet of adopting such strategies could be addressed by future research.

Removing product categories and brands from the portfolio. The decision to remove a product category or a brand should take into account how important the category or brand is for the most valuable customers. Even though the category or brand may have a low expected value, it may not be a good option to remove it if it is part of the product mix purchased by the most valuable customers. For instance, if a low value category is removed, these customers will probably search for such products in a competitor. By purchasing this from the competitor, these high value customers may also decide to purchase other items of the product mix from this competitor and, eventually, end-up migrating to this competitor.

Product recommendations. Customers that have a lower expected value in certain categories or brands than other customers with the same profile may be targeted with product recommendations in an attempt to increase its value up to the level of their similar peers. Additionally, product recommendations could take into account not only the customer propensity to purchase a given product category, but also the expected value of the recommendation made, estimated based on the CLVs of similar peers for each product category. It allows companies to prioritize cross-selling recommendations based on either which category the customer is more likely to purchase and which category is more likely to increase customer expected profitability.

Personalization of brand communication. By knowing who are the most valuable customers to each of the brands offered, a given company can personalize the experience of these customers in order to reward their patronage. It may involve personalized communications, loyalty rewards, discounts, invitation for the customer to interact with or attend to events related to the brand, and so on. It is expected to strengthen the ties of the customer with the brand, increasing brand loyalty, brand referral, and positive word-of-mouth.

Managing salespeople performance and setting their goals. Once the present values of expected cash flows of the CPB bottom-up approach are estimated, managers may sum the disaggregated cash flows per salesperson responsible to serve each customer to evaluate the expected performance of each salesperson. It allows managers, for instance, to anticipate a drop in the performance of a given salesman. Additionally, once the sum of expected cash flows of the customer, product category, and brand portfolios that the salesperson manages are known, these forward looking indicators may be used to set goals based on the present values that a given salesman is expected to generate out of the customer, product category, and brand portfolios he is responsible for.

Anticipating competitor's evolution within the market. Based on Figure 7, when competitors are considered, it becomes possible to monitor how competition is evolving over time in terms of expected future cash flows for any desired intersection within this broader framework. It would be more robust than using simple measures such as market-share, which takes only current revenues of players into account. Once each intersection contains a forward-looking measure, it is possible to differentiate a company that is consolidating a position, so it is more likely to bring future profits, from a company that is sacrificing future profits for current sales (Rust et al., 2004).

Potential CLV. The estimation of the CPB bottom-up approach for the entire market would also allow a more complete comprehension of customers, because their lifetime values will not only take customers' purchases from only one focal company into account, but also their purchases from other players in the market. This generates the possibility of estimating what may be called potential customer lifetime value. If we use the concept of share-of-wallet, potential CLV would mean estimating the present value of the future cash flows based on a given customer's entire wallet. By using such metric, a manager is able to calculate the share of potential customer lifetime value that its company has, defined as the customer lifetime value for a focal company over the potential customer lifetime value. Therefore, it allows targeting customers with higher probability that such efforts end-up increasing overall profitability, because the focal company knows which customers have high potential customer lifetime value and a low share of potential customer lifetime value. Likewise, retention efforts could be more effective, since managers would be able to identify customers with high potential customer lifetime value and also high share of potential customer lifetime value, which should be the customers prioritized for retention.

8. CONCLUSION

Customers, product categories, and brands have mostly been treated separately in the literature. Moreover, given the importance of adopting a customer orientation in today's dynamic market environment, metrics such as customer lifetime value and customer equity have been strongly recommended in extant research in detriment of product-oriented metrics such as brand equity and product category expected cash flows. Nevertheless, customer, product category, and brand management are tenets of marketing theory and practice as they contribute to one of the most important objectives of marketing: value creation. Additionally, even though companies should indeed organize their efforts around customers, decision-making at the product category and brand levels are still relevant for business success.

Firms create value for customer through investments in products and brands. These processes are enhanced and dynamic practices based on customer needs and wants to create perceived value. It generates positive customer behavior toward products and brands, long-term performance, more successful product line extensions, customer retention and acquisition, word-of-mouth, and so on. Besides impacting product and brand performance, they also influence customer equity.

On the other hand, customer management practices are also important once they deal with the extraction of the customer value created in the form of customer lifetime value. These customer-oriented practices drive firm's long-term success, enable better understanding of the value of each customer, even in large firms with millions of customers, guide marketing resource allocation at the customer level, improve customer retention and acquisition, and so on. Besides contributing to the maximization of customer equity, they also influence product category and brand performance.

In this sense, the objective of value creation is only one and customer, product category, and brand management ultimately contribute to achieving such objective. Therefore, instead of managing such perspectives separately, companies should manage them together to more precisely drive marketing efforts to maximize company's profitability. We incentivize future research on the subject to develop methods to empirically apply the proposed framework and validate the managerial implications aforementioned.

REFERENCES

Aaker, D. A. (1991). *Managing Brand Equity: Capitalizing on the value of a brand*. New York: The Free Press.

Aaker, D. A. (1996). *Building Strong Brands*. New York: The Free Press.

Ailawadi, K. L., Lehmann, D. R., & Neslin, S. A. (2003). Revenue premium as an outcome measure of brand equity. *Journal of Marketing*, *67*, 1-17.

Akbar, H., & Tzokas, N. (2013). Charting the organisational knowledge-creation process: An innovation-process perspective. *Journal of Marketing Management*, *29*(13–14), 1592-1608.

Anderson, J. (2011). Measuring the financial value of brand equity: the perpetuity perspective. *Journal of Business Administration Online, 10*(1), 1-11.

Atilgan, E., Akinci, S., Aksoy, S., & Kaynak, E. (2009). Customer-Based Brand Equity for Global Brands: A Multinational Approach. *Journal of Euromarketing*, *18*, 115-132.

Ambler, T., Bhattacharya, C. B., Edell, J., Keller, K. L., Lemon, K. N., & Mittal, V. (2002). Relating Brand and Customer Perspectives on Marketing Management. *Journal of Service Research*, *5*(1), 13-25.

Bahadir, S. C., Bharadwaj, S. G., & Srivastava, R. K. (2008). Financial value of brands in mergers and acquisitions: is value in the eye of the beholder? *Journal of Marketing, 72*(6), 49-64.

Bello, D. C., & Holbrook, M. B. (1995). Does an absence of brand equity generalize across product classes? *Journal of Business Research, 34*(2), 125-131.

Berger, P. D., & Nasr. N. (1998). Customer Lifetime Value: Marketing models and applications. *Journal Interactive Marketing*, *12*(1), 17-30.

Blattberg, R. C., & Deighton, J. (1996). Manage marketing by the customer equity test. *Harvard Business Review*, *74*(4), 136.

Blattberg, R. C., Getz, G., & Thomas, J. S. (2001). *Customer Equity: Building and Managing Relationships as Valuable Assets*. Boston: Harvard Business School Press.

Buil, I., De Chernatony, L., & Martínez, E. (2013). Examining the role of advertising and sales promotions in brand equity creation. *Journal of Business Research*, *66*, 115-122.

Burmann, C., Jost-Benz, M., & Riley, N. (2009). Towards an identity-based brand equity model. *Journal of Business Research*, *62*(3), 390-397.

Carrol, W. J., & Grimes, R. C. (1995). Evolutionary Change in Product Management: Experiences in the Car Rental Industry. *Interfaces*, *25*(5), 84-104.

Christodoulides, G., & De Chernatony, L. (2010). Consumer-based brand equity conceptualization and measurement: a literature review. *International Journal of Market Research*, *52*(1), 43-66.

Ding, Y., DeSarbo, W. S., Hanssens, D. M., Jedidi, K., Lynch, J. G. Jr., & Lehmann, D. R. (2020). The past, present, and future of measurement and methods in marketing analysis. *Marketing Letters*. June.

Fader, P. S., Hardie, B. G., & Lee, K. L. (2005). Counting your customers the easy way: an alternative to the Pareto/NBD model. *Marketing Science*, *24*(2), 275-284.

Fader, P. S., Hardie, B. G., & Shang, J. (2010). Customer-base analysis in a discrete-time noncontractual setting. *Marketing Science*, *29*(6), 1086-1108.

Farquhar, P. (1989). Managing Brand Equity. *Marketing Research*, *1*(September), 24-33.

Figueiredo, P. S., Travassos, X. L., & Loiola, E. (2015). The Effect of Longer Development Times on Product Pipeline Management Performance. *Revista de Administração Contemporânea*, *19*(4), 461-485.

Forza, C., & Salvador, F. (2008). Application support to product variety management. *International Journal of Production Research*, *46*(3), 817-836.

Grieves, M. (2006). *Product Lifecycle Management: Driving the Next Generation of Lean Thinking*. New York: McGraw Hill.

Gupta, S., & Lehmann, D. R. (2006). Customer Lifetime Value and Firm Valuation. *Journal of Relationship Marketing*, *5*(2/3), 87-110.

Gupta, S., Lehmann, D. R., & Stuart, J. A. (2004). Valuing customers. *Journal of Marketing Research*, *41*(1), 7-18.

Haigh, D. (1999). Understanding the Financial Value of Brands. European Association of Advertising *Agencies*, Brussels.

Hogan, J. E., Lemon, K. N., & Rust, R. T. (2002). Customer equity management charting new directions for the future of marketing. *Journal of Service Research*, *5*(1), 4-12.

Holbrook, M. B. (1992). Product quality, attributes, and brand name as determinants of price: The case of consumer electronics. *Marketing Letter*, *3*(1), 71-83.

International Organization for Standardization (ISO) (2010). *ISO 10668: Brand valuation - Requirements for monetary brand valuation*. Geneva.

Joo, S., & Choi, H. P. (2015). Assessing comparative production efficiencies for product line management. *International Journal of Production Research*, *53*(17), 5241-5250.

Kapferer, J. N. (2008). *The new strategic brand management: creating and sustaining brand equity long term*. 4ed. London: Kogan Page.

Kartono, B., & Rao, V. R. (2005). Linking consumer-based brand equity to market performance: An integrated approach to brand equity management. *ZIBS technical report*. Emory.

Kamakura, W. A., & Russell, G. J. (1993). Measuring brand value with scanner data. *International Journal of Research in Marketing*, *10*, 9-22.

Keller, K. L. (2013). *Strategic brand management: building, measuring and managing brand equity*. 4ed. Edinburgh: Pearson Education.

Keller, K. L., & Lehmann, D. R. (2006). Brands and Branding: Research Findings and Future Priorities. *Marketing Science*, *25*(6), 740-759.

Kumar, V., & Reinartz, W. (2016). Creating Enduring Customer Value. *Journal of Marketing*. *80*(6), 36-68.

Kumar, V., Lemon, K. N., & Parasuraman, A. (2006). Managing Customers for Value: An Overview and Research Agenda. *Journal of Service Research*, *9*(2), 87-94.

Kumar, V., & Shah, D. (2009). Expanding the Role of Marketing: From Customer Equity to Market Capitalization. *Journal of Marketing*, *73*(6), 119-136.

Kumar, V., Venkatesan, R., Bohling, T., & Beckmann, D. (2008). The Power of CLV: Managing Customer Value at IBM. *Marketing Science*, *27*(4), 585-599.

Lee, J.-Y., Kozlenkova, I. V., & Palmatier, R. W. (2015). Structural marketing: Using organizational structure to achieve marketing objectives. *Journal of the Academy of Marketing Science*, *43*(1), 73–99.

Lehmann, D. R., & Srinivasan, S. (2014). Assessing Brand Equity Through Add-on Sales. *Customer Needs and Solutions, 1*(1), 68–76.

Leone, R. P., Rao, V. R., Keller, K. L., Luo, A. M., Mcalister, L., & Srivastava, R. (2006). Linking brand equity to customer equity. *Journal of Service Research*, *9*(2), 125-138.

Leuthesser, L. (1988). Defining, Measuring, and Managing Brand Equity: *Conference Summary*. Marketing Science Institute. Cambridge, MA, MSI Report 2, 88-104.

Libai, B., Narayandas, D., & Humby, C. (2002). Toward an individual customer profitability model: A segment-based approach. *Journal of service Research, 5*(1), 69-76.

Liu, H., Pancras, J., & Houtz, M. (2015). Managing customer acquisition risk using co-operative databases. *Journal of Interactive Marketing*, 29, 39-56.

Ma, S., Fildes, R., & Huang, T. (2016). Demand forecasting with high dimensional data: the case of SKU retail sales forecasting with intra-and inter-category promotional information. *European Journal of Operational Research*, *249*(1), 245-257.

Netemeyer, R.G., Krishnan, B., Pullig, C., Wang, G., Yagci, M., Dean, D., Ricks, J., & Wirth, F. (2004). Developing and validating measures of facets of customer-based brand equity. *Journal of Business Research*, *57*, 209-224.

Oliveira, M. O. R., Silveira, C. S., & Luce, F. B. (2015). Brand equity estimation model. *Journal of Business Research*, *68*, 2560-2568.

Papinniemi, J., Hannola, L., & Maletz, M. (2014). Challenges in integrating requirements management with PLM. *International Journal of Production Research*, *52*(15), 4412-4423.

Park, C. S., & Srinivasan, V. (1994). A survey-based method for measuring and understanding brand equity and its extendibility. *Journal of Marketing Research*, *31*(2), 271-288.

Pfeifer, P. E., & Carraway, R. L. (2000). Modeling customer relationships as markov chains. *Journal of Interactive Marketing*, *14*(2), 43-55.

Randall, T., Ulrich, K., & Reibstein, D. (1998). Brand equity and vertical product line extent. *Marketing Science*, *17*(4), 356-379.

Rust, R. T., Lemon, K. N., & Zeithaml, V. A. (2004). Return on marketing: using customer equity to focus marketing strategy. *Journal of Marketing*, *68*, 109-120.

Rust, R. T.; Kumar, V.; Venkatesan, R. (2011). Will the Frog Change into a Prince? Predicting Future Customer Profitability. *International Journal of Research in Marketing*, *28*(4), 281–294.

Schmittlein, D. C., & Peterson, R. A. (1994). Customer Base Analysis: An Industrial Purchase Process Application. *Marketing Science*, *13*(1), 41-67.

Shankar, V., Azar, P., & Fuller, M. (2008). Bran*eqt: A model and simulator for estimating, tracking, and managing multicategory brand equity. *Marketing Science*, *27*(4), 567-584.

Simon, C., & Sullivan, M. W. (1993). The measurement and determinants of brand equity: A financial approach. *Marketing Science*, *12*(1), 28-52.

Sriram, S., Balachander, S., & Kalwani, M. U. (2007). Monitoring the Dynamics of Brand Equity Using Store-Level Data. *Journal of Marketing*, *71*(2), 61-78.

Stahl, F., Heitmann, M., Lehmann, D. R., & Neslin, S. A. (2012). The Impact of Brand Equity on Customer Acquisition, Retention, and Profit Margin. *Journal of Marketing*, *76*(4), 44-63.

Sunder, S., Kumar, V., & Zhao, Y. (2016). Measuring the Lifetime Value of a Customer in the Consumer Packaged Goods Industry. *Journal of Marketing Research*, *53*(6), 901-921.

Trent, L., Mohr, J. (2017). Marketers' methodologies for valuing brand equity: insights into accounting for intangible assets. *The CPA Journal*, July, 58-61.

Tong, X., & Hawley, J. M. (2009). Measuring customer-based brand equity: Empirical evidence from the sportswear market in China. *Journal of Product & Brand Management*, *18*(4), 262-271.

Vargo, S. L., & Lusch, R. F. (2004). Evolving to a New Dominant Logic for Marketing. *Journal of Marketing*. *68*(1), 1-17.

Villanueva, J., & Hanssens, D. M. (2007). *Customer equity: measurement, management and research opportunities*. Hanover: Now Publishers Inc.

Wu, Z.Y., Ming, X.G., Wang, Y.L., & Wang, L. (2014). Technology solutions for product lifecycle knowledge management: framework and a case study. *International Journal of Production Research*, *52*(21), 6314-6334.

Yoo, B., & Donthu, N. (2001). Developing and validating a multidimensional consumer-based brand equity scale. *Journal of Business Research*, *52*(1), 1-14.

Zhang, Y., Bradlow, E. T., & Small, D. S. (2015). Predicting customer value using clumpiness: From RFM to RFMC. *Marketing Science*, 34, 195–208.

UNIVERSIDADE FEDERAL DO RIO GRANDE DO SUL
ESCOLA DE ADMINISTRAÇÃO
DEPARTAMENTO DE CIÊNCIAS ADMINISTRATIVAS
PROGRAMA DE PÓS-GRADUAÇÃO EM ADMINISTRAÇÃO

RODRIGO HELDT

PhD DISSERTATION

BOTTOM-UP APPROACH TO MANAGE CUSTOMERS, PRODUCT CATEGORIES, AND BRANDS SIMULTANEOUSLY

PAPER 2:

PREDICTING CUSTOMER VALUE PER PRODUCT: FROM RFM TO RFM/P[1234]

Porto Alegre
2020

[1] Paper initially published in the Business Association for Latin American Studies (BALAS) Conference Proceedings 2017.

[2] Paper received the Luiz Sanz Best Student Paper Award at the Business Association of Latin American Studies (BALAS) Conference 2017

[3] Paper published in the Journal of Business Research, ISSN: 0148-2963.
DOI: https://doi.org/10.1016/j.jbusres.2019.05.001

[4] Co-authors: Cleo Schmitt Silveira and Fernando Bins Luce

ABSTRACT

Recency, frequency, and monetary (RFM) models are widely used to estimate customer value. However, they are based on the customer perspective and do not take the product perspective into account. Furthermore, predictability decreases when recency, frequency, and monetary values vary among product categories. A RFM per product (RFM/P) model is proposed to first estimate customer values per product and then aggregate them to obtain the overall customer value. Empirical applications for a financial services company and a supermarket demonstrate that RFM/P opens up the possibility to combine customer and product perspectives. Additionally, when there are changes in customer purchase behavior regarding recency per product and frequency per product, which is usual, RFM/P prediction accuracy was found to be better than traditional RFM.

Keywords: customer lifetime value; CLV; RFM; customer base analysis; product orientation; customer orientation

RESUMO

Modelos de Recência, Frequência e Valor Monetário (RFM) são amplamente utilizados para estimar o valor do cliente. No entanto, eles são baseados na perspectiva do cliente e não consideram a perspective do produto. Além disso, a acurácia preditiva reduz quando recência, frequência e valores monetários variam entre as categorias de produtos. Um modelo RFM por produto (RFM/P) é proposto para primeiro estimar os valores dos clientes por produto e, então, agregar eles para obter o valor total do cliente. Aplicações empíricas em uma empresa de serviços financeiros e em um supermercado demonstram que o RFM/P abre a possibilidade de combinar as perspectivas de clientes e de produto. Adicionalmente, quando há mudanças no comportamento de compra do cliente relacionado à recência e à frequência por produto, o que é usual, a acurácia preditiva do RFM/P foi maior do que o tradicional modelo RFM.

