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Identifying Customer-centric, Cross-category Product Groups: A Product Segmentation Approach and Its Relationship to Customer Segmentation Approaches

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ABSTRACT

As part of their customer management strategy, retailers with large, multi-category offerings need to present their products in ways that help target customers search and choose from those offerings. The authors propose a product segmentation approach that gives retailers a methodology for directly identifying customer-centric, cross-category, product segments from large numbers of products in multiple categories such that products within a segment are purchased by the same type of customers. In addition, the research examines the relationship between the proposed product segmentation approach and a parallel customer segmentation approach. The close relationship between the approaches suggests that the segments of products and customers inferred from each approach will be equivalent. However, the authors show that this is not the case because of the aggregation constraint imposed on customers in the product segmentation approach and on products in the customer segmentation approach. Further, the authors show that the product segmentation approach provides better recommendations of products for a customer to purchase, while the customer segmentation approach provides better recommendations of customers for a product to target.

Many retailers present their customers very large, multi-category product or service offerings. Category specialist retailers such as Best Buy, Bed Bath and Beyond, and Staples offer 20,000 to 40,000 SKUs in their stores (Levy and Weitz 2006), while a typical Wal-Mart supercenter offers over 150,000 SKUs (Daniels 2004). As part of their customer management strategies, retailers that offer such large numbers of products or services need to align their offerings with the types of customers they wish to target. That is, the retailers need to present their product or service offerings in ways that will help their target customers efficiently search and choose products or services from the large offerings. (Henceforth, we use the term "products" to refer equally to products or services.)

The following example illustrates how a retailer with a large, multi-category product offering might attempt to align its offering and its target types of customers. Wal-Mart sells thousands of products in a number of different categories including household products, personal care items, apparel, and groceries. Wal-Mart recently identified six types of customers it wishes to target: "Hispanics," "African-Americans," "Suburbanites," "Rural Residents," "Affluent," and "Empty-nesters" (McTaggert 2006). Currently, the retailer's store layouts are organized by category. However, to improve the in-store shopping experience of its six target types of customers, Wal-Mart could organize its store layouts into collections of products that attract each of the target customer-types. Similarly, to help its customers better navigate its online retail channel, Wal-Mart could structure its website format such that web pages feature collections of products that each customer-type is most likely to find appealing. To develop the store layouts or website format, the retailer needs to identify the subset of its products that is most attractive to each target customer-type.

In general, to present their offerings in a way that is more appealing to their target customers, retailers with large, multi-category product offerings require a methodology for identifying customer-centric, cross-category groups of products. We refer to these product groupings as "product segments". This terminology is commonly used in marketing practice to refer to groups of products that attract a particular customer-type. In the packaged goods industry, product segments are sometimes named by the benefit that attracts customers, e.g., low-carbohydrate, low-fat, organic, and sugar-free product segments

(Convenience Store News 2004). In the automobile industry, product segments are sometimes named by the demographic that characterizes attracted customers, e.g., young driver or family car segments (Economist 2005). However, such product segments are defined based on managerial intuition into which products should be included in a segment rather than empirical analysis of the type of customers attracted to the collection of products. In this research, we present a methodology for defining product segments by empirically identifying groups of products from multiple categories such that products in a group attract the same type of customers.

One approach that marketers have traditionally used to align customers and products is customer segmentation, and one of the most popular approaches to segmenting customers is to combine latent class analysis with a choice model (e.g., Heilman and Bowman 2002; Kamakura and Russell 1989). Latent class customer segmentation aligns customers and products by identifying groups of customers such that customers within a group prefer the same type of products. However, this approach may be limiting in two respects. First, the approach may be limiting for retailers that offer very large numbers of products because it requires the analyst to aggregate the many individual products into a smaller number of choice alternatives to make estimation and interpretation of the underlying choice model tractable. This aggregation is based on the analysts' assumption of the product attribute that drives customers' preferences and varies across applications. For example, Kamakura and Russell (1989) aggregated the SKUs in a single consumer packaged food category into four alternatives based on brand name: national brands A, B, and C, and a composite brand, P, representing private label and regional brands. Heilman and Bowman (2002) aggregated 40 SKUs in three categories of baby products – disposable diapers, formula and towels – into 20 alternatives based on market share: big/leading national brands, medium size brands, small brands, private label composites, and "other" brand composites. While aggregating choice alternatives is standard procedure in such models, this aggregation imposes a constraint on the analysis. That is, in aggregating SKUs, the analyst assumes that customers' preferences for each of the aggregated SKUs is identical and is equal to the estimated preference for the aggregate product. As such, the aggregation constraint can potentially obscure information and restrict the analyst's ability to understand the relationship between customers and products at the most disaggregated product level, such as a SKU.

Latent class customer segmentation may also have limitations in contexts where the retailer has defined the types of customers it wishes to target. Latent class customer segmentation first specifies managerially relevant types of products and then identifies, for each product-type, latent groups of customers that have the strongest preference for that product-type. For example, Heilman and Bowman (2002) define 20 product-types as described above and then identify latent customer segments based on individual customers' preferences for those product-types. If the latent customer segments identified do not correspond to the retailer-defined target customer-types, the customer segmentation approach could be limited in the extent to which its results are actionable.

Another approach marketers use to understand the relationship between customers and products is market structure analysis. One can think of the market structure literature as providing models that identify product segments; the goal typically stated for such models is to group together products that a consumer would be willing to substitute for one another. By definition, then, a group of products indirectly inferred from market structure analysis would be composed of products that tend to attract the same type of customers. Traditionally, however, market structure models tend to consider only those products within a single category, such as coffee (e.g., Cooper 1988; Fraser and Bradford 1983), soft drinks (e.g., DeSarbo and De Soete 1984; Rao and Sabavala 1981), and laundry detergent (e.g., Elrod and Keane 1995; Ramaswamy and DeSarbo 1990). While some market structure analyses do consider multiple categories, they typically evaluate preferences and identify structure in each category independently (e.g., Erdem 1996; Grover and Dillon 1985; Russell and Bolton 1988; Shugan 1987). Erdem and Winer (1999) estimate consumer preferences in two closely related categories (toothpaste and toothbrushes) comprising substitute and complementary products by allowing price and attribute preferences to be correlated across categories. However, Erdem and Winer (1999) focus on mapping competitive relationships among brands in each category separately. In general, market structure models have traditionally not addressed contexts that involve identifying groups of products with associations across categories.

The first objective of this research is to present a methodology for identifying latent product segments from large numbers of products in multiple categories. The proposed method adapts the widely applied latent class methodology for identifying customer segments. While the latent class approach is used in customer segmentation to identify groups of *customers*, such that customers within a group prefer the same type of products, we use a latent class approach to identify groups of *products* such that products within a group attract the same type of customers. The proposed product segmentation approach identifies these product groupings by first defining a set of managerially relevant "customer-types". For example, for Wal-Mart, those managerially relevant customer-types are "Empty-nesters," "Affluent," etc. McAlister, George and Chien (2007) develop the attraction model, which allows one to determine, for a given product, the strength with which that product attracts the defined customer-types. Our approach combines latent class analysis with the attraction model to identify groups of products such that products in an identified group attract the same customer-types. Thus, our first contribution is to provide retailers and analysts with an empirical methodology for directly identifying cross-category, customer-centric product segments from large, multi-category product offerings.

The second objective of this research is to investigate the relationship between product segmentation and customer segmentation. We examine the relationship between the two approaches by empirically comparing the proposed use of latent class analysis to identify product segments with analogous use of latent class analysis to identify customer segments. First, we compare the two approaches in terms of the product segments and customer segments identified by each approach when applied to the same customer product choice data set. In an illustrative application involving an education service provider, we show that, contrary to prior suggestions (see Grover and Srinivasan 1987), the product segments and customer segments identified by one approach are not identical to the product segments and customer segments identified by the other approach. This happens because each approach is impacted by the aggregation constraints imposed on customers in the product segmentation approach and imposed on products in the customer segmentation approach. Thus, our second contribution is to enhance our understanding of the relationship between customer segmentation and product segmentation by illustrating the impact of the aggregation constraint on the underlying models.

In addition, we examine the relationship between product segmentation and customer segmentation by empirically comparing each approach's ability to address two questions of managerial relevance: Which group of products would one recommend for a customer to purchase? Which group of customers would one recommend for a product to target? The results of our illustrative application indicate that the product segmentation approach is more effective at recommending a group of products for a customer to purchase, while the customer segmentation approach is more effective at recommending a group of customers for a product to target. As such, our third contribution is to suggest managerial applications for which the proposed product segmentation approach and the traditional customer segmentation approach are likely to be relatively more effective.

In the sections that follow, we describe the relationship between the proposed latent class product segmentation approach and the widely applied latent class customer segmentation approach. We develop the model underlying the product segmentation approach and contrast the elements of that model with those of the parallel customer segmentation approach. In a service provider context, we estimate the two models and compare the relative efficacy of each approach's recommendations of (1) a group of products for a customer to purchase and (2) a group of customers for a product to target. We conclude with research and managerial implications and directions for future research.

RELATIONSHIP BETWEEN PRODUCT SEGMENTATION AND CUSTOMER SEGMENTATION

In simultaneously estimating latent customer segments and market structure (or what we refer to as indirectly inferred product segments), Grover and Srinivasan (1987, p.140) suggest that, when brand choice probabilities are used as the basis for segmentation, the two analyses are "reverse sides of the same analysis." That is, customer segmentation, which directly identifies groups of customers, also implies product segments when one observes the products preferred by the different groups of customers. Similarly, then, product segmentation, which directly identifies groups of products, also implies customer segments when one observes the customers attracted to the different groups of products. Despite the parallel nature of the two analyses, however, it is not the case that they yield exactly the same results when applied to a given data set. In fact, the customer segments directly identified from a particular set of customer product choice data need not be identical to the customer segments inferred by product segmentation of the same data. Similarly, the product segments directly identified from a particular set of customer product choice data need not be identical to the product segments inferred by customer segmentation of the same data.