Palavras-chave: *customer lifetime value*; CLV; RFM; análise da base de clientes; orientação para produto; orientação para cliente.

FIGURES

TABLES

TABLE OF CONTENTS

1. INTRODUCTION

The growing availability of customer transaction data has enabled marketing managers to better understand the customer base of a firm. Despite a number of improvements in data collection in recent years, data analysis remains a challenge for companies. Executives and academics are committed to building a data analytics orientation capable of connecting customer and competitor data to marketing strategies (Venkatesan, 2016). This analytical process consists of extracting useful information from a huge amount of data, including unstructured data. In this sense, the first step is to determine whether the available data has already been fully exploited by the firm before spending efforts to collect even more data.

In addition, advances in technology have driven other changes in marketing management, such as shifts in perspectives from transaction to relationship with customers and from product-centric to customer-centric marketing strategies. This evolution has led to the emergence of key marketing metrics, such as brand equity and customer equity (measured as a sum of customer lifetime values), since they are more appropriate for contemporary marketing management orientation, which is also concerned with the intangible assets and long-term investment returns of companies. Adopting 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 branded products. On the other hand, in line with the customer-centric perspective, customer lifetime value (CLV) is the net present value of a given customer based on his/her future transactions with the company (Kumar & Reinartz, 2016).

Both perspectives can affect in different ways the capacity of a firm to grow, although there is overlap in some areas. The product-centric focus appears to enable companies to extend their product portfolio and acquire new customers in new markets. In turn, the customer-centric focus enables firms to retain and increase the earnings of current offerings from their customer portfolio (Ambler et al., 2002). Hence, the importance given to brand equity and customer equity (and CLV) has increased both in academia and practice.

There is a diverse and rich variety of CLV models in marketing literature (Kumar & Reinartz, 2016; Zhang, Bradlow, & Small, 2015). Among these approaches, CLV models based on recency-frequency monetary value (RFM) segmentation remain an important alternative, which is mostly because they require few variables to predict customer value[5] and are easy to implement (Fader & Hardie, 2009). Recently, Zhang et al. (2015) proposed an extension to these CLV models based on RFM that includes a new variable called clumpiness, which improves prediction power when compared to traditional RFM estimations in contexts that present excessive buying behaviors. Despite being a valuable extension, it continues to only address the customer perspective, a characteristic of traditional RFM models, in the sense that the estimation of customer value does not take into account the product perspective. Furthermore, given the existence of variability in recency, frequency, and monetary values among product categories, the prediction power of RFM models decreases.

Inspired by the challenge to solve these issues and summarize customer data into useful information for marketing managers, we propose a new approach to predict customer value based on an RFM per product model (RFM/P). This alternative consists of integrating the product and customer marketing perspectives by combining them to provide a more complete overview of the future cash flow of a firm. In this model, the customer values are first estimated for each product

[5] We adopted the term customer value as we understand it is more appropriate for both disaggregated (per product) and aggregated estimations. Therefore, in the aggregated context, the term customer value is used interchangeably with CLV.

(or product category) and then aggregated to obtain the overall customer value. In this manner, there is no need to choose between the product and customer perspectives.

In the remainder 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. Empirical validation of RFM/P was performed in two companies from different industries: a financial services company and a supermarket. In the analysis, the proposed RFM/P is compared with the traditional RFM model in terms of predictability of future customer value. We also suggest valuable data visualization alternatives that are made possible when RFM/P is implemented. Finally, the conclusions, limitations of the study, and suggestions for future research are presented.

2. PRODUCT AND CUSTOMER PERSPECTIVES AS SOURCES OF VALUE

Over the last few decades, firms have become more customer-centric, adding a customer perspective to the analysis of expected revenues, which had been previously predicted solely from expected product sales. Although this new perspective is very relevant, the previous perspective of product-orientation should not be forgotten. Even though a customer-centric orientation is relevant, companies still need products to satisfy their customers. In most cases, managers will want to make evaluations and decisions based on both perspectives: products (along with their 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 of both will most often be greater than either alone." Despite the importance of product and customer perspectives for managers, marketing metrics for each of them are mostly independently developed and there is rarely acknowledgment that one affects the other (Gupta et al., 2006). Shah, Rust, Parasuraman, Staelin, and Day (2006), for instance, suggested that companies should shift from product centricity to customer centricity. Among other proposed changes in management paradigms, this would mean managing customer portfolios instead of product portfolios. Even though the relevance of managing customer portfolios is undeniable, branded product portfolios also have to be managed by marketers.

For Kumar and Reinartz (2016), a successful firm has to create or co-create (Vargo & Lusch, 2004) perceived value for/with customers through the development of products and brands. Its customers, in response, provide value to the firm. Peppers and Rogers (2005) argued that relevant long-term marketing metrics for products and customers – brand equity and customer equity – are understood “simply as two different lenses, each of which can provide different insights into how a company creates value.” For Leone et al. (2006), both perspectives matter – the branded products are sold to customers and customers buy them. Thus, the insights from performing product and customer analysis together will probably be better than those gained from separate analysis. The expected total cash flow from products must be a good proxy for the expected total cash flow from customers and vice-versa. Therefore, matching products with profitable customers, such as in Table 1, will help companies to efficiently manage their marketing assets. It is important to clarify that the aim of this paper is not to empower companies to conduct one-to-one cross-selling recommendations for customers (e.g. Kamakura, Ramaswami, & Srivastava, 1991; Li, Sun, & Wilcox, 2005), but provide a global assessment that enables companies to adopt integrated strategies for product and customer management.

Strategies usually adopted by firms to maximize customer equity are known as add-on selling and consist of increasing sales as a result of offering other products to their customers, more expensive (upgraded) products or a larger quantity of the same product (Villanueva & Hanssens,

Table 1. Customer and product portfolio

	Product 1	Product 2	Product n	Product Portfolio
Customer 1				
Customer 2				
Customer n				
Customer Portfolio				Total Expected Revenue

2007). Despite this common practice to increase the amount of money spent by customers, many CLV models do not capture it since they assume that the average revenue for an individual customer is stationary, so it does not vary over time (Villanueva & Hanssens, 2007). To deal with it, our suggestion is to compute the expected customer value separately per product (or product category) and then aggregate the values to estimate the CLV. The disaggregated analysis will open up the possibility to consider changes in customer purchase behavior, since the model will assume a stationary average margin per product, which, together with the probability of buying that product, can predict differences in the total customer 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 interpurchase times and recency among products. The data necessary to compute CLV, as in the traditional RFM model, is available in most companies that record customers purchase history: recency, frequency, and monetary value per 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 increased sales due to increased quantities of the same product.

Given that, we will present one hypothetical situation of a customer purchase history to illustrate changes in the average revenue and differences in the interpurchase times among products that can be addressed by splitting the estimation of customer value per product using

RFM models. These models are based on some sufficient statistics – recency, frequency, and monetary value – that are useful for predicting customer transaction behavior. Note that the order of the variables – RFM – represents their discriminating power and, consequently, the importance for CLV estimation (Hughes, 2006; Fader, Hardie, & Lee, 2005b). Additionally, it is important to consider that most RFM models assume an individual stationary average transaction contribution margin. Our suggestion, however, assumes an individual stationary average transaction contribution margin per product.

A hypothetical example is presented in Figure 1, in which the circles indicate the occurrence of purchases and their size represents the amount of contribution margin. The customer made purchases in all time periods. He/she started buying product 1 and, 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, the aggregated model will not capture the up-selling process and underestimate the customer value. This will occur due to the impact of recency and frequency on model estimation and assumption of a stationary average contribution margin. Therefore, as the customer continued to buy in the same frequency, the probability of being alive will be high in the aggregated model. However, if we use a disaggregated model per product, the increased recency for product 1 will result in a low purchase probability of this product. On the other hand, as the customer started to buy product 2, the likelihood of continuing to buy this product is expected to be high. Regarding the contribution margin, product 2 provides a higher value than product 1. In this case, the aggregated model is likely to predict a high purchasing probability with a contribution margin below the actual value. Notwithstanding, the disaggregated model is likely to predict a low purchasing probability with a low contribution margin for product 1, in addition to a high purchasing probability with a high and more precise contribution margin for product 2, which results in more accurate estimations.

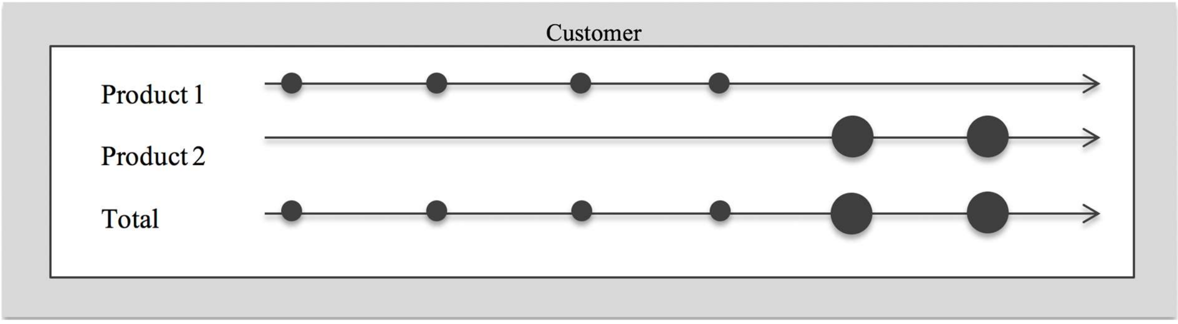

Figure 1. Example of customer transaction data

Therefore, we argue that computing the expected customer value separately per product and then aggregating the values to estimate the CLV will allow analysts to better predict customer value and identify key products for valuable customers. This will enable managers to have a more complete overview of the future cash flows of the company. Additionally, it will be possible to evaluate the dependence of cash flow and the risk associated to certain products and customers. Predicting customer value per product enables firms to find the answer to relevant questions such as: Given that the customer is going to repurchase, what are the products he/she is likely to repurchase?

3. PRODUCT PERFORMANCE ANALYSIS

Traditionally, managers analyze product sales revenue and profitability to make decisions regarding which products should be kept in the market and which should be replaced. Product sales forecast approaches, such as time series analysis, causal models (Stadtler, Kilger, & Meyr, 2015), and monitoring product market share over time (Bendle, Farris, Pfeifer, & Reibstein, 2016) are commonly used to accomplish such objective.

According to Rust, Zeithaml, and Lemon (2000), the profitable product paradigm consists of estimating and measuring product profitability, determining the minimum acceptable level of profitability of the firm, and eliminating the ones below this threshold. However, in contemporary companies that are based on service and aim to build relationships with their customers, products can be replaced, but customers should remain. As a consequence of this new scenario, Rust, Lemon, and Zeithaml (2004) argued in favor of a new metric that focuses on customers: customer equity share. It is a similar metric when compared to market share, however, instead of focusing on products and considering past sales revenue, it focuses on customers and is based on the firm customer equity percentage regarding the total market customer equity. According to these authors, customer equity share differs from market share because it considers the expected sales revenue and not historical sales, therefore, it allows managers to identify the most competitive companies in the future, not in the past.

This shift of focus from product management to customer-centric management reflects the increasing importance of building long-term relationships with customers for firms to succeed in the market. Managers that adopt an exclusive product perspective can lead companies to a common mistake known as death spiral (Rust et al., 2000), which occurs when managers make decisions based solely on product profitability analysis. As a result, if a product has a high market share and is profitable, it will likely be kept in the market and deserve more attention from managers. The opposite happens if a product has low market share and is not profitable: it will likely be removed from the market. The decision to keep products in the company product mix is based on profitability and market share. Thus, customer needs are not taken into at all, which may have serious implications for the firm.

Suppose that a product that is not profitable is essential to a high profitability customer segment. Even though such customers do not buy significant quantities of the product, they desire it. If the company discontinues this product, it is possible that these customers will look for it in another competitor and may become their customers. Consequently, the firm may lose money as the managers incorrectly decided to discontinue an important yet unprofitable product. Customers do not usually choose products in an isolated manner, but buy an assortment of products from a company, as a result, managers should analyze products and customer profitability in a combined way.

4. RFM/P MODEL

In order to demonstrate our proposal for integrating customer and product perspectives by computing the expected customer value in the disaggregated form represented in Table 1, we selected BG/NBD and BG/BB as representatives of CLV models based on RFM segmentation and compared the results between the aggregated and disaggregated estimations. The general CLV formula is defined in Equation 1 (Rosset, Neumann, Eick, & Vatnik, 2003):

$$E(CLV) = \int_0^\infty E[v(t)]\, S(t)\, d(t)\, dt, \qquad (1)$$

where $E[v(t)]$ is the expected value of the customer 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, the expected value of the customer

$(v(t))$ can be expressed as the product of the expected contribution margin per transaction (m) and expected number of transactions $(z(t))$. Thus, it is possible to rewrite Equation 1 as follows:

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

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 our suggestion consists of estimating customer value per product (or product category) and assuming that the products are independent of each other, Equation (1) is modified to:

$$E(CLV) = \sum_{p=1}^{P} E\left[m_p\right] \int_0^{\infty} E\left[z_p(t)\right] S_p(t)\, d(t)\, dt, \qquad (3)$$

where $E\left[m_p\right]$ is the expected contribution margin per transaction per product p, $E\left[z_p(t)\right]$ is the expected number of purchases of product p in period t, $S_p(t)$ 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.

Based on the BG/NBD model (Fader et al., 2005b), the expected number of transactions in a future period of length t for a customer with past observed behavior $(X_p = x_p, tx_p, T_p)$ for product p is:

$$E\left[Y_p(t)|X_p = x_p, tx_p, T_p, r_p, \alpha_p, a_p, b_p\right] = \frac{a_p + b_p + x_p - 1}{a_p - 1} \times$$

$$\frac{\left[1 - \left(\frac{\alpha_p + T_p}{\alpha_p + T_p + t}\right)^{r_p + x_p} {}_2F_1\left(r_p + x_p, b_p + x_p; a_p + b_p + x_p - 1; \frac{t}{\alpha_p + T_p + t}\right)\right]}{1 + \delta_{x_p > 0} \frac{a_p}{b_p + x_p - 1}\left(\frac{\alpha_p + T_p}{\alpha_p + tx_p}\right)^{r_p + x_p}}, \quad (4)$$

where r_p, α_p, a_p, b_p are BG/NBD parameters per product p, X_p represents the purchase history (x_p, tx_p, T_p) per product p, x_p is the number of transactions, tx_p is the time of the last transaction (recency), T_p is the length of the calibration time period, and ${}_2F_1(\cdot)$ is the Gaussian hypergeometric function.

Furthermore, based on the BG/BB model (Fader, Hardie, & Shang, 2010), the expected number of future transactions for product p across the next n^* transaction opportunities by a customer with purchase history (x_p, tx_p, n_p) is:

$$E\left[Y_p\left(n_p, n_p + n_p^*\right)|\alpha_p, \beta_p, \gamma_p, \delta_p, x_p, tx_p, n_p\right] =$$

$$\frac{1}{L\left(\alpha_p,\ \beta_p,\ \gamma_p,\ \delta_p\middle|x_p,\ tx_p,\ n_p\right)} \frac{B\left(\alpha_p\ +\ x_p\ +\ 1,\ \ \beta_p\ +\ n_p\ +\ x_p\right)}{B\left(\alpha_p,\ \ \beta_p\right)} \times \quad (5)$$

$$\left(\frac{\delta_p}{\gamma_p - 1}\right) \frac{\Gamma(\gamma_p + \delta_p)}{\Gamma(1 + \delta_p)} \cdot \left\{\frac{\Gamma(1 + \delta_p + n_p)}{\Gamma(\gamma_p + \delta_p + n_p)} - \frac{\Gamma(1 + \delta_p + n_p + n_p^*)}{\Gamma(\gamma_p + \delta_p + n_p + n_p^*)}\right\},$$

where $\alpha_p, \beta_p, \gamma_p, \delta_p$ are BG/BB parameters per product p, the purchase history per product p is represented by (x_p, tx_p, n_p), x_p is the number of transactions, tx_p is the transaction opportunity at which the last observed transaction occurred (recency), n_p is the number of transaction opportunities, and n_p^* is the number of future transaction opportunities per product p.

Regarding the expected contribution margin per transaction per product, $E\left[m_p\right]$, Fader, Hardie, and Lee (2005a) suggested that the expected contribution margin per transaction follows a gamma-gamma distribution, resulting in a weighted average between the population mean, $\frac{\gamma_p \nu_p}{q_p - 1}$, and the customer transaction value mean per product, mx_p:

$$E\left[M_p | \nu_p, q_p, \gamma_p, mx_p, x_p\right] = \left(\frac{q_p - 1}{\nu_p x_p + q_p - 1}\right) \frac{\gamma_p \nu_p}{q_p - 1} + \left(\frac{\nu_p x_p}{\nu_p x_p + q_p - 1}\right) mx_p \ , \tag{6}$$

where ν_p, q_p, γ_p are parameters of the transaction value model per product p, x_p is the number of transactions per product p, and mx_p is the observed average customer transaction value per product p. 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 where the time to "drop out" is modeled using the BG (beta-geometric mixture) timing model, which is similar to the Pareto (exponential-gamma mixture) timing model, however 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 "randomly" purchases around his/her (time-invariant) mean transaction rate, which is characterized by the Poisson distribution, and that heterogeneity in the transaction rate across customers follows a gamma distribution. The latter assumes that the customer purchase history can be expressed as a binary string that follows a beta-Bernoulli distribution, being more adequate for companies whose transactions can only occur at fixed regular intervals or are related to specific events or when transaction data are reported in this way. Therefore, model selection depends on the situation and data availability.

5. EMPIRICAL APPLICATION

In order to validate the proposed model, we implemented it in multiple datasets from two companies operating in different industries. The first is a large financial services company with national operations and the second is a medium-sized supermarket with regional operations. The data contains, among other variables, all of their customer transactions per product category. Analyses were conducted for four samples based on two cohorts extracted from each dataset. Cohorts 1 and 2 from the financial services company and 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.

Each sample was divided into calibration and holdout subsamples. The models were estimated for the calibration subsamples using the software R based on the aforementioned BG/NBD or BG/BB models. For the proposed disaggregated model (RFM/P) estimation, one model should be adjusted for each product category considered, whereas for the aggregated model (traditional RFM) estimation, only one model for the overall values of transactions should be adjusted.