Directly identified product segments will differ from the product segments inferred by customer segmentation approaches because of the aggregation constraint applied to the individual choice alternatives when estimating the choice model underlying the customer segmentation approach. Because there typically are a large number of individual choice alternatives in a raw consumer choice data set, such as a customer management database or scanner panel, analysts group those alternatives into managerially relevant aggregates and then estimate choice model parameters by considering the strength with which customers prefer those aggregates. To simplify exposition, we refer to individual choice alternatives as "products", and refer to the analyst-imposed, managerially relevant aggregates of those individual choice alternatives as "product-types." For example, we refer to the "big national brand" and "private label composite" defined by Heilman and Bowman (2002) as product-types. While the constraint of aggregating products into product-types makes choice model estimation feasible, the aggregation constraint also obscures some information about customers' preferences for the underlying products. For example, Heilman and Bowman's (2002) assumption that a customer will equally prefer all "private label composite" diapers may obscure heterogeneity in the degree to which that customer prefers individual SKUs defined as "private label composite".

Just as the choice model underlying the customer segmentation approach requires imposing an aggregation constraint on products, the attraction model (McAlister, George and Chien 2007) underlying our product segmentation approach requires imposing an aggregation constraint on customers. Because the number of individual customers in a consumer choice data set can be large, we first group individual customers into managerially relevant aggregates and then estimate attraction model parameters by considering the strength with which products attract those aggregates. To simplify exposition, we refer to individual customers as "customers", and refer to the analyst-imposed, managerially relevant aggregates as "customer-types." For example, we refer to the "Affluent" and "Empty-nesters" targeted by Wal-Mart as customer-types. While the constraint of aggregating customers into customer-types makes attraction model estimation feasible, the aggregation constraint also obscures some information about the strength with which different products attract individual customers. For example, Wal-Mart's assumption that a product will equally attract all "Empty-nesters" would obscure heterogeneity in the degree to which that product attracts individual customers defined as "Empty-nesters".

Because some information is obscured when imposing the product-type aggregation constraint in the customer segmentation approach, we expect this will adversely affect the quality of the product segments inferred from this approach. Similarly, because some information is obscured when imposing the customer-type aggregation constraint in the product segmentation approach, we expect this will adversely affect the quality of the customer segments inferred from this approach. Managerially, the quality of the results will impact each approach's applicability in addressing different marketing problems. That is, we expect that the customer segmentation approach should be more effective than the product segmentation approach at recommending a group of customers for a product to target.

Conversely, we expect that the proposed product segmentation approach should be more effective than the customer segmentation approach at recommending a group of products for a customer to purchase.

In summary, our proposed product segmentation approach and the parallel customer segmentation approach yield related results. However, because of the aggregation constraint imposed on customer data when applying the product segmentation approach and the aggregation constraint imposed on product data when applying the customer segmentation approach, one should not expect to identify the same product groupings and customer groupings when the two approaches are applied to the same data set. Further, it is likely that each approach will be better suited to addressing different managerial applications.

MODEL DEVELOPMENT

Proposed Product Segmentation Approach

The proposed product segmentation approach begins with data for a sample of customers' choices across many products in multiple categories. The problem is made tractable by reducing the large number of individual customers to a few managerially relevant customer-types. For each product, we determine the relative strength with which that product attracts the different customer-types. We then identify a finite number of latent product segments such that products in a segment attract the same customer-types. Finally, in a posterior analysis, we probabilistically assign products to segments.

Determine the strength with which a product attracts different customer-types. To determine the relative strength with which a product attracts different customer-types, we apply McAlister, George and Chien's (2007) attraction model. This model represents the strength with which a product attracts each customer-type as the conditional probability that a given purchase of the product, p, was made by a particular customer-type, C, on a particular transaction, t, $prob_{p,C,t}$. Specifically, given a set of customer-types, C =1,2,…, N_C and a set of individual products, p = 1,2,…,n_P, we define, for the randomly selected t^{th} transaction on which product p was chosen, the probability that the purchase was made by a customer of type C as:

(1) $$prob(C,t \mid p) = \exp\{\alpha_{p,C,t}\} \Big/ \sum_{C=1}^{N_C} \exp\{\alpha_{p,C,t}\}$$

Given a set of M observable customer, product, and market environment variables that influence the strength with which product p attracts different customer-types, the deterministic component of the strength with which product p attracts a customer of type C on the t^{th} transaction is calculated as:

(2) $$\alpha_{p,C,t} = \sum_{m=1}^{M} w_m x_{p,C,t}$$

where $x_{p,C,t}$ is the observed value of characteristic m for customer-type C and product p on the t^{th} transaction, and w_m is the attraction weight of characteristic m. The calculated probabilities represent a product's probability of attracting each customer-type on the t^{th} transaction. We refer to this set of probabilities as a product's "customer mix". The objective, assumptions, and specification of the attraction model are further outlined in Appendix A.