Given the need to check the predicted purchase frequencies and customer values against the actual purchase frequencies and customer values to compare the performance of the aggregated estimation with that of the proposed disaggregated model (RFM/P), we restricted the validation period of the expected customer values to six months. In order to check the estimation precision of each customer purchase frequency and customer value, we used six measures organized into three domains: (1) predicting the individual – frequency and CLV – level, (2) predicting the individual – frequency and CLV – ordering, and (3) valuing the customer base. To analyze how well each model predicted the individual level, we used mean absolute error (MAE), median absolute error (MDAE), root mean squared error (RMSE), and Pearson Correlation. To analyze how well each model predicted the ordering, we used Spearman correlation. Finally, to analyze how well each model predicted the customer base value, the summation of CLVs of all customers analyzed, we used the percentage of deviation between the predicted and actual value.

In this section, we first describe each dataset used. Then, we use a customer transaction history we chose to explain the rationale behind RFM/P by exemplifying one of the possible scenarios that leads to better prediction precision by using RFM/P. Finally, we present the results and analysis of the estimation of purchase frequencies and customer values for the validation period for both the financial services company and the supermarket.

5.1. DATASETS

5.1.1. Financial services company

The dataset from the financial services company contains 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 that month for each product category. The dataset has a transaction history of approximately 90 K customers during 28 months (divided into 22 months for model calibration and 6 months for model validation).

The product categories considered for the financial services company were based on the product segmentation currently used by company. There are three product categories that are related to the type of investment made by each customer. Because the company required that the name of the product categories remain anonymous, we named them products 1, 2, and 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. In addition, the customers have more unstable purchasing behavior across product categories, meaning that they vary in recency, frequency, and monetary values among product categories.

Since the transaction data was available in binary information, the BG/BB model was chosen. In the disaggregated model, the expected number of future transactions for the validation period was estimated based on Equation 5 and the expected contribution margin per transaction was estimated based on Equation 6.

5.1.2. Supermarket

The dataset from the supermarket contains the full transaction history with every purchase made by each customer for each product category. The dataset has a transaction history of approximately 3 K customers during 22 months (16 months for model calibration and 6 months for model validation). It comprises only customers who are part of the supermarket loyalty program. Therefore, this dataset has the particular characteristic that customer purchasing behavior does not vary much among product categories. This situation contrasts the financial services company and we, therefore, decided to verify the performance of the proposed disaggregated RFM/P model in this 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. 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, the BG/NBD model was chosen. In the disaggregated model, the expected number of future transactions for the validation period was estimated based on Equation 4 and the expected contribution margin per transaction was estimated based on Equation 6.

5.2. RATIONALE BEHIND RFM/P

In order to explain the rationale behind our proposed RFM/P model, we chose a specific customer purchasing history that demonstrates why it is important to consider the customer purchasing behavior of each product category instead of using only the aggregated transaction history. Demonstrating a behavior similar to the one in Figure 1, the customer transaction history presented in Figure 2 is from the financial services company. The first three lines represent the customer purchases of products 1, 2, and 3. The fourth line represents the aggregated purchasing history, summing up the three product categories. Again, the size of the circles represents the contribution margin of each purchase and this monetary value is also shown right above each circle. Figure 2 shows how customer behavior may differ across product categories and how this may influence the precision of RFM prediction.

Regarding the amount of months with transaction x, the recency value tx, and the amount of transaction opportunities n from Equation 5, if only the aggregated binary transaction history of this customer (the line "Total" in Figure 2) is considered and the first month with transactions is removed, the values x = 15, tx = 17, and n = 19 are obtained. In addition, the customer average contribution margin is approximately $307. Therefore, the estimated value of this customer for the validation period is $421.

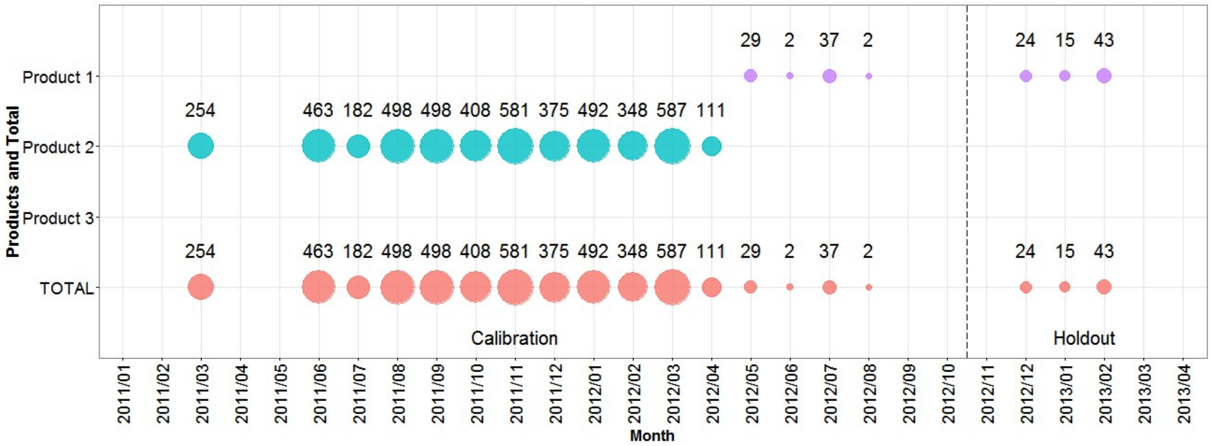

Figure 2. Example of aggregated (Total) and disaggregated (Products 1, 2, and 3) transaction history of a given financial services company customer

In turn, based on the proposed disaggregated estimation (RFM/P), once we take into account the binary transaction history of this customer for each product category (product 1, 2, and 3 in Figure 2) and remove the first month with transactions, the following values of x, tx, and n for each product category are obtained: product 1 (x = 3, tx = 3, n = 5), product 2 (x = 11, tx = 13, n = 19), and product 3 does not have any month with transaction. In terms of customer average contribution margin per product category, the values are: product 1 ($41), product 2 ($413), and product 3 does not have any month with transaction. Here, it is possible to reduce the influence of the relatively high customer average contribution margin of product 2 since its transaction history has a recency of only 13 out of 19 transaction opportunities and, thus, the probability that the customer will buy product 2 again is very low. As a result, the estimated value of this customer for the validation period based on the disaggregated model is $23.

In the validation period, the actual value of this customer was $82. This 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 of improving aggregated RFM estimation precision.

5.3. MODEL VALIDATION – FINANCIAL SERVICES COMPANY

In order to test the consistency of our results, the analysis was conducted using two different customer cohorts, named cohort 1 and cohort 2. The precision of predicted purchase frequencies and customer values from the financial services company for the validation period are presented in Tables 2 and 3, respectively. The Web Appendix provides details for the evaluation of predicted purchase frequencies per product category. The results of Table 2 show that when the disaggregated RFM/P model is used, all of the five measures of purchase frequency prediction accuracy were slightly improved in comparison to the results of the aggregated RFM model. Concerning the analysis of customer value predictions, the results of Table 3 show that when the disaggregated RFM/P model is used, all of the six measures of customer value prediction accuracy considerably improved in comparison to the results of the aggregated RFM model.

Regarding the customer base value, the disaggregated model overestimated the actual amount by about 15%, while the aggregated model generated estimates of up to twice the actual customer base value. In relation to individual estimates, the errors of the disaggregated model were lower considering all of the measures (MAE, MDAE, and RMSE) and the correlation values were higher, both linearly and in relation to the order. In other words, the proposed disaggregated RFM/P model led to more accurate predictions of the customer values for the validation period than the traditional aggregated RFM model adopted as a benchmark. This is possible because the financial services company customers have very diversified and sometimes volatile purchasing behaviors in each product category. Therefore, given that the transaction history generates different frequency, recency, and monetary values for each product category, RFM/P performed better.

Table 2. Evaluation of purchase frequency predictions by RFM and RFM/P using BG/BB model – financial services company

	Individual frequency levels				Individual frequency ordering
Model	MAE	MDAE	RMSE	Pearson Correlation	Spearman Correlation
RFM (Aggregated) Cohort 1	0.922	1.000	1.520	0.758	0.767
RFM/P (Disaggregated) Cohort 1	0.923	1.000	1.514	0.760	0.768
RFM (Aggregated) Cohort 2	1.052	1.000	1.639	0.730	0.742
RFM/P (Disaggregated) Cohort 2	1.040	1.000	1.597	0.743	0.747

Table 3. Evaluation of customer value predictions by RFM and RFM/P using BG/BB model – financial services company

	Individual frequency levels				Individual frequency ordering	Customer base
Model	MAE	MDAE	RMSE	Pearson Correlation	Spearman Correlation	% Deviation
RFM (Aggregated) Cohort 1	$ 985.91	$ 31.18	$ 5,913.43	0.60	0.63	+76.9
RFM/P (Disaggregated) Cohort 1	$ 530.63	$ 21.68	$ 3,653.05	0.71	0.68	+13.7
RFM (Aggregated) Cohort 2	$ 1,595.85	$ 49.22	$ 7,704.44	0.71	0.63	+96.3
RFM/P (Disaggregated) Cohort 2	$ 771.65	$ 30.81	$ 5,399.77	0.83	0.71	+15.6

5.4. 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 3, 4, and

5 summarize the customer value estimations per product category for the validation period for customers of both cohort 1 and cohort 2 using the expected contribution margin Equation 6.

In Figure 3, the matrix presented in Table 1 is applied to the product and customer portfolios of the financial services company. Even though it is possible to analyze the complete matrix considering each individual customer, given the large number of customers, the customer portfolio was summarized in deciles determined by ordering the customers based on their values. Figure 3 is a heatmap that shows the mean customer values per 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 validation period 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 3. Heatmap of product and customer value portfolio – financial services company

In Figure 4, the intersections of mean customer values per deciles and product categories from Figure 3 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 shows how the mean overall customer values for each decile from the bar plot above are distributed among the product categories. Thus, the plots from Figure 4 demonstrate that the value brought by all the customers are highly concentrated among 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.

In Figure 5, by estimating the expected values of customers from the financial services company for the validation period, once again, it was possible to take advantage of the combination of product and customer perspectives. For the sake of exploring the new possibilities associated to

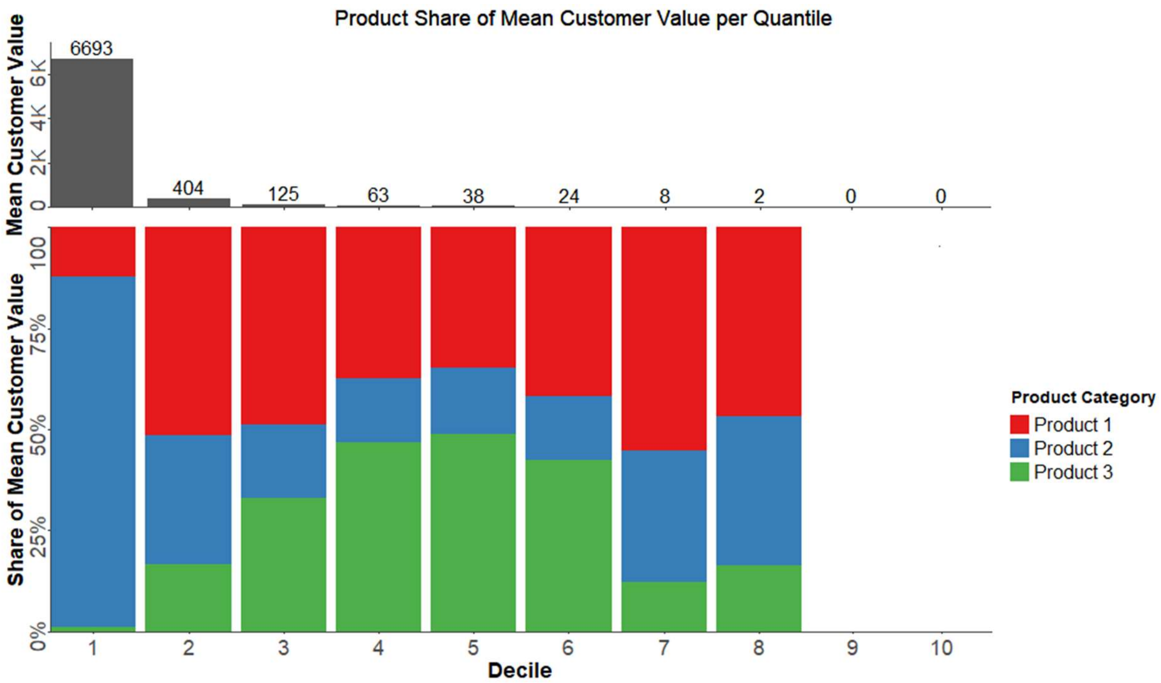

Figure 4. Product category share of mean customer value per decile – financial services company

the proposed RFM/P model, in Figure 5, we demonstrate another possible situation that also provides interesting managerial insights both for product and customer management. The bar plot at the top of Figure 5 shows the total customer value for each product category, while the stacked plot underneath the top bar plot displays how the total customer values for each product category from the bar plot above are distributed among the deciles determined after ordering the customers from the most valuable to the least valuable. This figure demonstrates that the sum of customer values for product 2 (cohorts 1 and 2) is approximately $4.8 million and most 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, which means that the difference in terms of value between the most valuable customers and the least valuable ones is lower.

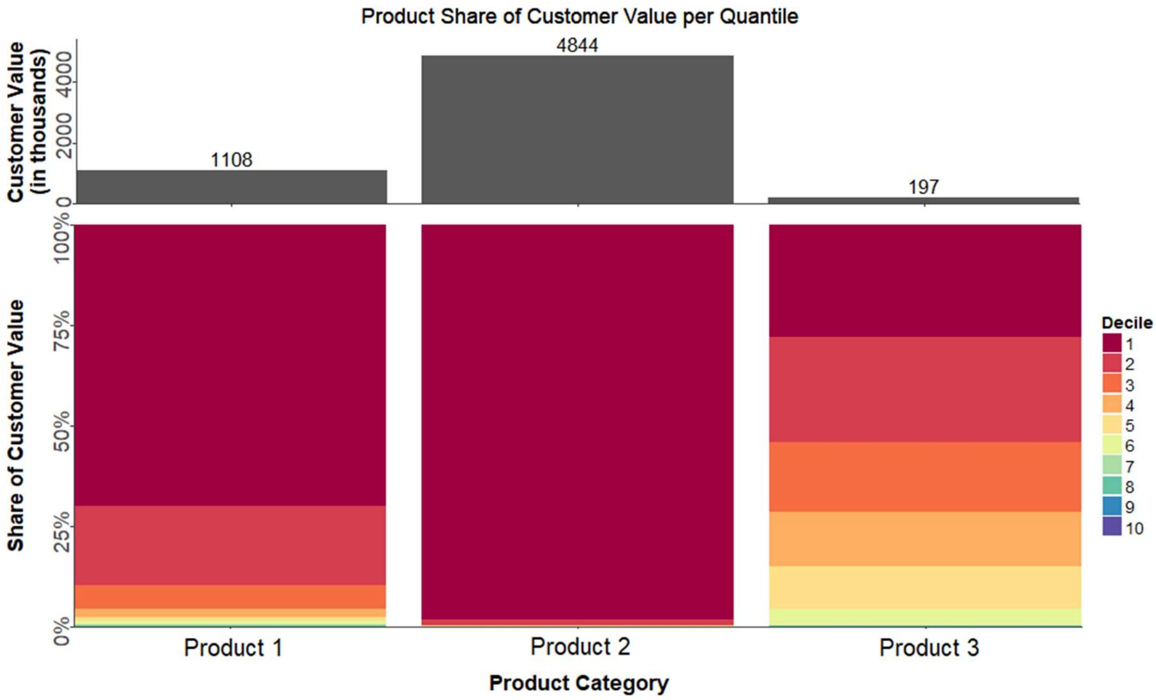

Figure 5. How total customer values for each product category are distributed among the deciles – financial services company

The results presented in Figures 3, 4, and 5 were possible because the customer value estimations for the validation period were calculated based on the 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 new view that enables managers to improve decision-making about both customer and product management. In the financial services company case, it is important to note that, not only is the expected value of the company almost entirely dependent on its top customer decile, but the value of this most valuable decile is also almost entirely dependent on only one product category (product 2). As product 2 is the product category with the highest cash flow volatility, future earnings are subjected to a quite risky situation. Additionally, if marketing managers do not consider the combination between the customer and product portfolios, they may end up proposing marketing efforts aim to incentivize the type of purchasing behavior of the most valuable customers. However, this would mean promoting product 2, which is not as relevant for all the other customers as it is for the customers from the first decile. As a result, there would be an even higher concentration of value over the most valuable customer decile, thus increasing the risk of the company.

5.5. MODEL VALIDATION – SUPERMARKET

In order to check the consistency of our results, we also analyzed the supermarket dataset using two different customer cohorts from the whole dataset: cohort 1 and cohort 2. The precision of predicted purchase frequencies and customer values from the supermarket for the validation period are presented in Tables 4 and 5, respectively. The Web Appendix provides details for the evaluation of predicted purchase frequencies per product category.

Such results confirmed our expectation about the prediction accuracy of the disaggregated RFM/P model compared to the traditional aggregated RFM estimation when applied to a case in which recency, frequency, and monetary values are more stable among the product categories. The results in Table 4 show that when the disaggregated RFM/P model is used, for cohort 1, all of the five measures of purchase frequency prediction accuracy slightly improved in comparison to the results of the aggregated RFM model. However, for cohort 2, all of the five measures of purchase frequency prediction accuracy slightly worsened in comparison to the results of the aggregated RFM model.

Concerning the analysis of customer value predictions (Table 5), the accuracy measures demonstrate that the estimation of the two methods was more similar than in the case of the financial services company. All of the measures for cohort 1, again, were slightly better with the disaggregated RFM/P estimation. On the other hand, the results for cohort 2 were equivalent. The percentage of deviation of customer base value between the predicted and actual values, correlations measures, and RMSE were slightly better with the traditional aggregated RFM estimation. Nevertheless, MAE and MDAE were better with the disaggregated RFM/P estimation.

These results demonstrate that even in an extreme case in which recency, frequency, and monetary values are more stable across product categories, the disaggregated RFM/P model performed quite well. Even though the comparison between the models in terms of purchase frequency prediction accuracy was inconclusive, because of the different results between the two cohorts analyzed, the customer value prediction accuracy, one of the main objectives of this study, was better in cohort 1 for the RFM/P method and quite equivalent in cohort 2 between the models compared. Albeit more extensive tests in a wider variety of settings should be performed, the results obtained so far for the customer value predictions indicate that the disaggregated RFM/P model may be used as a substitute for traditional RFM models without loss of customer value prediction accuracy. Additionally, to compare the accuracy of both models for different levels of purchase frequency and difference between the contribution margins of two product categories, we also performed a sensitivity analysis. The results were consistently better when using the disaggregated RFM/P model. The Web Appendix provides details of the sensitivity analysis.

Table 4. Evaluation of purchase frequency predictions by RFM and RFM/P using BG/NBD model – supermarket

	Individual frequency levels				Individual frequency ordering
Model	MAE	MDAE	RMSE	Pearson Correlation	Spearman Correlation
RFM (Aggregated) Cohort 1	5.808	2.000	13.148	0.712	0.808
RFM/P (Disaggregated) Cohort 1	5.552	2.000	11.225	0.785	0.825
RFM (Aggregated) Cohort 2	3.820	1.000	7.567	0.916	0.874
RFM/P (Disaggregated) Cohort 2	4.692	1.000	9.225	0.875	0.841

Table 5. Evaluation of customer value predictions by RFM and RFM/P using BG/NBD model – supermarket

	Individual frequency levels				Individual frequency ordering	Customer base
Model	MAE	MDAE	RMSE	Pearson Correlation	Spearman Correlation	% Deviation
RFM (Aggregated) Cohort 1	$ 253.71	$ 98.02	$ 657.32	0.89	0.80	+16.4
RFM/P (Disaggregated) Cohort 1	$ 243.73	$ 93.27	$ 618.33	0.91	0.84	+13.4
RFM (Aggregated) Cohort 2	$ 198.41	$ 121.49	$ 335.76	0.90	0.80	+15.9
RFM/P (Disaggregated) Cohort 2	$ 188.51	$ 71.99	$ 340.61	0.89	0.79	+17.2

5.6. COMBINING PRODUCT AND CUSTOMER PERSPECTIVES – SUPERMARKET

By estimating the expected values of customers from the supermarket for the validation period, we can again take advantage of the combination of product and customer perspectives. Although it is also possible to perform the same analyses presented in Figures 4 and 5 for the financial services company, only Figure 6 is presented for the supermarket with the heatmap of the product and customer value portfolio. By exploring the heatmap, it is easy to identify which product categories have the highest mean customer values across the different deciles: grocery (food) and produce. Furthermore, the product categories produce and fresh food also have an important participation in the overall customer values. Finally, this figure demonstrates how the supermarket customer values are more evenly distributed across product categories and also across customer value deciles. This contrasts with the financial services company, where customer value was highly concentrated in product 2 and in the first decile.

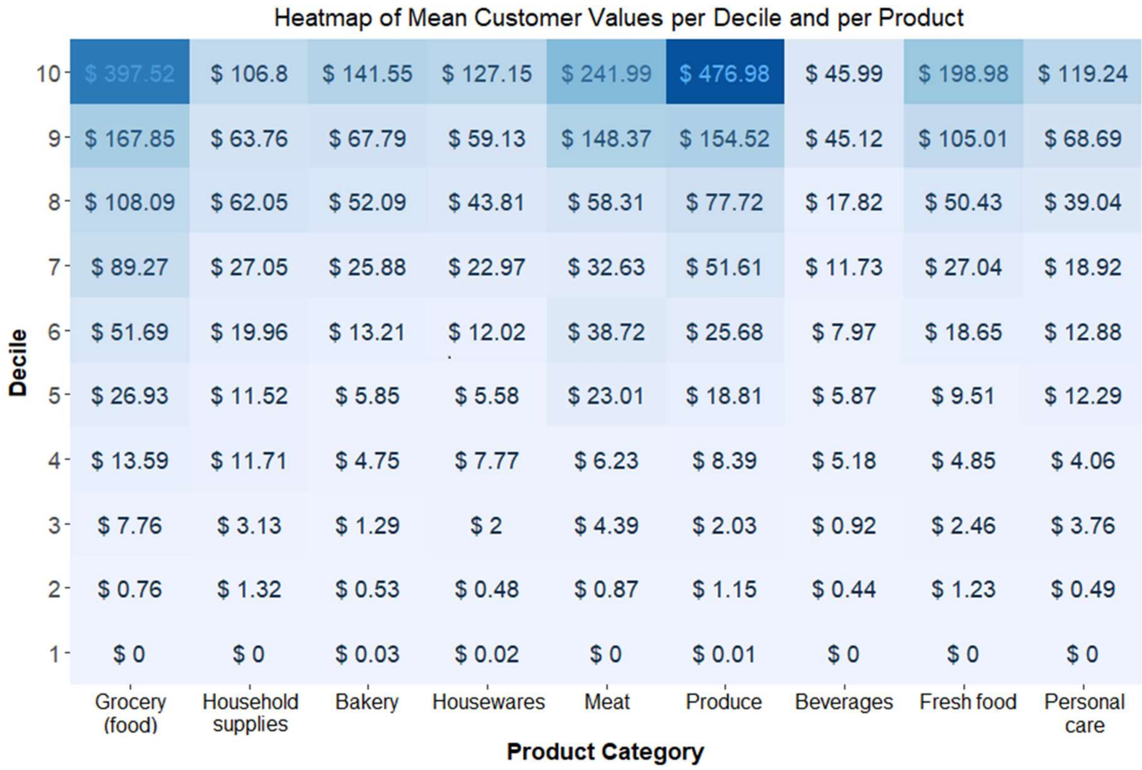

Figure 6. Heatmap of product and customer value portfolio – supermarket

6. CONCLUSION

The move toward customer-centric management does not necessarily mean that managers may not consider important data from products that can provide valuable insights. The proposed RFM/P model enables managers to have a more complete overview of future firm profits. It is an alternative for traditional RFM models, integrating two important marketing perspectives that are usually treated separately in the prediction of cash flows: customer and product perspectives. Splitting the analysis into customer value and product (or product category) provided relevant information for improving management of marketing assets and added prediction power to CLV models based on RFM. The main reason for this lies in the fact that the disaggregated model can identify some changes in customer purchase behavior 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, which assume a stationary average customer contribution margin. Moreover, the disaggregated approach also includes differences in frequency and recency existent among products in the estimation, which improves the accuracy of the predicted customer values.

The results from this study demonstrate that product data can add useful information to manage marketing assets and estimate CLV more precisely. In addition, it can reduce customer base value prediction error, improve individual customer value forecasting errors, and help companies to better manage their customer base. There is evidence that the RFM/P model may estimate CLV more accurately than traditional aggregated RFM models, performing better or at least equivalent to them. We, therefore, argue in favor of using RFM/P to predict customer value.

Additionally, the RFM/P disaggregated model enables managers to get a more complete strategic view of the product mix and the company customer portfolio. The proposed model provides the identification of which products are relevant to the most valuable customers and which customers buy the most profitable products. Focusing exclusively on product profitability may lead the company to the process known as death spiral aforementioned. On the other hand, focusing only on customer profitability may lead to increased overall firm risk by possibly encouraging excessive concentration of marketing efforts on a small group of customers. In this manner, managers can identify opportunities for product and service enhancements to better match the company offerings to key customers, launch brand extensions for valuable existing product categories to acquire new customers, and enable marketing strategies that have a positive expected impact on CLV.

Finally, we highlight the limitations of the present study and provide suggestions for future research. One of the limitations is that the proposed model does not consider competition in the market. Incorporating it is beyond the scope of this study because it would require data about customer transactions with competitors and may further complicate the model.

Furthermore, the proposed disaggregated model assumes independence among product categories. The low cross-product purchase correlations observed for both cases analyzed support such assumption. However, this may be a non-trivial issue depending on the context (see Seetharaman et al., 2005). Thus, one should be aware that ignoring potential unobserved correlations across categories may be a problem when they are present. To deal with this, we suggest that future studies extend the RFM/P method in order to consider cross-product purchase correlations. Additionally, it may also be important to extend the application of RFM/P to other companies from different industries. Lastly, we also believe the same disaggregated estimation of customer value may be tested in other CLV models that are not related to the family of RFM models.

REFERENCES

Ambler, T., Bhattacharya, C. B., Edell, J., Keller, K. L., Lemon, K. N., & Mittal, V. (2002). Relating brand and customer perspectives on marketing management. *Journal of Service Research*, 5, 13–25.

Bendle, N. T., Farris, P. W., Pfeifer, P. E., & Reibstein, D. J. (2016). *Marketing metrics: The manager's guide to measuring marketing performance*. Upper Saddle River: Pearson.

Fader, P. S., & Hardie, B. G. (2009). Probability models for customer-base analysis. *Journal of Interactive Marketing*, 23, 61–69.

Fader, P. S., Hardie, B. G., & Lee, K. L. (2005a). RFM and CLV: Using iso-value curves for customer base analysis. *Journal of Marketing Research*, 42, 415–430.

Fader, P. S., Hardie, B. G. S., & Lee, K. L. (2005b). Counting your customerİ the easy way: An alternative to the Pareto/NBD model. *Marketing Science*, 24, 275–284.

Fader, P. S., Hardie, B. G. S., & Shang, J. (2010). Customer-base analysis in a discrete-time noncontractual setting. *Marketing Science*, 29, 1086–1108.

Gupta, S., Hanssens, D., Hardie, B., Kahn, W., Kumar, V., Lin, N., ... Sriram, S. (2006). Modeling customer lifetime value. *Journal of Service Research*, 9, 139–155.

Hughes, A. M. (2006). Strategic database marketing. New York: McGraw-Hill.

Kamakura, W. A., Ramaswami, S. N., & Srivastava, R. K. (1991). Applying latent trait analysis in the evaluation of prospects for cross-selling of financial services. *International Journal of Research in Marketing*, 8, 329–349.

Kumar, V., & Reinartz, W. (2016). Creating enduring customer value. *Journal of Marketing*, 80, 36–68.

Leone, R. P., Rao, V. R., Keller, K. L., Luo, A. M., McAlister, L., & Srivastava, R. (2006). Linking brand equity to customer equity. *Journal of Service Research*, 9(2), 125–138.

Li, S., Sun, B., & Wilcox, R. T. (2005). Cross-selling sequentially ordered products: An application to consumer banking services. *Journal of Marketing Research*, 42, 233–239.

Peppers, D., & Rogers, M. (2005). *Return on customer: Creating maximum value from your scarcest resource*. New York: Doubleday.

Rosset, S., Neumann, E., Eick, U., & Vatnik, N. (2003). Customer lifetime value models for decision support. *Data Mining and Knowledge Discovery*, 7, 321–339.

Rust, R. T., Lemon, K. N., & Zeithaml, V. A. (2004). Return on marketing: Using customer equity to focus marketing strategy. *Journal of Marketing*, 68, 109–127.

Rust, R. T., Zeithaml, V. A., & Lemon, K. N. (2000). *Driving customer equity: How customer lifetime value is reshaping corporate strategy*. New York: The Free Press.

Seetharaman, P. B., Chib, S., Ainslie, A., Boatwright, P., Chan, T., Gupta, S., Strijnev, A. (2005). Models of multi-category choice behavior. *Marketing Letters*, 16, 239–254.

Shah, D., Rust, R. T., Parasuraman, A., Staelin, R., & Day, G. S. (2006). The path to customer centricity. *Journal of Service Research*, 9, 113–124.

Stadtler, H., Kilger, C., & Meyr, H. (2015). *Supply chain management and advanced planning: Concepts, models, software, and case studies*. New York: Springer.

Vargo, S. L., & Lusch, R. F. (2004). Evolving to a new dominant logic for marketing. *Journal of Marketing*, 68, 1–17.

Venkatesan, R. (2016). Building a data analytics orientation. http://www.msi.org/video/building-a-data-analytics-orientation.

Villanueva, J., & Hanssens, D. M. (2007). Customer equity: Measurement, management and research opportunities. *Foundations and Trends in Marketing*, 1, 1–95.

Zhang, Y., Bradlow, E. T., & Small, D. S. (2015). Predicting customer value using clumpiness: From RFM to RFMC. *Marketing Science*, 34, 195–208.

WEBAPPENDIX A - EVALUATION OF PURCHASE FREQUENCY PREDICTIONS BY RFM AND RFM/P PER PRODUCT CATEGORY

The results for the evaluation of predicted purchase frequencies per product category for both datasets are presented in Tables A.1 and A.2 below:

Table A.1. Evaluation of purchase frequency predictions by RFM and RFM/P per product category using BG/BB model - financial services company

		Individual frequency levels				Individual frequency ordering
Model		MAE	MDAE	RMSE	Pearson Correlation	Spearman Correlation
RFM/P (Disaggregated) Cohort 1	Product 1	0.868	0.0	1.494	0.66	0.64
	Product 2	0.437	0.0	1.059	0.69	0.68
	Product 3	0.970	0.0	1.610	0.78	0.80
RFM/P (Disaggregated) Cohort 2	Product 1	0.958	1.0	1.538	0.72	0.70
	Product 2	0.638	0.0	1.298	0.70	0.72
	Product 3	1.189	1.0	1.770	0.74	0.75

Table A.2. Evaluation of purchase frequency predictions by RFM and RFM/P per product category using BG/NBD model – supermarket

		Individual frequency levels				Individual frequency ordering
Model		MAE	MDAE	RMSE	Pearson Correlation	Spearman Correlation
RFM/P (Disaggregated) Cohort 1	Grocery (food)	3.983	1.0	8.419	0.77	0.80
	Household supplies	2.196	1.0	3.530	0.85	0.81
	Bakery	2.646	1.0	5.386	0.85	0.79
	Housewares	2.228	1.0	4.059	0.72	0.72
	Meat	2.241	1.0	4.120	0.81	0.70
	Produce	3.103	1.0	6.633	0.81	0.80
	Beverages	2.260	1.0	4.641	0.75	0.82
	Fresh food	2.569	1.0	4.683	0.85	0.82
	Personal care	2.214	1.0	4.205	0.71	0.77

RFM/P (Disaggregated) Cohort 2	Grocery (food)	2.865	0.0	5.337	0.92	0.90
	Household supplies	1.794	1.0	3.063	0.91	0.80
	Bakery	2.719	1.0	5.223	0.89	0.79
	Housewares	1.562	1.0	2.693	0.87	0.81
	Meat	1.857	1.0	3.738	0.82	0.72
	Produce	2.389	0.5	4.558	0.88	0.85
	Beverages	2.687	1.0	5.019	0.77	0.69
	Fresh food	2.272	1.0	3.973	0.93	0.78
	Personal care	1.655	0.0	3.096	0.91	0.87

WEB APPENDIX B - SENSITIVITY ANALYSIS

We performed a sensitivity analysis with 23 simulated databases to compare the accuracy of the aggregated and disaggregated models. We tested different levels of purchase frequency and difference between the contribution margins of two product categories.

Simulated databases. The simulated data is based on the assumption that the contribution margin follows a normal distribution. The number of transactions performed by each customer follows a negative binomial distribution. The customers dropout rate follows the Pareto distribution. We defined as the starting point a dataset containing purchases of ten thousand customers across two product categories, during 36-months period.

The variability of the contribution margin among customers was set as half of the customer base average contribution margin. Regarding the variability of the contribution margin of a given customer for a product category along the periods, it was defined as one-tenth of its average contribution margin. In order to evaluate the upselling behavior, it was considered that product category 2 replaces product category 1, so customers could buy at each time only one of these categories. The assumption was that the customer had the same probability of acquiring these two categories of products in the initial period and that he/she would be able to switch between these product categories in two different occasions during the period analyzed. For the initial database, we assumed that product category 2 generates an average contribution margin 50% higher than the contribution margin of product category 1. We created 10 additional variations of databases considering a range from 0 to 100% for the differences between the contribution margin of the two product categories.

Regarding the purchase frequency, we defined the average frequency of purchases of the initial dataset to be quarterly (90 days), allowing the variability among customers to be 45 days maximum. We created 12 alternative datasets considering a purchase frequency ranging from bimonthly to semiannual. Concerning defection, the annual average retention rate was set around 80% and allowed both customer dropping out at any time and staying in the base until the end of the reporting period.

Results. We observed that the disaggregated model performed better than the aggregated model in the different scenarios of contribution margins for product categories: from similar contribution margins to twice the value for product category 2. Insofar, as the difference in the contribution margin between the categories increases, in both models, there is an increase in the percentage of the mean absolute error (MAE) over the average contribution margin. However, this increase is higher for the aggregated model, when compared to the disaggregated model (see Figure B.1).

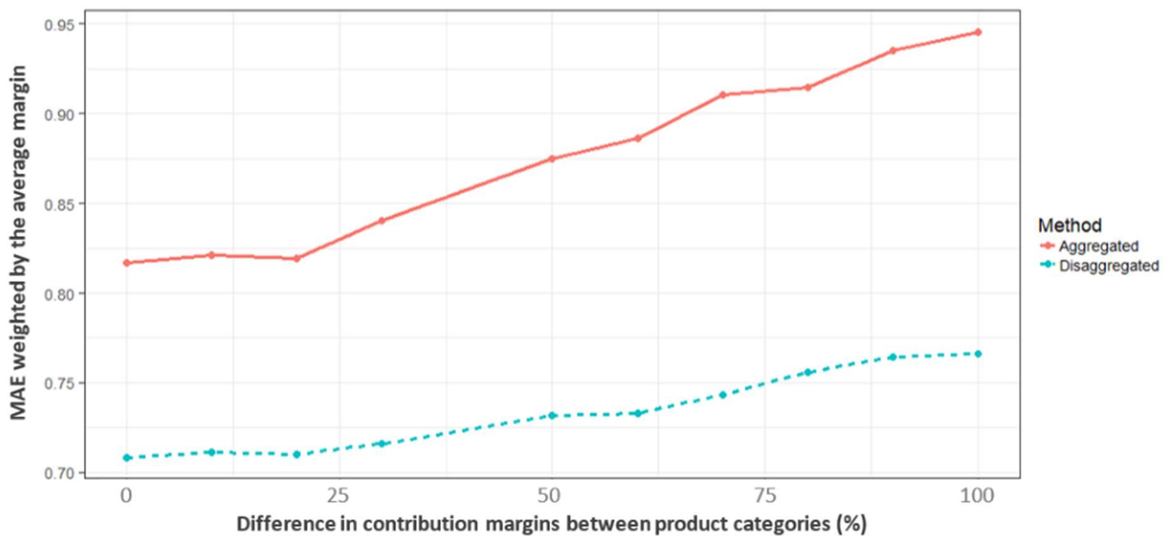

Figure B.1. Sensitivity to different levels of the difference between the contribution margins of the product categories

In the scenarios with different average purchase frequencies, both models performed better in less frequent purchase situations. However, regarding the percentage of the mean absolute error

(MAE) over the average contribution margin, as purchase frequency increases, the disaggregated model performs better than the aggregated model (see Figure B.2).