Identify product segments. We define product segments by identifying products that have the same customer mix. That is, we allow for heterogeneity in the strength with which products attract different customer-types. We group together products using a mixture model that combines latent class analysis with the attraction model. Specifically, we assume there exists a finite number of product segments N_Π and define, for any given purchase of product p in product segment Π, the probability that the purchase was made by customer-type C on the t^{th} transaction as:

(3) $$prob(C,t \mid p\varepsilon\Pi) = Q_\Pi * prob(C,t \mid p)$$

where $Q_{\Pi} = \exp\{\theta_{\Pi}\} \Big/ \sum_{\Pi=1}^{N_{\Pi}} \exp\{\theta_{\Pi}\}$ is the unconditional probability that a given product p is included in product segment Π, and θ_{Π} is the estimated product segment size parameter. We refer to this as the product segmentation (PS) approach. We estimate the model using maximum likelihood procedures to obtain estimates of the attraction weights for each product segment and the size of each product segment. Letting H_p be the collection of all transactions in which product p was chosen, the likelihood function is:

(4)
$$L(H_p) = \sum_{\Pi=1}^{N_{\Pi}} Q_{\Pi} * L(H_p \mid \Pi)$$

where $L(H_p \mid \Pi) = \prod_{C=1}^{N_C} \prod_{t=1}^{T} prob(C, t \mid p \varepsilon \Pi)$.

Assign products to product segments. Finally, in a posterior analysis, we probabilistically assign each product to a product segment such that items assigned to a product segment attract the same customer-types. Specifically, we employ a Bayesian calculation to compute the probability that product p is included in product segment Π and assign each product to the product segment for which it has the highest inclusion probability. The segment assignment probabilities are calculated as:

(5)
$$prob(p \varepsilon \Pi \mid H_p) = L(H_p \mid \Pi) * Q_{\Pi} \Big/ \sum_{\Pi=1}^{N_{\Pi}} [L(H_p \mid \Pi) * Q_{\Pi}]$$

Parallel Customer Segmentation Approach

The proposed product segmentation approach parallels latent class approaches that identify customer segments such that customers in a segment prefer the same product-types. In particular, the approach most closely parallels the approach first presented by Kamakura and Russell (1989) and recently presented by Heilman and Bowman (2002) to identify customer segments based on customers' preferences for product-types in multiple categories. We refer to this as the customer segmentation (CS) approach. In multi-category contexts, the CS approach begins with data for a sample of customers' choices across many products in multiple categories. In this case, the problem is made tractable by reducing the large number of products to a few managerially relevant product-types. Using a multinomial logit choice model, for each customer, the CS approach determines the relative strength with which that customer prefers the different product-types. Using latent class analysis, the CS approach identifies a finite number of latent customer segments and, in a posterior analysis, probabilistically assigns customers to segments. We compare in further detail the specification and estimation of the proposed PS approach and the CS approach in Appendix A.

Comparing Approaches

Given that the PS approach and the CS approach are parallel methodologies for aligning products and customers, we compare the approaches by testing their effectiveness in two managerial applications. The first test investigates each approach's effectiveness at recommending a group of products for a customer to purchase. Specifically, we compare the set of products each approach recommends for a withheld customer to purchase with the set of products that customer actually purchased. The second test investigates each approach's effectiveness at recommending a group of customers for a product to target. In this case, we compare the set of customers each approach recommends for a withheld product to target with the set of customers who actually purchased that product. In both tests, for each approach, we test the success of the approach using the leave-one-out variation of the n-fold bootstrapping technique (see Mitchell 1997). In a data set with N observations, this technique involves estimating the model N separate times on all of the data except for one observation (i.e., estimate the model with N-1 observations) and then making a prediction for the withheld observation.

First test: Recommend products for a customer to purchase. In the first test, we apply the PS approach and CS approach to recommend a group of products for a customer to purchase. For a withheld customer, we disregard all information about the customer except the customer-type, estimate the model using the purchase histories of all other customers in the data set, and then identify a group of products to recommend to the withheld customer. We repeat the process for each customer in the data set and calculate the hit rate of our recommendations (i.e., the extent to which the recommended products were actually purchased by the withheld customer) for each customer.

In the first test, recommendations of a group of products for a particular customer-type, C_0, to purchase are based on conditional probabilities $prob(\Pi \mid C_0)$ for the PS approach and $prob(P \mid C_0)$ for the CS approach (calculation of the conditional probabilities is presented in the top half of Appendix B). Both quantities report the probability that a particular kind of product was chosen (product from segment Π for the PS approach and product of type P for the CS approach) given that a customer of type C_0 did the choosing. Note, however, that for the PS approach, latent class analysis identifies the products to include in product segment Π, while for the CS approach, the products included in product-type P are determined a priori by the analyst. As such, we expect that the PS approach, which groups products using latent class analysis rather than analyst judgment, will be more effective at identifying a group of products to recommend for a customer to purchase.

Second test: Recommend customers for a product to target. In the second test, we apply the PS approach and the CS approach to recommend a group of customers for a product to target. For a withheld product, we disregard all information about the product except its product-type, P_0, estimate the model using the purchases of all other products in the data set, and then identify a group of customers to whom the withheld product should be targeted. We repeat the process for each product in the data set and calculate the hit rate of our recommendations (i.e., the extent to which the recommended customers actually purchased the product) for each product.