Therefore, in the 23 scenarios the disaggregated model had a performance equivalent to or higher than the aggregated model. An increase in the difference between the contribution margins of the product categories has a negative impact on the performance of the models, however the disaggregated model is still more accurate. Likewise, an increase in the purchase frequency reduces the performance of both models, however the aggregated model is more sensitive to such changes. The same pattern holds for raw MAE values (unweighted) as well.

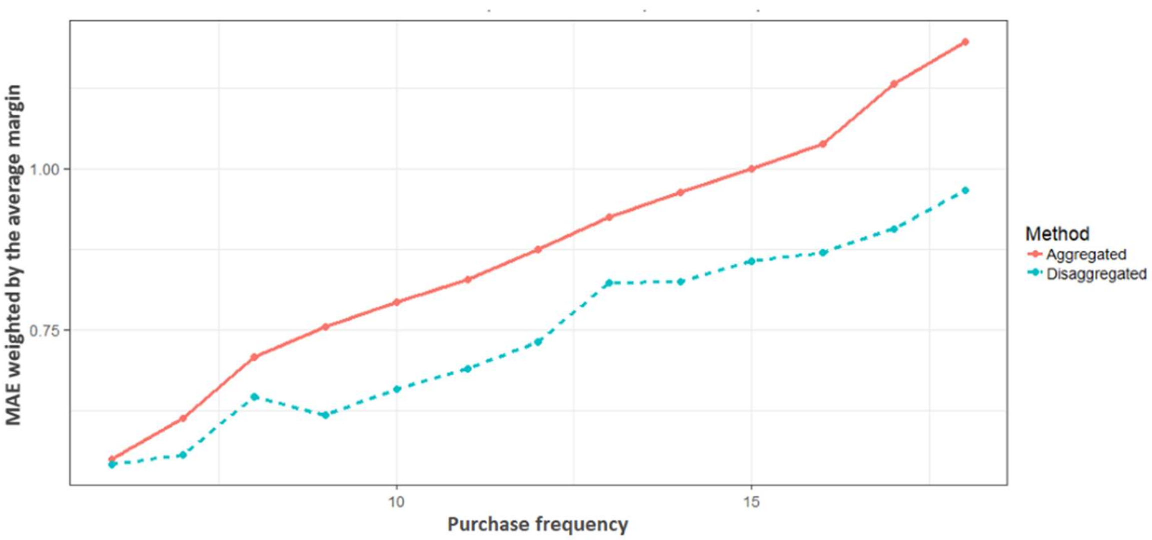

Figure B.2. Sensitivity to different levels of purchase frequency

UNIVERSIDADE FEDERAL DO RIO GRANDE DO SUL
ESCOLA DE ADMINISTRAÇÃO
DEPARTAMENTO DE CIÊNCIAS ADMINISTRATIVAS
PROGRAMA DE PÓS-GRADUAÇÃO EM ADMINISTRAÇÃO

RODRIGO HELDT

PhD DISSERTATION

BOTTOM-UP APPROACH TO MANAGE CUSTOMERS, PRODUCT CATEGORIES, AND BRANDS SIMULTANEOUSLY

PAPER 3:

CUSTOMER CENTRICITY IN A PRODUCT-CENTRIC MARKETPLACE: BOTTOM-UP APPROACH TO MANAGE CUSTOMERS, PRODUCT CATEGORIES, AND BRANDS SIMULTANEOUSLY[1][2][3]

Porto Alegre
2020

[1] Paper initially published in the Business Association for Latin American Studies (BALAS) Conference Proceedings 2020.

[2] Paper received the Lourdes S. Casanova Best Applied Paper Award at the Business Association of Latin American Studies (BALAS) Conference 2020.

[3] Co-authors: Fernando Bins Luce and Sarang Sunder

ABSTRACT

Owing to the availability of disaggregate databases, the concept of customer centricity gained importance in business practice and academia. Although customer centricity has been shown to have great benefits, traditionally product-centric firms have been slow to adapt. This is often attributed to challenges in reconciling category and brand performance metrics with customer level performance metrics since category and brand management still depend on category and brand level metrics. In this study, we propose a bottom-up CLV based approach to manage customer, category, and brand profitability simultaneously. We modify the commonly used BG/NBD model to measure CLV to account for brand and category levels purchase and apply the proposed methodology to data from a large consumer-packaged goods (CPG) distributor. Through various analyses, we highlight the predictive accuracy improvements of the proposed approach and develop key managerial insights that would not be possible using extant methods. We show that not integrating category and brand purchases within the CLV framework can lead to a 11.1 % under estimation in customer equity. Additionally, we show that the Pareto rule can have different meaning for different categories and brands. Lastly, the results suggest that ignoring categories and brand purchases when evaluating CLV can lead to up to 20 % misclassification of the most/least valuable customers at the brand-level as well as up to 18 % misclassification at the category-level and we show how such discordances may be used as input to drive product recommendations to increase profitability.

Keywords: customer lifetime value; customer management; product management; brand management; RFM method.

RESUMO

Devido à disponibilidade de bases de dados desagregadas, os conceitos ligados à centralidade no cliente ganharam importância nas empresas e na academia. Embora tenha-se evidências de que a centralidade no cliente possui grandes benefícios, empresas tradicionalmente centradas no produto têm apresentado dificuldades para se adaptar. Isso é frequentemente atribuído a desafios em reconciliar métricas de performance de marcas e categorias de produtos com métricas de performance no nível de clientes, uma vez que a gestão de marcas e categorias de produtos permanece dependente de métricas no nível de marcas e categorias. Neste estudo, é proposta uma abordagem de baixo para cima baseada na estimação do *customer lifetime value* (CLV) para gerir a lucratividade de clientes, categorias de produtos e marcas simultaneamente. Adaptou-se o modelo BG/NBD comumente utilizado para mensurar CLV para considerar também compras no nível de categoria de produto e marca e aplicou-se a metodologia proposta usando os dados de um grande distribuidor de bens de consumo embalados. Por meio de diversas análises, observou-se uma melhora na acurácia preditiva e implicações gerenciais chave que não seriam possíveis utilizando métodos tradicionais. Evidenciou-se que não integrar a categoria de produtos e a marca no método de CLV pode levar a 11.1 % de subestimação no valor do *customer equity*. Adicionalmente, mostra-se que a regra de Pareto pode ter diferentes resultados para diferentes categorias de produtos e marcas. Por fim, os resultados sugerem que ignorar as compras por categoria de produtos e marca quando avalia-se o CLV pode levar até a 20 % de erros de classificação entre quais são os clientes mais/menos valiosos entre as marcas e até a 18 % de erros de classificação entre as categorias de produtos e mostra-se ainda como tais discordâncias podem ser usadas para direcionar esforços de recomendações de produtos para aumentar a lucratividade.

Palavras-chave: *customer lifetime value*; gestão de clientes; gestão de produtos; gestão de marcas; método RFM

FIGURES

TABLES

TABLE OF CONTENTS

1. INTRODUCTION

The value of customer centricity as a paradigm in today's business marketplace is unquestioned. Technological innovations in recent years have facilitated closer engagement between the firm and its customers and this process have also greatly improved the firm's capabilities to collect detailed disaggregate data about its customers. Access to this disaggregate data through customer relationship management (CRM) platforms in the recent past has given way to the development and implementation of customer-centric marketing strategies across various business contexts. There are numerous examples of extant research highlighting the marketing (and financial) implications of adopting a customer-centric marketing paradigm (Lee, Kozlenkova, & Palmatier, 2015; Kumar & Reinartz, 2016; Kumar & Shah, 2009; Wiesel, Skiera, & Villanueva, 2008). As such, the marketing practice shifts from purely flow-based metrics such as sales/revenue or growth metrics to customer level metrics and there is a need for guidance on how to implement customer level metrics (such as customer lifetime value (CLV)) across various industries (Sunder, Kumar, & Zhao, 2016). In this research, we address one such implementation question: How to implement a primarily customer-centric metric (such as CLV) in a product-centric marketplace (such as consumer-packaged goods, consumer durable goods, and clothing)? Specifically, how can a customer-centric metric like CLV be adapted and implemented in firms where relevant decisions are also needed at the product category and brand levels.

This is a key dilemma faced by managers in traditionally product-centric businesses who have the aspiration to adopt customer centricity but are unable to because of legacy issues pertaining to managing product category and brand performance. Despite the adoption of a customer-centric paradigm at the C-suite, it fails at the category and brand management levels because managers simultaneously need to manage and make decisions concerning product categories and brands (such as category strategy, assortment optimization, brand extensions, etc.). Past research on the issue of CRM implementation has mostly focused on industries where customer relationships are clearly defined and contexts where transaction data are readily trackable through various CRM systems or loyalty programs. Further, the CLV literature has largely focused on predicting lifetime value at the customer level without providing predictions or expected contribution of a customer for each brand and product that a firm offers (e.g. Kumar, 2010; Kim, Ko, Xu, & Han, 2012; Lin et al., 2017). This is especially important to product-centric firms that may offer multiple categories and brands, but would like to align product and brand management to customer level metrics. Our work shares similarities with Sunder et al. (2016) who propose a structural approach to assessing CLV when competitive information is fully observable (e.g. scanner panel data). Their application, however, is contingent on the availability of data on a customer's full basket of category purchases (including competition) and becomes unfeasible to be estimated for a higher number of categories and brands.

Our primary objective in this paper is to propose a flexible customer-centric bottom-up approach for brand and product category management in a product-centric environment. Specifically, we aim to use customer lifetime value (CLV) metric to manage not only customers, but also product categories and brands simultaneously. Such approach helps traditionally product-centric firms to align their category and brand performance metrics to the most granular level, the customer, without changing too much their decision-making process. In this research, we also provide a dashboard where a manager can have a unified view of customer, category, and brand performance (all estimated through CLV), thus allowing them to slice the data in whatever way they choose.

To achieve our research objectives, we adapt the Beta Geometric/Negative Binomial Distribution (BG/NBD) model (Fader, Hardie, & Lee, 2005b) to estimate CLV for each customer, category, and brand combination simultaneously. Notably, the level of analysis in all the models is at the customer transaction (cash flow) level. We highlight the performance improvements of our proposed customer, product category, and brand bottom-up approach (hereafter CPB bottom-up approach) to extant customer-based and flow-based metrics and develop managerial insights that would not be possible using extant methods. We show that not integrating brand and category purchases within the CLV framework can lead to a 11.1 % under estimation in customer equity. Additionally, we show that the Pareto rule can have different meaning for different brands and categories. While in some categories or brands 80% of the present value of expected cash flows is provided by less than the 20% of the customers, in others it is provided by more than 20% of the customers. Lastly, the results suggest that ignoring brand and category purchases when evaluating CLV can lead to up to 20 % misclassification of the most/least valuable customers at the brand-level as well as up to 18 % misclassification at the category-level and we show how such discordances may be used as input to drive marketing efforts in order to increase profitability.

2. CONCEPTUAL FOUNDATION

The benefits of using CLV have been widely documented in extant research: it contributes for managers to demonstrate the financial return on marketing investment (Rust, Zeithaml, & Lemon, 2004); customer equity is positively related to company's market capitalization (Kumar & Shah, 2009); and CLV may be used to segment customer base in order to drive marketing efforts toward the most profitable customers, increasing overall profitability (Kumar & Shah, 2009). However, while the benefits of CLV are well known, its adoption is asymmetric. Traditionally product-centric industries continue to remain product-centric because many decisions (such as brand/category performance, brand extensions etc.) are made at the product category and brand-levels.

Even though these product-centric companies may benefit from embracing customer centricity, it is not sufficient for them to rely purely on customer level metrics such as CLV. This mismatch between 'what the firm does' (in terms of strategy) and 'what the customer does' (in terms of purchase behavior) was highlighted in the "Systems Model" proposed in Keller and Lehmann (2006). In Figure 1, we have adapted Keller and Lehmann's (2006) Systems Model thinking to form the conceptual foundation of this research. At the top level, decisions have to be made concerning firm's strategy, including strategic direction and quality standards, and programs, including budget and target markets. At the bottom level, following the concept of customer centricity, managers conduct a set of decisions at the customer-level, such as customer base analysis and profiling. At this point, computing CLV shows the expected cash flows generated by such decisions at the customer-level.

However, these cash flows are not only a result of strategic and customer level decisions. The middle level of Figure 1 highlights that there are also several decisions at the category and brand levels to create marketing value for a given target market. Managers have to make category decisions regarding new product development, product-mix range, packaging options, and setting category sales goals. Additionally, they also make brand decisions regarding brand development, brand positioning, brand extension, and setting brand sales goals. Customers decide to purchase from the company not only based on strategic and customer-level decisions. Thus, without the middle level of decisions, the link between strategic and customer-level is broken.

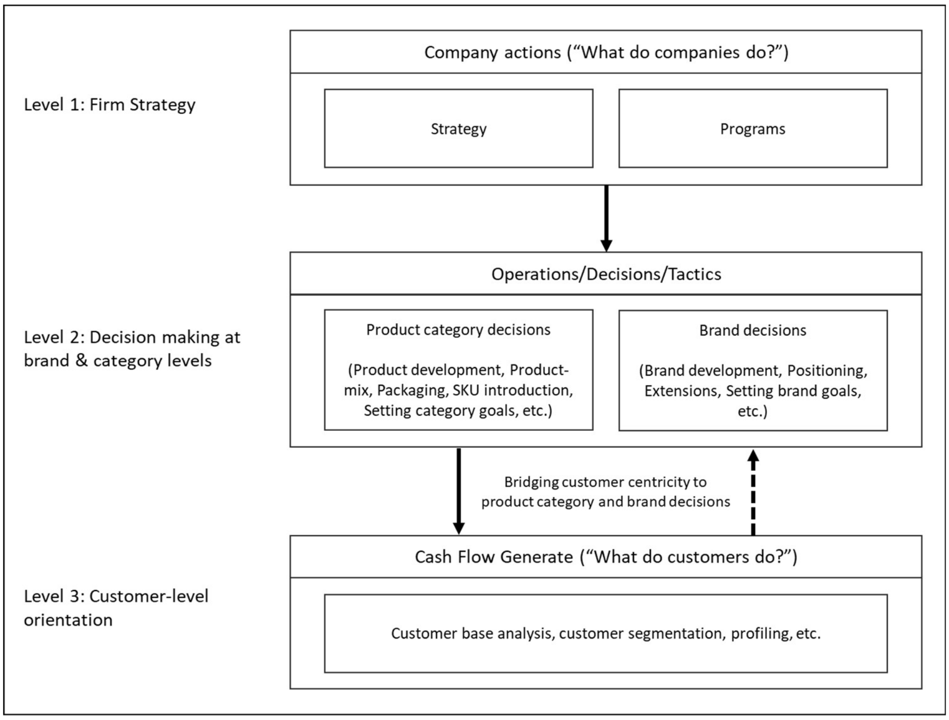

Figure 1. Value creation chain in product-centric firms

Category and brand levels of decisions are needed to bridge strategic and customer levels. Therefore, marketing performance management should be conducted at the middle and the bottom levels. Unfortunately, customer-centric metrics such as CLV do not provide any information on the result of such decisions in terms of expected category or brand performance. Consequently, because extant research has provided a great deal of knowledge on how to access performance at the middle and bottom levels of decisions separately (e.g. El-Ansary, 2006; Keller & Lehmann, 2006; Mantrala et al., 2009; Fader et al., 2005b; Kumar & Shah, 2009), performance management at the category and brand-levels become disconnected to the one conducted at the customer-level.

3. UNIFIED FRAMEWORK WITH SHARED METRICS/GOALS

In the widest sense, the creation of customer perceived value by the company is expected to generate positive customer behavior toward the company's offerings and, ultimately, to bring cash flow to the company. Such cash flow is only one and it is the data we normally observe. Thus, it may be used to estimate expected cash flows from customer, product category, and brand perspectives. However, in product-centric firms, the outcomes of decisions regarding product categories and brands end-up being assessed by traditional aggregate measures, which are not connected with the recommended customer-centric metrics, such as CLV (Sunder et al., 2016). Thus, despite having customer-level data and metrics, it is not enough as managers maintain several of their strategic activities aligned with product-centric metrics.

Past conceptual discussions about the relationship between brands and customers have suggested that these clearly inextricably linked perspectives should be jointly taken into account when managing marketing profitability (Ambler et al., 2002; Keiningham, Aksoy, Perkins-Munn, & Vavra, 2005; Leone et al., 2006; Romero & Yagüe, 2015, Ding et al., 2020). By including product categories, which is of great relevance for product-centric firms, we suggest that these companies should expand their focus to simultaneously manage customer, product category, and brand portfolios through the bottom-up approach represented in Figure 2.

In Figure 2, panels 1, 2, and 3 represent the traditional approach to evaluate the performance at each of these three dimensions when a company has several brands or categories. They are accessed separately even though the overall cash flow is the same. Conversely, in panel 4, we present the proposed CPB bottom-up approach, which unifies panels 1, 2, and 3, providing the present value of expected cash flows for each customer, product category, and brand existing combination. Each black dot in Figure 2 represents the intersections with present values of expected cash flows greater than 0. Given that the overall cash flow is only one, each face of the cube represents the total equity value created by a company. Thus, the CPB bottom-up approach connects the product category and brand performance management to CLV. It allows managers to adopt customer centricity while considering the same forward-looking measures for analyzing the performance of any level of aggregation among customers, product categories, and brands, which may be calculated through bottom-up summations.

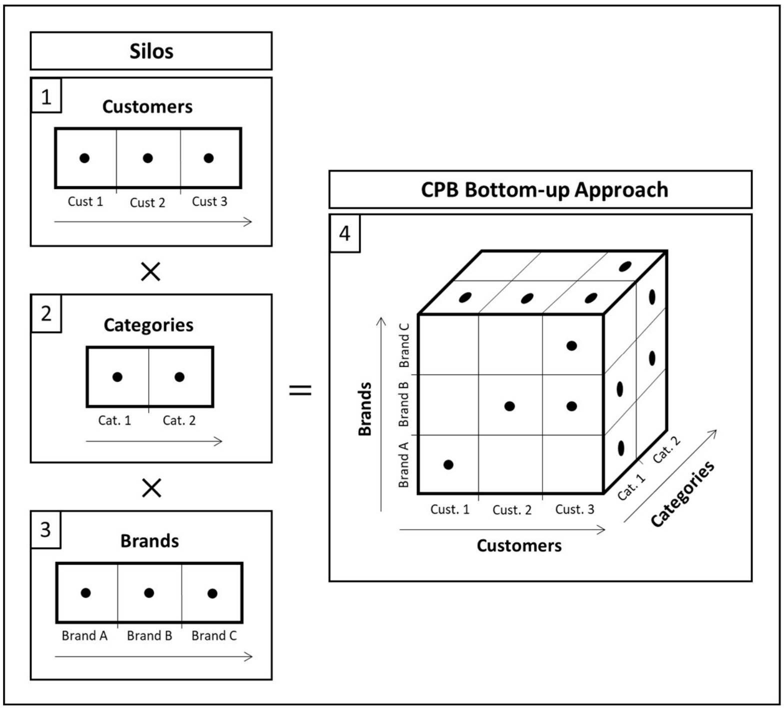

Figure 2. Conceptual CPB bottom-up approach

In order to compare the proposed CPB bottom-up approach with the traditional CLV methods, we show the transaction log used to estimate both alternative methods in Figure 3. Traditional CLV methods use the total transaction log from each customer and only customer-level analysis can be reached through the prediction of CLVs. On the other hand, by adopting the CPB bottom-up approach, the transaction log from each existing customer, product category, and brand combination is used to estimated expected cash flows for each of them. In Figure 3, the two shades of grey identify the customer level of aggregation, representing the CLVs, the square brackets are used to represent product category and brand levels of aggregation. Therefore, the CPB bottom-up approach allows managers in product-centric companies to incorporate a customer-level metric into their program evaluations while also maintaining control over product category and brand performance.