In the second test, recommendations of a group of customers for a particular product-type to target are based on conditional probabilities: $prob(C \mid P_0)$ for the PS approach and $prob(\chi \mid P_0)$ for the CS approach (calculation of the conditional probabilities is presented in the bottom half of Appendix B). Both quantities report the probability that a particular kind of customer did the choosing (customer of type

C for the PS approach and a customer from segment χ for the CS approach) given that a product of type P_0 was chosen. Note, however, that for the CS approach, latent class analysis identifies the customers to include in customer segment χ, while for the PS approach the customers included in customer-type C are determined a priori by the analyst. As such, we expect that the CS approach, which groups customers using latent class analysis rather than analyst judgment, will be more effective at identifying a group of customers to recommend for a product to target.

Converting conditional probabilities into recommendations. We considered four rules for converting the conditional probabilities into recommendations. For ease of exposition, we discuss only one of these rules and present the additional rules and the results of their related statistical tests in Appendices C and D. The rule for which we report results recommends a product or customer if the conditional probability is greater than one would expect randomly. Specifically, for the first test, this rule recommends a group of products to a customer of type C_0 if the conditional probability of selecting a product from the group is greater than one would expect randomly (i.e., > [1 / number of sets of products]). In this test, we define the "hit rate" as the proportion of products the withheld customer actually purchased that the approach recommended. For the second test, this rule recommends a group of customers for a product of type P_0 to target if the conditional probability of selecting a customer from the group is greater than one would expect randomly (i.e., > [1 / number of sets of customers]). In this test we define the "hit rate" as the proportion of customers who actually purchased the withheld product that the approach recommended as targets.

ILLUSTRATIVE APPLICATION

To illustrate the PS approach and compare the relative efficacy of the PS and CS approaches for different managerial objectives, we apply both approaches in a service context. Specifically, we examine the elective courses chosen by MBA students in the business school at a large southwestern university. As a service provider, the business school offers a large number of elective courses to meet the needs of different types of students. Specifically, the business school offers a range of elective courses across multiple departments (accounting, finance, management, management of information systems, and marketing) to meet the needs of students obtaining an MBA degree to pursue careers in investment banking, corporate finance, technology management, general management, brand management, and consulting, among other fields. As such, the business school is a service provider for which the products (services) are courses and the product-types (service-types) can be defined by the departments that offer those courses; and for which the customers are students and the customer-types can be defined by the careers that students want to pursue.

The problem of aligning the elective courses offered by the business school with the needs of different types of students can be viewed from two perspectives. First, consistent with the PS approach, one can consider the different courses that attract a particular student-type to determine the set of courses that could be recommended to that student-type. Understanding the set of courses that attracts a certain student-type can help the business school in a number of student management activities including preparing promotional materials to recruit students and recommending elective courses consistent with students' job placement objectives. Alternatively, consistent with the CS approach, one can consider the different students who prefer a particular course-type to determine the set of students to whom that course-type could be targeted. Understanding the set of students that prefers a certain course-type allows the business school to target a particular course to those students most likely to be interested in that course and to tailor a course's content to the goals of the students attracted to the course.

Description of Data

The data used to estimate the models includes two sets of information. The first data set describes the products and comprises course enrollment data for 32 elective MBA courses offered during the 1998-99 and 1999-2000 academic years as reported by the university's MBA program office. Compulsory courses were omitted from the analysis because these courses are required of all students and, therefore, have no observable variation in attraction across students. We find variation among elective course choices because students in this MBA program are not required to declare a concentration, but rather can choose courses offered by any department based on their interests, strengths and perspectives on how best to prepare for a particular career. Based on input from MBA program administrators on factors that might help explain courses' attraction for different students, the product attributes included in the analysis were the department in which the course is offered and the average course evaluation score. Courses are offered by five different departments: (1) Accounting, (2) Finance, (3) Management of Information Systems, (4) Management, and (5) Marketing. For estimation of the CS approach, we define the product-types by the department in which the course is offered. A summary of the product characteristics is presented in Table 1.

The second data set describes the sample of 326 customers (students) who graduated from the MBA program in 2000. This information was derived from a survey completed by all students upon graduation. The student characteristics included in the model were also based on input from MBA program administrators and help explain students' background and career orientation. For estimation of the PS approach, we define customer-types by the first job the student took after graduation: (1) Investment Banker, (2) Corporate Finance, (3) Technology Manager, (4) General Manager, (5) Brand Manager, (6) Consultant, and (7) Other. An additional student characteristic included in the model indicates whether the student has a technical bachelor's degree. A summary of the student characteristics is presented in Table 1.