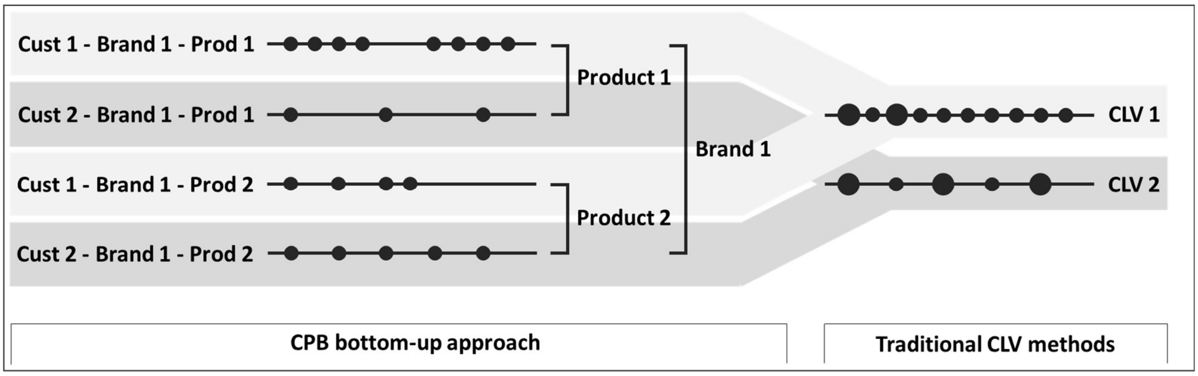

Figure 3. CPB bottom-up approach accounting for different purchasing patterns

4. ESTIMATING CPB BOTTOM-UP APPROACH - RFM/PB METHOD

Even though CPB bottom-up approach can be implemented using multiples methods, we have adopted a recency, frequency, and monetary value method per product category and brand (hereafter RFM/PB method) to estimate the cash flows. RFM methods are easily applicable to large datasets and relies only on few sufficient statistics for estimation: customer purchase recency, customer purchase frequency, the time from beginning of the customer's relationship with the firm until the current time, and customer contribution margin per transaction (Zhang, Bradlow, & Small, 2015; Mzoughia, Borle, & Limam, 2017). The RFM/PB method uses the BG/NBD model, which lends itself very well to estimate CLV in a non-contractual context given that it is known to perform quite well in estimating customer repeated purchases (Fader et al., 2005b).

We begin with the standard CLV formulation (Rosset et al 2003) in Equation 1.

$$E[CLV] = \int_0^\infty E[v(t)]\, S(t)\, d(t)\, dt, \tag{1}$$

where $E[v(t)]$ is the expected customer value 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.

Once we assume that the customer contribution margin is stationary and independent of the purchase frequency, the expected customer value ($v(t)$) can be expressed as the product of the expected customer contribution margin per transaction (m) and expected number of transactions ($y(t)$). In order to accomplish it, the estimation of customer lifetime values per product category p and brand b combination ($E[CLV_{pb}]$), assuming that the product category and brand combinations are independent of each other, is defined based on the following general equation:

$$E[CLV_{pb}] = E[m_{pb}] \int_0^\infty E[y_{pb}(t)]\, S_{pb}(t)\, d(t)\, dt, \qquad (2)$$

where $E[m_{pb}]$ is the customer expected contribution margin per transaction per product category p and brand b, $E[y_{pb}(t)]$ is the customer expected number of purchases per product category p and brand b in period t, $S_{pb}(t)$ is the survivor function that defines the probability of the customer buying product category p and brand b in period t, and $d(t)$ is the discount factor that reflects the present value of money in period t.

Equation 2 may be implemented by using the BG/NBD model (Fader et al., 2005b) per product category and brand combination to estimate the customer expected number of purchases per product category p and brand b in period t $\left(E[y_{pb}(t)]\right)$ considering the survivor function that defines the probability of the customer buying product category p and brand b in period t ($S_{pb}(t)$). Regarding the estimation of the customer expected contribution margin per transaction per product category p and brand b $\left(E[m_{pb}]\right)$, we have followed the method proposed by Fader, Hardie, & Lee (2005a).

Following Fader et al. (2005b), we assume that a given customer randomly purchases around her time-invariant mean transaction rate (characterized by the Poisson distribution), and corresponding heterogeneity in transaction rate (characterized by the Gamma distribution). The time to customer "drop out", in turn, is modeled using the beta-geometric mixture (BG) timing model. Based on Fader et al. (2005b), the BG/NBD model used to estimate the expected number of transactions in a future period of length t for a customer with past observed behavior ($X_{pb} = x_{pb}, tx_{pb}, T_{pb}$) for product category p and brand b is:

$$E\left[Y_{pb}(t)|X_{pb} = x_{pb}, tx_{pb}, T_{pb}, r_{pb}, \alpha_{pb}, a_{pb}, b_{pb}\right] = \frac{a_{pb} + b_{pb} + x_{pb} - 1}{a_{pb} - 1} \times$$

$$\frac{\left[1 - \left(\frac{\alpha_{pb} + T_{pb}}{\alpha_{pb} + T_{pb} + t}\right)^{r_{pb} + x_{pb}} {}_2F_1\left(r_{pb} + x_{pb}, b_{pb} + x_{pb}; a_{pb} + b_{pb} + x_{pb} - 1; \frac{t}{\alpha_{pb} + T_{pb} + t}\right)\right]}{1 + \delta_{x_{pb} > 0} \frac{a_{pb}}{b_{pb} + x_{pb} - 1}\left(\frac{\alpha_{pb} + T_{pb}}{\alpha_{pb} + tx_{pb}}\right)^{r_{pb} + x_{pb}}}, \tag{9}$$

where $r_{pb}, \alpha_{pb}, a_{pb}, b_{pb}$ are BG/NBD parameters per product category p and brand b, X_{pb} represents the purchase history (x_{pb}, tx_{pb}, T_{pb}) per product category p and brand b, x_{pb} is the number of transactions, tx_{pb} is the time of the last transaction (recency), T_{pb} is the length of the calibration time period, and ${}_2F_1(\cdot)$ is the Gaussian hypergeometric function.

In turn, in order to estimate the customer expected contribution margin per transaction per product category p and brand b, $E[m_{pb}]$, we have followed Fader et al. (2005a), who defined that the expected contribution margin per transaction follows a gamma-gamma distribution, resulting in a weighted average between the population mean, $\frac{\gamma_{pb}\nu_{pb}}{q_{pb}-1}$, and the average customer transaction value per product category p and brand b, mx_{pb}:

$$E\left[M_{pb}|\nu_{pb}, q_{pb}, \gamma_{pb}, mx_{pb}, x_{pb}\right] = \left(\frac{q_{pb}-1}{\nu_{pb}x_{pb}+q_{pb}-1}\right)\frac{\gamma_{pb}\nu_{pb}}{q_{pb}-1} + \left(\frac{\nu_{pb}x_{pb}}{\nu_{pb}x_{pb}+q_{pb}-1}\right)mx_{pb}, \tag{4}$$

where $\nu_{pb}, q_{pb}, \gamma_{pb}$ are parameters of the transaction value model per product category p and brand b, x_{pb} is the number of transactions per product category p and brand b, and mx_{pb} is the observed average customer transaction value per product category p and brand b. Thus, the weighted average is obtained from the product category p and brand b average transaction value and customer average purchase amount of product category p and brand b.

Deriving from the general equation presented in Equation 2, the estimation of customer lifetime values per product category p and brand b was calculated based on a discrete prediction horizon of 36 months. Therefore, given the estimations from Equation 3 and Equation 4 and based on Fader et al. (2005a), a given customer's CLV per product category p and brand b for a discrete prediction horizon (N) of 36 months is defined as:

$$E[CLV_{pb}] = \frac{E[Y_{pb}(t=1)] \times E[M_{pb}]}{(1+d)^1} + \sum_{t=2}^{N} \frac{\{E[Y_{pb}(t)] - E[Y_{pb}(t-1)]\} \times E[M_{pb}]}{(1+d)^t} \tag{5}$$

Where $E[Y_{pb}(t)]$ is the expected number of transactions in a future period of length t for a customer with past observed behavior ($X_{pb} = x_{pb}, tx_{pb}, T_{pb}$) for product category p and brand b, x_{pb} is the number of transactions, tx_{pb} is the time of the last transaction (recency), T_{pb} is the length of the calibration time period, $E[M_{pb}]$ is the expected contribution margin per transaction for a given customer per product category p and brand b, d is the discount rate (monthly rate of 0.0125, equivalent 0.15 annual rate), and t is index for future periods (months in this case).

5. DATA & EMPIRICAL CONTEXT

We have applied the proposed CPB bottom-up approach using the RFM/PB method to data from a large CPG distributor of products from one of the world's largest manufacturers in the chocolates & confectionaries category in Brazil. As with most supply chain intermediaries in this industry, the distributor purchases products from the manufacturer and is responsible to sell them to retailers. In other words, from the distributor's perspective, the retailer is the customer. As far decision-making goes, the distributor is traditionally product-centric, wherein brand and category decisions are made based on aggregated flow-based metrics such as total sales, market share, etc.[4] Similar to other emerging markets (Kumar, Sunder, & Sharma, 2015), the focal market is characterized by a highly unorganized retail sector comprising of a large number of small retailers and mom and pop stores which are independently owned. This is a unique aspect of this research context since most of the extant work in customer orientation has focused on mature and developed economies with little focus on emerging economies. Given the small size of the stores, retailers tend to stock fewer products and purchase/inventory decisions are made by the store owner frequently without guidance of information systems. The distributor 'markets' to their customers through salespeople who make door-to-door visits. A CLV-based targeting strategy to understand what brand/category to sell to which customer could be very useful in such contexts.

To estimate the proposed CPB bottom-up approach, we only need to observe the following transaction level information: customer id, transaction date, purchased product, purchased brand, and contribution margin. We obtained the above transaction log information for a 60 months period from January 2013 to December 2017. It contains every product purchase from a cohort of 5,974 retailers. There are 4 product categories in total and the manufacturer may offer multiple brands within each category: (1) Drops (1 brand); (2) Gums (5 brands); (3) Chocolates (7 brands); and (4) Truffles (2 brands).

[4] We have conducted several in-depth interviews with the company C-Suite and field observation with salespeople to learn their business practices and decision-making process.

6. MODEL-FREE DATA DESCRIPTIVES

We begin by plotting the share of total purchases per product category over time in Figure 4. The gum category sells the most in terms of share of purchases (58.7% on average), however its share has dropped over time (from ~70% share in 2013 to ~50% share in 2017). On the other hand, the other three categories' average share of purchases range from 10.5% to 18.6% throughout the data. Figure 4 is a visual representation of typical data that a category manager uses to make decisions on categories. Although such flow-based product-centric metrics are useful to assess overall performance, it only presents an aggregate view of the marketplace. What is left out in Figure 4 is the customer level transactions that have contributed to the aggregated performance. Similar aggregations could be made at the brand level (to aid brand managers). Again, this ignores the customer value that contributes toward each brand's performance.

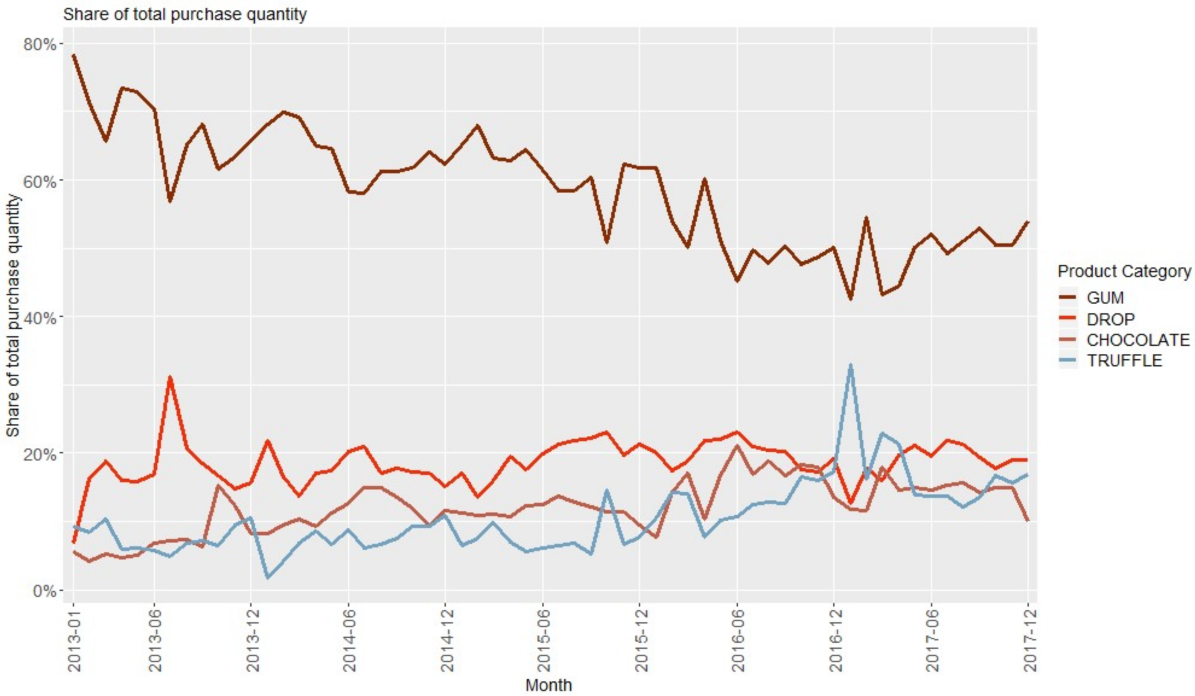

Figure 4. Share of total purchase quantity per product category

Based on the purchase decisions made by each customer, it is important to note that not all of them purchase every product category. Truffle is the category with the lowest number of customers who purchased it at least once, 4,779 customers, and the lowest total number of transactions, 93,994. On the other hand, gum is the one with the highest number of customers who purchased it at least once, 5887 customers, and the highest total number of transactions, 474,449.

Likewise, not all the customers purchase every brand. Brand 12 is the one with the lowest number of customers who purchased it at least once, 2173 customers, and the lowest number of transactions, 8717. Whereas Brand 6 is the one with the highest number of customers who purchased it at least once, 5741 customers, and the highest number of transactions, 203,846.

Given the relevance of customer level information, in Figure 5, we have also considered the customer perspective by analyzing the distributions of the share of customer's total purchase quantity per product category, defined as the percentage of product category purchases relative to each customer's total purchase quantity. The distributions in Figures 5, as it was also found by Sunder et al. (2016), evidence that there is heterogeneity among customers within a product category, which should be considered, suggesting the need to use customer-level metrics in product-centric settings. Additionally, another relevant conclusion should be highlighted. The wide variation in the distributions observed across product categories indicate that there are customers with different purchasing behaviors across product categories. Similar results were observed when we have conducted the same analysis of Figure 5 for the brands. Therefore, it indicates that only using customer-level metrics is not sufficient, once such variability across categories and brands should also be considered in product-centric settings. It may be accomplished by predicting customer lifetime values per product category and brand.

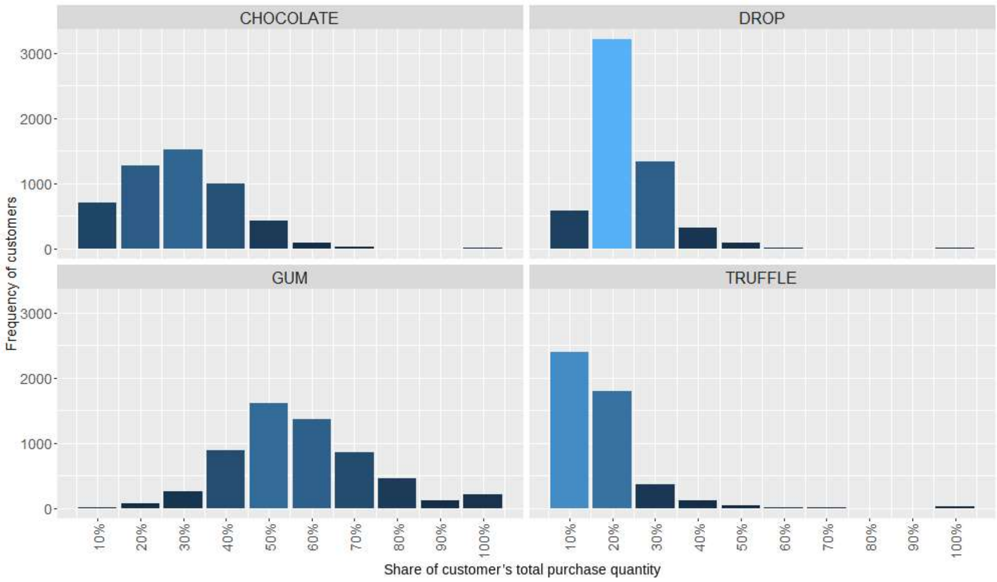

Figure 5. Share of customer's total purchase quantity per product category

7. MODEL ESTIMATION & VALIDATION

In this section, we present the results for the estimation of the RFM/PB method used to apply the CPB bottom-up approach, including the log-likelihoods and parameters estimated: r_{pb} and α_{pb} are unobserved parameters for the Negative Binomial Distribution transaction process whereas a_{pb} and b_{pb} are unobserved parameters for the Beta Geometric dropout process. The RFM/PB method was also compared with the traditional RFM method as proposed by Fader et al. (2005b) in terms of prediction accuracy. In Table 1, we present the estimation results for the proposed bottom-up approach (where the BG/NBD parameters are estimated for each brand and category combination). and for the traditional BG/NBD model ignoring brand/product category hierarchies (where the parameters are estimated using only customer level data). Instead of having only point estimates for the parameters as it is the case for the traditional RFM method, the RFM/PB method generates estimates at each brand and category combination. For instance, the parameter r_{pb} is 1.004 when using the traditional method. When considering the RFM/PB method, the estimates for this parameter range from 0.549 to 1.481.