TABLE 1
SAMPLE CHARACTERISTICS

Products (Courses)		**Customers (Students)**	
Product-type sample shares		Customer-type sample shares	
Accounting	9%	Investment banker	15%
Finance	28%	Corporate finance	9%
Management of information systems	22%	IT manager	10%
Management	32%	General manager	12%
Marketing	9%	Brand manager	18%
		Consultant	19%
		Other	17%
Product attribute:		Customer characteristic:	
Mean course evaluation score (min=1 / max=5)	4.12	Students with technical undergraduate degrees	34%

Model Specification

We consider three alternative model specifications for the PS approach. In the first specification, Model 1, we include only customer-type-specific constants. To further our understanding of a product's strength of attraction for different customer-types, the second model specification includes an additional customer characteristic. Because certain courses (such as quantitative courses) may have higher attraction for students with technical backgrounds, the second specification, Model 2, adds to Model 1 an additional dummy variable that indicates whether a particular student has a technical undergraduate degree. Finally, we consider the impact of a particular product attribute on the strength with which a product attracts different customer-types. Because courses that receive higher evaluations may attract different students, Model 3 adds to Model 2 a variable indicating the average evaluation score for each course[1]. Each of the model specifications for the PS approach is presented in Appendix E. We apply each of the three model specifications sequentially to evaluate the information provided by the additional predictors. Within each model specification, we systematically increase the number of product segments in the model and monitor

[1] Because some courses are offered more than once during our period of observation, we are not able to link students who take the course to a particular offering of a given course. Hence, we represent the evaluation of the course by the average evaluation the course received during the period of observation.

the change in the log-likelihood and Consistent Akaike Information Criterion (CAIC). Across model specifications and product segment levels, we select the model with the lowest CAIC while maximizing the log-likelihood as the model with the best fit.

We also consider three alternative model specifications for the CS approach. In the first specification, Model 4, we include only product-type-specific constants. To further our understanding of a customer's preference for different product-types, the second CS model specification includes an additional product attribute. Because certain students may prefer courses with higher course evaluations, the second specification, Model 5, adds to Model 4 the variable that indicates the average course evaluation score for the particular course. Finally, we consider the impact of a particular customer characteristic on a customer's preference for different product-types. Because students who have technical backgrounds might prefer different courses, Model 6 adds to Model 5 the dummy variable indicating whether a student has a technical undergraduate degree. Each of the model specifications for the CS approach is presented in Appendix E. As with the PS approach, we sequentially apply each of the three specifications of the CS approach, systematically increase the number of customer segments within each model specification, and, across specifications, select the model with the lowest CAIC as the model with the best fit.

Product Segmentation Approach Results

Directly identified product segments. As indicated in Table 2, the 4-product segment solution of Model 1 has the lowest CAIC compared to other solutions for Models 1, 2, and 3. Hence we find that the explanatory power provided by the customer- and product-specific predictor variables in Models 2 and 3 was not great enough to overcome the cost of including those additional parameters. From Table 3, which summarizes the results of assigning courses to product segments using posterior probabilities, the 4-product segment solution of Model 1 indicates that Product Segment 1, "Quantitative" courses, is made up of some Finance, Accounting, and MIS courses; Product Segment 2, "Technical" courses, is exclusively made up of MIS courses; Product Segment 3, "Analytical" courses, is made up of Marketing courses with some Management and MIS courses; and Product Segment 4, "General Appeal" courses, is made up of Management courses with some Finance and Accounting courses. Thus, contrary to what one might expect, the identified segments indicate that all courses offered by a particular department do not attract the same types of students. For example, the MIS courses assigned to Product Segment 1 attract a different mix of students compared to the MIS courses assigned to Product Segment 2 or 3.

Customer-types attracted to each product segment. Table 3 also reports estimated attraction weights for the PS approach. Because the significance levels of the coefficients depend on the customer-type selected as the baseline, we cannot directly infer the mix of customers attracted to each product segment from those coefficients. Instead, we refer to the probabilities, prob($\Pi|C_0$) that are used to compare the relative effectiveness of product recommendations for the PS approach. We present those probabilities in the bottom section of Table 3 and highlight all instances in which the calculated recommendation probability exceeds the recommendation rule, (1/# product segments) = .25. That is, we can say that courses in product segment Π are more likely to be chosen by a customer of type C_0 than one would expect if that customer-type were choosing randomly among the four product segments. Combining this information with knowledge of the mix of courses in each product segment, the top half of Table 4 shows that, as we might expect, the "Quantitative" courses (Finance, Accounting, and MIS) in Product Segment 1 attract students who pursue careers as Investment Bankers, Corporate Financiers, and Other careers; "Technical" courses (MIS) in Product Segment 2 attract students who pursue IT Management careers; and "Analytical" courses (Marketing, Management, and MIS) in Product Segment 3 attract students who pursue careers in Brand Management. However, the results also reveal findings that one may not have expected. In particular, we find that the "General Appeal" courses in Product Segment 4, which includes not only Management courses, but also Finance, and Accounting courses, attract all student-types.

TABLE 2
PRODUCT SEGMENTATION APPROACH: SELECTION OF BEST-FITTING MODEL

	Model 1 Customer-type-specific constants only					**Model 2 Customer-type-specific constants and customer characteristic**					**Model 3 Customer-type-specific constants, customer characteristic and product attribute**			
Model specification[a]														
No. segments	1	2	3	**4**	5	1	2	3	4	5	1	2	3	4
No. parameters	6	13	20	**27**	34	7	15	23	31	39	13	27	41	55
Predictor variables														
Customer-type-specific constants	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Technical undergrad degree						✓	✓	✓	✓	✓	✓	✓	✓	✓
Course evaluation score											✓	✓	✓	✓
Fit statistics														
Log-likelihood	-5296	-5133	-5072	**-5038**	-5035	-5295	-5126	-5070	-5036	-5034	-5283	-5109	-5057	-5025
CAIC	10646	10383	10323	**10317**	10382	10655	10387	10345	10350	10406	10682	10459	10481	10542