Table 1. Parameters and log-likelihoods of the BG/NBD models estimated

Model	Product Category	Brand	r	α	a	b	Log-likelihood
RFM/PB method	Drop	Brand 1	0.895	1.382	0.164	4.888	-155,312
	Gum	Brand 2	0.785	1.866	0.185	4.684	-104,248
	Gum	Brand 3	0.549	1.540	0.543	4.633	-72,664
	Gum	Brand 4	0.667	2.144	0.163	4.941	-72,752
	Gum	Brand 5	0.710	1.603	0.303	7.112	-103,262
	Gum	Brand 6	0.909	1.164	0.166	5.008	-165,700
	Chocolate	Brand 7	1.481	3.067	0.001	549.459	-25,137
	Chocolate	Brand 8	1.297	2.168	0.349	7.271	-77,963
	Chocolate	Brand 9	0.889	3.558	0.459	12.736	-64,981
	Chocolate	Brand 10	0.581	3.771	1.189	16.715	-27,170
	Chocolate	Brand 11	0.818	2.768	0.426	11.035	-66,274
	Chocolate	Brand 12	0.555	3.489	1.168	7.695	-13,856
	Chocolate	Brand 13	0.655	2.858	1.415	30.330	-47,051
	Truffle	Brand 14	0.729	2.262	0.288	7.561	-76,371
	Truffle	Brand 15	0.785	3.523	0.589	22.746	-57,323
Traditional RFM method	-	-	1.004	1.028	0.145	4.393	-181,770

Next, we have assessed the predictive performance of the proposed method against a traditional RFM method. Specifically, we have calculated the expected present values for the 12 months of the holdout sample across the proposed method as well as the traditional CLV method. Table 2 describes the predictive performance of both methods. We have considered six measures of predictive accuracy: (1) mean absolute error (MAE), (2) median absolute error (MDAE), (3) root mean squared error (RMSE), (4) the Pearson correlation between actual and predicted present values, (5) rank ordering of predicted versus actual values was evaluated by using Spearman correlation, and (6) the predicted total equity versus actual total equity.

At the customer level, the traditional RFM method performs quite well in predicting future behavior (MAE = $ 631.28; MDAE = $ 122.95; RMSE = $ 1742.47). Further, the customer values also correlate quite well with the actual customer values in the holdout period (Pearson correlation = 0.84; Spearman correlation = 0.87). However, the proposed RFM/PB, also at the customer-level, performs better than the traditional method across all the metrics above (MAE = $ 571.85; MDAE = $ 115.81; RMSE = $ 1,594.47; Pearson correlation = 0.85; Spearman correlation = 0.88). Turning to the overall prediction of customer equity earned in the holdout period, the proposed method significantly outperforms the traditional RFM method. The percentage deviation (Actual vs. Predicted) improves by 11.1% (from 28.3% in the traditional method to 17.2% in the proposed method). This result is important for two main reasons. First and more obviously, the proposed method predicts customer behavior better than the traditional one. Secondly, it underscores the fact that even small prediction inaccuracies at the individual level (MAE, MDAE, RMSE, Pearson, and Spearman correlations) can result in quite significant deviations in the aggregate (% deviation in customer equity). Thus, even small improvements in prediction at the individual level can go a long way in terms of predictive overall performance.

Table 2. Evaluation of prediction accuracy by using the RFM and RFM/PB methods

		Individual level				Individual ordering	Equity value
Model	Level of aggregation	MAE	MDAE	RMSE	Pearson Corr.	Spearman Corr.	% deviation
Traditional RFM method	Customer	$ 631.28	$ 122.95	$ 1,742.47	0.84	0.87	-28.3%.
RFM/PB method	Customer	$ 571.85	$ 115.81	$ 1,594.47	0.85	0.88	-17.2%
	Customer/ category/brand	$ 51.57	$ 1.11	$ 271.07	0.79	0.74	

8. EXPECTED CASH FLOWS

The underlying objective of using the CPB bottom-up approach is to unify customer level of decision-making (customer-centric) to product category and brand levels of decision-making (product-centric). Managers usually assess the expected value of such facets separately and end up having different overall present values for each one. By using the CPB bottom-up approach, the total expected cash flow generated is only one and may be analyzed from any combination among customer, product category, and brand perspectives. Therefore, by adopting such holistic perspective, it is possible to link customer, product category, and brand performance management, which is especially relevant in companies operating in traditionally product-centric industries aiming to adopt customer centricity. In this section, we present how performance assessment is conducted when these three perspectives are intertwined based on the use of the CPB bottom-up approach.

In Figure 6, we present the two highest levels of aggregation that evidence how the performance management may be assessed through a coherent disaggregation of present values for every existing customer, product category, and brand. It is coherent, because the sum of present values inside each of these three possible second levels of aggregation (customer, product category, and brand) add up to the same total equity.

By analyzing customer performance, one can easily identify how the majority of the customer base value is concentrated within the first two customer deciles. From here, all the body of knowledge accumulated in the customer management literature could be applied just as it is conducted when traditional CLV models are used.

In turn, the product categories present values are less concentrated. Gum and chocolate are the categories with the highest present values. However, drop and truffle also represent a relevant

Equity	$ 14,849,925.73					
2º level of aggregation	**Customers**		**Product Categories**		**Brands**	
	1º Decile	$ 8,161,742.54	Gum	$ 7,531,443.42	Brand 6	$ 5,675,802.03
	2º Decile	$ 2,798,733.20	Chocolate	$ 3,136,723.65	Brand 1	$ 2,276,281.21
	3º Decile	$ 1,681,725.60	Drop	$ 2,276,281.21	Brand 14	$ 1,312,769.39
	4º Decile	$ 1,096,458.29	Truffle	$ 1,905,477.44	Brand 8	$ 1,265,037.18
	5º Decile	$ 678,444.45			Brand 7	$ 1,027,832.22
	6º Decile	$ 342,538.50			Brand 5	$ 690,641.65
	7º Decile	$ 82,753.91			Brand 15	$ 592,708,06
	8º Decile	$ 6,829.22			Brand 2	$ 476,838.74
	9º Decile	$ 700.02			Brand 4	$ 421,777.00
	10º Decile	$ 0.00			Brand 11	$ 314,193.19
					Brand 3	$ 266,384.00
					Brand 9	$ 252,904.94
					Brand 13	$ 128,609.81
					Brand 12	$ 74,952.46
					Brand 10	$ 73,193.84

Figure 6. Total equity disaggregated per customers, product categories, or brands

percentage of the total equity. Finally, the analysis of the brands present values reveals how, within the geographic area covered by the distributor, Brand 6 is by far the most valuable one, followed by Brand 1, which also have a relative higher present value compared to the remaining brands. Another interesting result for the company is that several brands have a reasonable contribution to the total equity, which suggests that it has been worth offering them. On the other hand, brands such as Brand 12 and Brand 10 should have their potential to generate future cash flows better evaluated, once they have considerably lower present values.

Although the results of Figure 6 bring an interesting overall assessment of customers, product categories, and brands, by adopting the holistic perspective provided by the CPB bottom-up approach, it is possible to go further on the assessment of present values. In Table 3, we present the customer quartiles' average customer lifetime values per product category and brand. Such type of analysis is not achieved when we use separated methods to estimate the present values of expected cash flows of customers, product categories, and brands.

It shows, for instance, how Brand 6, the most valuable brand, has the highest average customer lifetime value in all customer deciles. It is also relevant to observe that despite not being among the most valuable product categories on Figure 6, truffle brands have relatively high average customer lifetime values along customer quartiles in Table 3. It may indicate that these categories could be better harnessed by the company, once they generate relatively high average customer lifetime values. Additionally, within the truffle category, Brand 14 has average customer lifetime values along customer quartiles of around twice the average customer lifetime values for Brand 15. Finally, among chocolate brands, we identify that Brand 8 and Brand 7 are the brands that have the highest average customer lifetime values.

Table 3. Customer quartile's average customer lifetime values per product category and brand

		Customer quartile			
Category	Brand	1	2	3	4
Drop	Brand 1	$1,191.18	$ 281.09	$ 51.39	$ 0.25
Gum	Brand 2	$ 233.86	$ 69.54	$ 15.78	$ 0.12
	Brand 3	$ 144.87	$ 28.95	$ 4.41	$ 0.08
	Brand 4	$ 212.07	$ 57.93	$ 12.20	$ 0.12
	Brand 5	$ 358.09	$ 84.09	$ 20.12	$ 0.14
	Brand 6	$3,048.49	$ 650.49	$ 100.83	$ 0.35
Chocolate	Brand 7	$ 562.14	$ 112.00	$ 14.07	$ 0.00
	Brand 8	$ 693.82	$ 138.70	$ 14.42	$ 0.04
	Brand 9	$ 124.14	$ 36.21	$ 8.84	$ 0.12
	Brand 10	$ 40.30	$ 6.96	$ 1.70	$ 0.03
	Brand 11	$ 160.58	$ 41.28	$ 8.39	$ 0.09
	Brand 12	$ 41.55	$ 7.45	$ 1.16	$ 0.01
	Brand 13	$ 66.97	$ 15.91	$ 3.17	$ 0.05
Truffle	Brand 14	$ 757.47	$ 102.54	$ 18.70	$ 0.11
	Brand 15	$ 325.42	$ 58.90	$ 12.33	$ 0.14

Customer management research on customer lifetime value and customer equity mostly addresses only the relationship between total equity and customer lifetime value. The intersections between customers and product categories, customers and brands, and product categories and brands have not received much focus in the literature. However, especially for companies in product-centric industries, they should be considered. Then, by using the results from the CPB bottom-up approach presented in Figure 7, managers that want to go customer-centric in contexts in which dealing with product categories and brands is essential do not need to face the dilemma of having to make a trade-off between customer centricity and product centricity. They may set the organizational structure around customers while not losing sight of product category and brand performance. In Figure 7, all the existing relationships among customers, product categories, and brands conceptually defined in Figure 2 are represented. It ultimately leads to bridging product category level and brand level decisions to customer level decisions, once category and brand performance management are fully integrated into the customer-centric perspective. In Figure 7, the size of the rectangles indicates the present value of the respective dimension represented, while

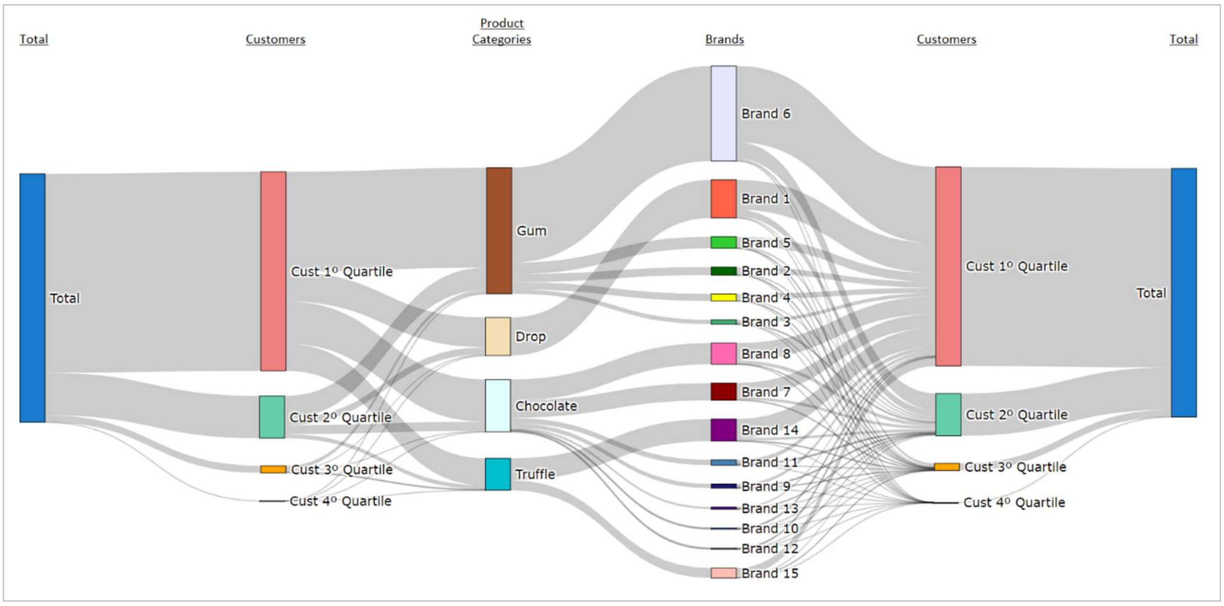

Figure 7. CPB bottom-up approach representing the expected values of customers, brands, and product categories

the width of the paths between the rectangles indicates the present value of the intersection among the dimensions. Therefore, it provides a full representation of the proposed CPB bottom-up approach.

9. GENERATING INSIGHTS FROM CPB BOTTOM-UP APPROACH

Based on the results presented in the last section, the CPB bottom-up approach allows managers to assess the present values of customers, product categories, and brands in an integrated and coherent manner, which is not possible if separated estimations were conducted for each of these dimensions. However, besides the gains in performance management aforementioned, bridging product category and brand levels performance assessment to customer level performance assessment provides additional insights for driving marketing efforts that are not reached when traditional CLV models are used. In order to accomplish it, we have studied (1) whether the percentage of customers that represent 80% of the values at the customer level is maintained when we analyze the same measure per product categories and brands; (2) what are discordances regarding who are the most valuable customers across product categories and brands; and (3) how to use the observed discordances regarding who are the most valuable customers across product categories and brands to drive marketing efforts to increase total equity.

9.1 WHERE DOES THE VALUE COME FROM? RE-EXAMINING THE PARETO RULE

By analyzing the customer deciles presented in Figure 6, one can easily identify how the majority of the customer base value is concentrated within the first two customer deciles. In order to precisely define such level of concentration, we have analyzed two measures based on the pareto distribution of customer lifetime values: (1) percentage of the top customers that accumulate 80%

of the total equity; (2) percentage of total equity accumulated by the top 20% of customers, which hereafter we refer to as Pareto ratio (Kim, Singh, & Winer, 2017; McCarthy and Winer, 2019).

In Figure 8, we present the distribution of the sum of CLVs per customer decile, indicating that 25% of the customers represent 80% of the total equity. In turn, when analyzing the Pareto ratio, we have observed that 74% of total equity is accumulated by the top 20% of customers. These results tell us only the aggregate level of concentration of value. From here, again, all the body of knowledge accumulated in the customer management literature could be applied just as it is conducted when traditional CLV models are used.

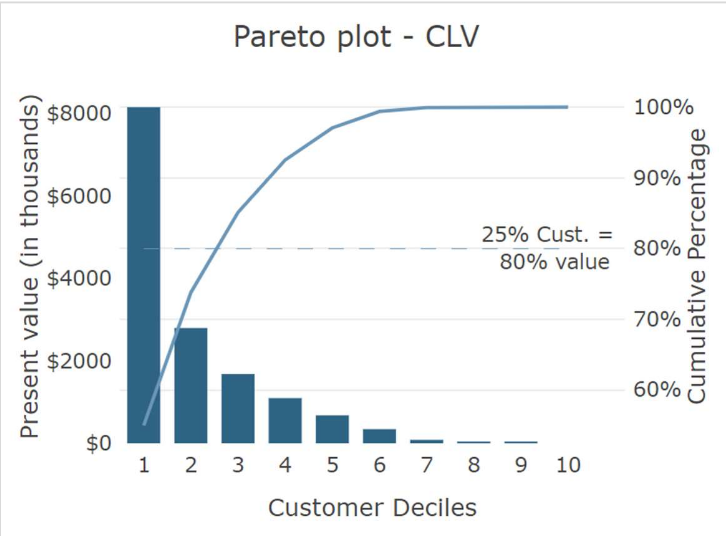

Figure 8. Pareto plot using CLV

However, unifying product category and brand levels to customer level provides additional insights for driving marketing efforts that are not reached when traditional CLV models are used to only estimate cash flows at the customer level. We are able to study whether the result at the aggregate level of concentration is maintained when we analyze the two measures per product category and brand.

In Figure 8, we have identified that, when analyzing overall customer lifetime values, 25% of the customers represented 80% of the total equity and the Pareto ratio was 74%. However, if we observe the results of the same analyses per product categories and brands (Table 4), we observe that they differ considerably from one case to another.

Table 4. Pareto rule using customer values per product category and brand

	Level of aggregation of customer values	% of top customers that accumulate 80% of the equity value	Pareto ratio
	Overall	25%	74%
Category	Drop	23%	75%
	Gum	24%	74%
	Chocolate	21%	79%
	Truffle	13%	88%
Brand	Brand 1	23%	75%
	Brand 2	21%	78%
	Brand 3	12%	93%
	Brand 4	16%	85%
	Brand 5	16%	85%
	Brand 6	23%	76%
	Brand 7	17%	84%
	Brand 8	17%	84%
	Brand 9	22%	77%
	Brand 10	11%	95%
	Brand 11	19%	81%
	Brand 12	8%	99%
	Brand 13	16%	87%
	Brand 14	11%	89%
	Brand 15	14%	86%

In Table 4, while truffle and chocolate categories have higher concentrations of value, 13% and 21% of the customers, respectively, represent 80% of the total equity of these product categories, drop and gum categories are less concentrated and have similar results to that of the overall customer lifetime value, 23% and 25% of the customers, respectively, represent 80% of the total equity of these product categories. When we analyze the Pareto ratio, we also observe that truffle and chocolate categories have higher concentration, 88% and 79% respectively, and drop and gum categories are less concentrated, 75% and 74% respectively.

Similarly, the brands also have different levels of concentration of value. In Table 4, Brand 12 and Brand 14, for instance, have the highest concentrations of value: 8% and 11%, respectively, of the customers represent 80% of the total equity of these brands. Likewise, the Pareto ratio for these brands are 99% and 89% respectively. On the other hand, brands such as Brand 2, Brand 9, Brand 6 and Brand 1 have the lowest concentrations of value: 21%, 22%, 23%, and 23%, respectively, of the customers represent 80% of the total present value of these brands. The Pareto ratio for these brands are 78%, 77%, 76%, and 75% respectively.

These results evidence how important it is to take product categories and brands into account when analyzing customer lifetime values in product-centric industries. Once the overall aggregated behavior does not hold when we have analyzed the distribution of customer lifetime values per product category and brand, managers should consider the level of concentration when defining marketing strategies for their product category and brand portfolios.

9.2. COMPARING BEST CUSTOMERS ACROSS BRANDS AND CATEGORIES

In order to identify whether there are discordances regarding who are the most valuable customers across product categories and brands, we have ordered customers from the most valuable one to the least valuable one in the following levels of aggregations: customer and product category and customer and brand. After, following the pareto distribution, we have labeled as the most valuable customers, those which their values for the respective level of aggregation analyzed summed up to 80% of the total present value of this particular level of aggregation. The other customers were labeled as out of the group of the most valuable customers. Finally, we have conducted pairwise counting to obtain the percentage of discordance, defined as the number of mismatched customers between the pair analyzed over the total number of customers. If no discordances were observed, the resulting value should be 0. The percentages of discordance among every pair of product categories are presented in Figure 9, whereas the percentages of discordance among every pair of brands are presented in Figure 10. In both figures, we have also included the percentage of discordances with the overall customer lifetime value.

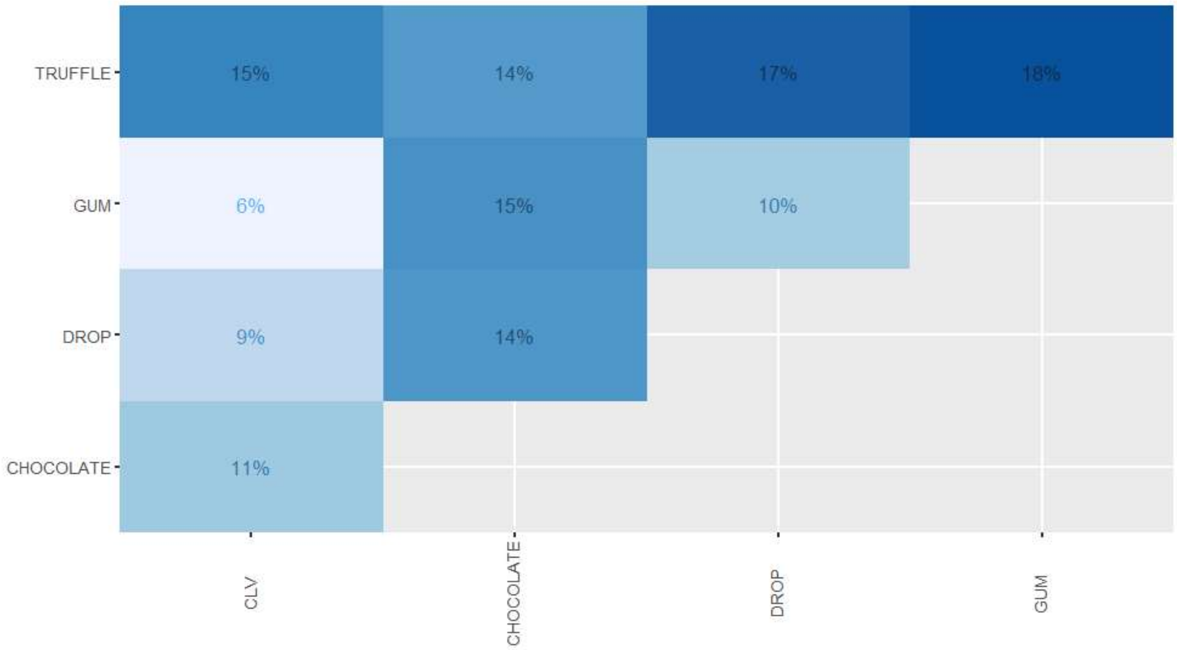

Figure 9. Pairwise percentages of discordance among the most valuable customers - product categories

According to Figure 9, there are cases in which up to 18% of the most valuable customers are different across product categories. For instance, 18% of the most valuable customers are different between truffle and gum categories. Likewise, 15% of the most valuable customers are different between chocolate and gum categories. Additionally, when compared to the overall customer lifetime value, which is the traditional metric analyzed in customer management literature, we have also found that there are discordances among the customers which have higher overall values and the most valuables ones in each product category.

Similar results were also observed when the brands were compared. Based on Figure 10, for instance, 20% of the most valuable customers are different between Brand 6 and Brand 4. Additionally, when compared to the overall customer lifetime value, we could also observe discordances when it is compared to each brand.

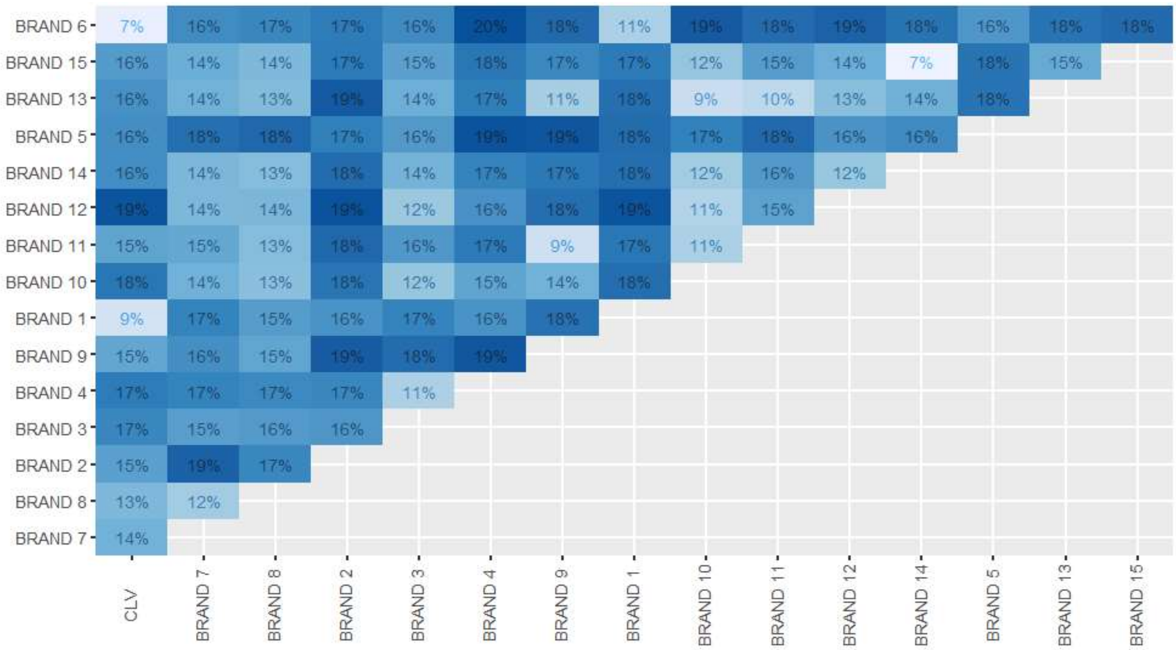

Figure 10. Pairwise percentages of discordance among the most valuable customers - brands

Such discordances highlight that when we analyze customer lifetime values per product category and brand, we discover valuable information which is not available when we analyze only aggregated customer lifetime values. In the case of the high discordance between Brand 6 and Brand 4, for instance, given that both are gum brands, it means that there are opportunities for salespeople to understand why some customers are not expected to purchase as much Brand 6 as they likely to purchase Brand 4 and vice-versa. It will lead to more precise cross-selling efforts.

9.3. IMPROVED TARGETING STRATEGIES

Given the observed discordances among categories and brands, unknown when traditional CLV models or aggregate metrics of product/brand performance are used, more precise inputs are available to drive marketing efforts to increase the total equity value. Based on the indication provided by the managers of the CPG distributor company about which are the pairs of product categories that do not cannibalize each other and should be offered together by salespeople, the gum and drop pair of product categories was chosen to conduct an analysis to reveal potential opportunities for the company to increase its total equity based on the results of the CPB bottom-up approach proposed.

Gum and drop have a discordance of 10.2% regarding who are the most valuable customers in these product categories (see Figure 9). Breaking down such score, we find that 335 customers are among the high value customers in gum category and among the low value customers in drop category (High gum/Low drop). On the other hand, there are 278 customers that are among the high value customers in drop category and among the low value customers in gum category (Low gum/High drop). Such discordances are presented in the red boxes in Figure 11, while the green boxes represent the satisfactory cases in which the customers are high value or low value in both categories.

The median CLV of gum category when customers have high values in both categories (High gum/High drop) is \$ 3,338 and the median CLV of drop category in the same quadrant is \$ 1,093. Therefore, the ratio between gum and drop median CLVs is 3.05 in the cases in which the levels of CLV are high in both categories, thus meeting marketing managers' expectations for the sales of these categories.

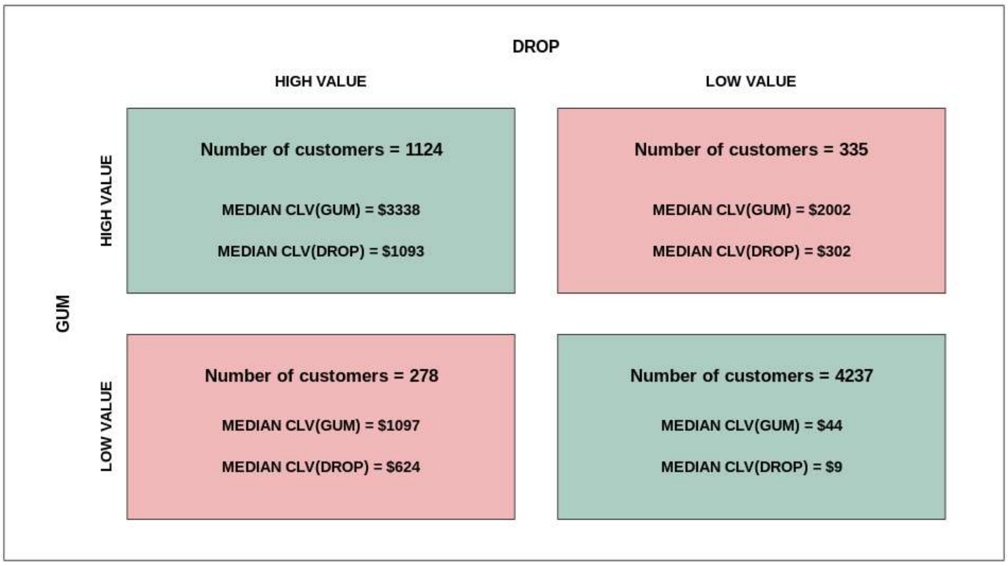

Figure 11. Comparison low value and high values customer between gum and drop categories

However, when analyzing the High gum/Low drop quadrant, the observed ratio is 6.63 and, in the Low gum/High drop quadrant, the observed ratio is 1.76. Such results evidence that there are 335 customers (5.6% of the total number of customers analyzed) which represent potential to be targeted in order to increase their CLVs of drop category. Likewise, there are 278 customers (4.6% of the total number of customers analyzed) who represent potential to be targeted in order to increase their CLVs of gum category. The goal for such marketing efforts may be set as the 3.05 ratio for the CLV of gum over the CLV of drop for each customer.

Therefore, based on the discordances between gum and drop categories, the total equity has potential to be increased up to 2.3% if all of the 355 customers who have a low CLV of drop category were eventually taken up to the level of the target ratio (3.05) by increasing their CLVs of drops and the 278 customers who have a low CLV of gum category were eventually taken up to the level of the target ratio (3.05) by increasing their CLVs of gums. It shows the potential to increase profitability by identifying opportunities for more precise targeting strategies based on the analyses provided by the use of the CPB bottom-up-approach.

10. CONCLUSION

Extant marketing research has recommended a customer-centric orientation and it is well accepted that even the organizational structure should be set around customers. Even though it is correct, in product-centric settings in which the company's success depend intrinsically on also making several decisions at the product category and brand levels, managers face a dilemma when they have to adopt customer-centric metrics such CLV and CE. On one hand, they use traditional aggregated marketing measures, such as market-share and revenue, and may end up having their departments organized by brands or product lines. On the other hand, they understand the benefits of organizing marketing efforts around customers and using individual level and forward-looking measures such as CLV and CE to maximize customer values.

Instead of engaging in such dilemma, we have proposed a different viewpoint over this problem. Product categories and brands have not lost their importance inside companies. They are, in fact, the means for companies to create value for customers. The customers, in turn, react to it by experimenting the value provided and generating cash flows when they purchase the branded products. Therefore, it should be seen as an opportunity to integrate customer, product category, and brand performance management, reaching a single framework to assess marketing activities performance and drive marketing efforts.

In order to accomplish it, firstly, we have proposed the so called CPB bottom-up approach to unify product category and brand levels performance management and customer level performance management. The results of the empirical application of this approach evidence the capacity to coherently manage the expected values of customers, product categories, and brands, extending marketing literature toward a holistic perspective attuned with the idiosyncrasies of traditional product-centric industries.

Concerning the managerial implications of adopting the CPB bottom-up approach, managers in product-centric firms are able to adopt customer centricity while also not losing sight over their product categories and brands. Additionally, they gain valuable information regarding the expected values of all possible intersections among customers, product categories, and brands.

These additional levels of analysis based on forward-looking values are relevant, because they reveal that there are different concentrations of value across product categories and brands which should be considered when defining the marketing programs. Furthermore, they allow identifying discordances regarding who are the most valuable customers across product categories or brands, providing more precise guidance to organize marketing efforts to increase overall expected profitability.

Even though the present research has provided the aforementioned managerial and theoretical contributions, the main limitation lies on fact that the proposed method to estimate the CPB bottom-up approach does not take into account the possible correlations between product categories and brands. Future research on the topic could address such issue.

Besides this, future research opportunities also include the possibility of using product recommendation algorithms to more precisely define which of the customers with discordances across product categories or brands are most likely to purchase the product category or brand to even more precisely drive the increase in total equity value. Finally, the RFM/PB method adopted does not rely on covariates, so it does not help managers to understand why customers are not expected to purchase. The adoption of different CLV models that use covariates may be a good alternative to solve this issue.

REFERENCES

Ambler, T., Bhattacharya, C. B., Edell, J., Keller, K. L., Lemon, K. N., & Mittal, V. (2002). Relating Brandand Customer Perspectives on Marketing Management. *Journal of Service Research*, *5*(1), 13–25.

Ding, Y., DeSarbo, W. S., Hanssens, D. M., Jedidi, K., Lynch, J. G. Jr., & Lehmann, D. R. (2020). The past, present, and future of measurement and methods in marketing analysis. *Marketing Letters*. June.

El-Ansary, A. I. (2006). Marketing strategy: Taxonomy and frameworks. *European Business Review*, *18*(4), 266–293.

Fader, P. S., Hardie, B. G., & Lee, K. L. (2005a). RFM and CLV: Using iso-value curves for customer base analysis. *Journal of Marketing Research*, *42*(4), 415–430.

Fader, P. S., Hardie, B. G. S., & Lee, K. L. (2005b). “Counting Your Customers” the Easy Way: An Alternative to the Pareto/NBD Model. *Marketing Science*, *24*(2), 275–284.

Keiningham, T. L., Aksoy, L., Perkins-Munn, T., & Vavra, T. G. (2005). The Brand-Customer Connection. *Marketing Management*, (July), 33–37.

Keller, K. L., & Lehmann, D. R. (2006). Brands and Branding: Research Findings and Future Priorities. *Marketing Science*, *25*(6), 740–759.

Kim, K. H., Ko, E., Xu, B., & Han, Y. (2012). Increasing customer equity of luxury fashion brands through nurturing consumer attitude. *Journal of Business Research*, *65*(10), 1495–1499.

Kim, B. J., Singh, V., & Winer, R. S. (2017). The Pareto rule for frequently purchased packaged goods: an empirical generalization. *Marketing Letters*, *28*(4), 491-507.

Kumar, V. (2010). A Customer Lifetime Value-Based Approach to Marketing in the Multichannel, Multimedia Retailing Environment. *Journal of Interactive Marketing*, *24*(2), 71–85.

Kumar, V., & Reinartz, W. (2016). Creating enduring customer value. *Journal of Marketing*, *80*(6), 36–68.

Kumar, V., & Shah, D. (2009). Expanding the Role of Marketing: From Customer Equity to Market Capitalization. *Journal of Marketing*, *73*(6), 119–136.

Kumar, V., Sunder, S., & Sharma, A. (2015). Leveraging Distribution to Maximize Firm Performance in Emerging Markets. *Journal of Retailing*, *91*(4), 627–643.

Leone, R. P., Rao, V. R., Keller, K. L., Luo, A. M., McAlister, L., & Srivastava, R. (2006). Linking Brand Equity to Customer Equity. *Journal of Service Research*, *9*(2), 125–138.

Lee, J.-Y., Kozlenkova, I. V., & Palmatier, R. W. (2015). Structural marketing: Using organizational structure to achieve marketing objectives. *Journal of the Academy of Marketing Science*, *43*(1), 73–99.

Lin, H.-H., Li, H.-T., Wang, Y.-S., Tseng, T. H., Kao, Y.-L., & Wu, M.-Y. (2017). Predicting Customer Lifetime Value for Hypermarket Private Label Products. *Journal of Business Economics and Management*, *18*(4), 619–635.

McCarthy, D. M., & Winer, R. S. (2019). The Pareto rule in marketing revisited: is it 80/20 or 70/20?. *Marketing Letters*, *30*(2), 139-150.

Mantrala, M., Levy, M., Kahn, B., Fox, E., Gaidarev, P., Dankworth, B. & Shah, D. (2009). Why is Assortment Planning so Difficult for Retailers? A Framework and Research Agenda. *Journal of Retailing*, *85*(1), 71-83.

Mzoughia, M. B., Borle, S., & Limam, M. (2017). A MCMC approach for modeling customer lifetime behavior using the COM-Poisson distribution. *Applied Stochastic Models in Business and Industry*, *34*(2), 113–127.

Romero, J., & Yagüe, M. J. (2015). Relating Brand Equity and Customer Equity: An Exploratory Study. *International Journal of Market Research*, *57*(4), 631–652.

Rosset, S., Neumann, E., Eick, U., & Vatnik, N. (2003). Customer lifetime value models for decision support. *Data Mining and Knowledge Discovery*, *7*(3), 321–339.

Rust, R. T., Lemon, K. N., & Zeithaml, V. A. (2004). Return on Marketing: Using Customer Equity to Focus Marketing Strategy. *Journal of Marketing*, *68*(1), 109–127.

Sunder, S.; Kumar, V.; Zhao, Y. (2016). Measuring the Lifetime Value of a Customer in the Consumer Packaged Goods Industry. *Journal of Marketing Research*, *53*(6), 901–921.

Wiesel, T., Skiera, B., & Villanueva, J. (2008). Customer Equity: An Integral Part of Financial Reporting. *Journal of Marketing*, *72*(2), 1-14.

Zhang, Y, Bradlow, E. T., & Small, D. S. (2015). Predicting Customer Value Using Clumpiness: From RFM to RFMC. *Marketing Science*, *34*(2), 195-208.