[a] Values in bold/underlined indicate the selected model specification

TABLE 3
PRODUCT SEGMENTATION APPROACH: PRODUCTS ASSIGNED TO SEGMENTS, CUSTOMER-TYPES ATTRACTED BY SEGMENTS, AND PRODUCT RECOMMENDATIONS

	Model 1: 4-Product Segment Solution			
Product-types	**Product Segment 1 "Quantitative" % of segment**	**Product Segment 2 "Technical" % of segment**	**Product Segment 3 "Analytical" % of segment**	**Product Segment 4 "General Appeal" % of segment**
Accounting courses	.20	.00	.00	.08
Finance courses	.70	.00	.00	.17
MIS courses	.10	1.00	.20	.00
Management courses	.00	.00	.20	.75
Marketing courses	.00	.00	.60	.00
Customer-types	**Estimated attraction weight[a]**	**Estimated attraction weight**	**Estimated attraction weight**	**Estimated attraction weight**
Investment banker	**.89**	**-1.90**	**-1.44**	-.14
Corporate finance	.21	**-1.08**	**-1.33**	**-.57**
IT manager	**-1.25**	**.68**	**-.90**	**-.65**
General manager	**-.63**	**-.52**	.03	-.16
Brand manager	**-1.00**	-.32	**.77**	.06
Consultant	.06	**.53**	.22	**.19**
Other	.00	.00	.00	.00
Product segment size	.30	.16	.16	.38
Customer-types	**Probability of recommending segment[b,c]**	**Probability of recommending segment**	**Probability of recommending segment**	**Probability of recommending segment**
Investment banker	**.63**	.02	.03	**.31**
Corporate finance	**.52**	.08	.06	**.34**
IT manager	.12	**.46**	.10	**.32**
General manager	.20	.12	.22	**.45**
Brand manager	.11	.11	**.35**	**.43**
Consultant	.24	.21	.16	**.39**
Other	**.29**	.15	.16	**.40**

[a] Estimated attraction weights in bold are significant at $p < .05$
[b] Recommendation probability = $\text{prob}(\Pi \mid C_0)$
[c] Recommendation probabilities in bold exceed recommendation rule (1 / # product segments) = .25

As discussed earlier, the PS approach uses latent class analysis to directly identify product segments, but the approach can also be used to infer customer segments. To infer customer segments, we again refer to the probabilities used to compare the relative performance of the PS and CS approaches. In this case, we consider the probabilities, prob($C|P_0$) used to compare the relative effectiveness of customer target recommendations from the PS approach. We present those probabilities in Table 5 and highlight all instances in which the calculated recommendation probability exceeds the recommendation rule, (1/# customer-types) = .14. In these cases we say that courses of type P_0 attract customers of type C more strongly than one would expect if courses of type P_0 attracted all customer-types with equal strength.

Indirectly inferred customer segments. By observing the customer-types targeted by each of the product-types in Table 5, we can identify patterns in the recommendations across customer-types. We indirectly infer customer segments by grouping together customer-types for which we observe the same pattern of recommendations. As such, from the results of the PS approach we indirectly infer four customer segments: Investment Bankers and Corporate Financiers (who are targeted by Accounting and Finance courses), Consultants and Others (who are targeted by all course types), Brand Managers and General Managers (who are targeted by Management and Marketing courses), and IT Managers (who are targeted by MIS courses). We summarize the customer segments inferred from the PS approach in the bottom half of Table 4.

TABLE 4
PRODUCT SEGMENTATION APPROACH: SUMMARY OF PRODUCT SEGMENTS AND CUSTOMER SEGMENTS

Directly Identified Product Segments	**Product Segment 1 "Quantitative"**	**Product Segment 2 "Technical"**	**Product Segment 3 "Analytical"**	**Product Segment 4 "General Appeal"**
Product-types in segment	Accounting Finance MIS	MIS	Marketing MIS Management	Management Finance Accounting
Customer-types to which segment is recommended	Investment Bankers Corporate Finance IT Managers	Consultants Other	Brand Managers	All student-types
Indirectly Inferred Customer Segments	**Customer Segment 1 "Financiers"**	**Customer Segment 2 "Consultants"**	**Customer Segment 3 "General Mgrs"**	**Customer Segment 4 "Tech Mgrs"**
Customer-types in segment	Investment Bankers Corporate Finance	Consultants Other	Brand Managers General Managers	IT Managers
Product-types targeted to segment	Accounting Finance	All course-types	Management Marketing	MIS

TABLE 5
PRODUCT SEGMENTATION APPROACH: PROBABILITY OF RECOMMENDING CUSTOMERS FOR PRODUCT-TYPES TO TARGET

	Probability of Recommending Customer-types[a,b]						
Product-types	**Investment Banker**	**Corporate Finance**	**Other**	**Consultant**	**Brand Manager**	**General Manager**	**IT Manager**
Accounting	**.28**	**.15**	**.15**	**.17**	.09	.10	.06
Finance	**.30**	**.16**	**.15**	**.16**	.08	.09	.05
MIS	.07	.07	**.15**	**.24**	.13	.10	**.23**
Management	.13	.09	**.16**	**.20**	**.19**	**.14**	.08
Marketing	.04	.04	**.16**	**.20**	**.34**	**.16**	.06

[a] Recommendation probability = prob(C | P_0)
[b] Probabilities in bold exceed recommendation rule (1 / # customer-types) = .14

TABLE 6
CUSTOMER SEGMENTATION APPROACH: SELECTION OF BEST-FITTING MODEL

	Model 4 Product-type-specific constants only				**Model 5 Product-type-specific constants and product attribute**				**Model 6 Product-type-specific constants, product attribute and customer characteristic**			
Model specification[a]												
No. segments	1	2	3	4	1	**2**	3	4	1	2	3	4
No. parameters	4	9	14	19	5	**11**	17	23	9	19	29	39
Predictor variables												
Product-type-specific constants	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Course evaluation score					✓	✓	✓	✓	✓	✓	✓	✓
Technical undergrad degree									✓	✓	✓	✓
Fit statistics												
Log-likelihood	-4144	-4025	-4001	-3998	-3695	**-3634**	-3627	-3624	-3694	-3630	-3624	-3621
CAIC	8323	8130	8127	8166	7435	**7365**	7405	7453	7469	7430	7506	7590

[a] Values in bold/underlined indicate the selected model specification

Customer Segmentation Approach Results

Directly identified product segments. As indicated in Table 6, the 2-customer segment solution of Model 5, which includes average course evaluation as a predictor, has the lowest CAIC relative to all other solutions for Models 4, 5, and 6. Hence we find that including course evaluation scores as a predictor helps explain students' preference for courses. From Table 7, which summarizes the results of assigning students to customer segments using posterior probabilities, the 2-customer segment solution of Model 5 indicates that Customer Segment 1 is primarily made up of "Quantitative" students, (Investment Bankers, Corporate Financiers, Consultants, and Others), while Customer Segment 2 is primarily made up of "Analytical" students (Brand Managers, General Managers, IT Managers, Consultants, and Others). Thus, contrary to what one might expect, the identified segments indicate that all students pursuing a particular career do not prefer the same types of courses. For example, the Consultants assigned to Customer Segment 1 prefer a different mix of courses compared to the Consultants assigned to Customer Segment 2.

Product-types preferred by each customer segment. Table 7 also reports estimated preference weights for the CS model. Because the significance levels of the product-type-specific coefficients depend upon the product-type selected as the baseline, we cannot directly infer the types of courses preferred by each customer segment from those coefficients. Instead, we refer to the probabilities, prob(χ|P_0), which are used to compare the relative effectiveness of customer target recommendations from the CS approach. We present those probabilities in the bottom section of Table 7 and highlight all instances in which the calculated recommendation probability exceeds the recommendation rule, (1/# customer segments) = .50. That is, we can say that courses of type P_0 attract customers from segment χ more strongly than one would expect if courses of type P_0 attracted all customer segments with equal strength. Combining this information with knowledge of the mix of students in each customer segment in the top half of Table 8, shows that, as we might expect, "Quantitative" students in Customer Segment 1 prefer Accounting, Finance, and MIS courses, while "Analytical" students in Customer Segment 2 prefer Marketing and Management courses.

TABLE 7
CUSTOMER SEGMENTATION APPROACH: CUSTOMERS ASSIGNED TO SEGMENTS, PRODUCT-TYPES PREFERRED BY SEGMENTS, AND CUSTOMER RECOMMENDATIONS

	Model 5: 2-Customer Segment Solution	
Customer-types	**Customer Segment 1 "Quantitative" % of segment**	**Customer Segment 2 "Analytical" % of segment**
Investment bankers	.28	.02
Corporate finance	.16	.02
IT managers	.03	.18
General managers	.10	.14
Brand managers	.11	.24
Consultants	.16	.22
Other	.16	.18
Product-types	**Estimated preference weight**[a]	**Estimated preference weight**
Accounting	.00	.00
Finance	**1.00**	-.08
MIS	**-.60**	**.65**
Management	-.05	**.51**
Marketing	-.01	**.33**
Course evaluation	**4.62**	**3.48**
Customer segment size	.49	.51
Product-types	**Probability of recommending segment**[b, c]	**Probability of recommending segment**
Accounting	**.54**	.46
Finance	**.76**	.23
MIS	**.52**	.47
Management	.18	**.82**
Marketing	.12	**.87**

[a] Estimated preference weights in bold are significant at $p < .05$
[b] Recommendation probability = prob(χ | P_0)
[c] Recommendation probabilities in bold exceed recommendation rule (1 / # customer segments) = .50

Indirectly inferred product segments. As discussed earlier, the CS approach uses latent class analysis to directly identify customer segments, but this approach can also be used to infer product segments. To infer product segments, we again refer to the probabilities used to compare the relative performance of the PS and CS approaches. This time we consider the probabilities, prob($P|C_0$), used to compare the relative effectiveness of product recommendations from the CS approach. We present those probabilities in Table 9 and highlight all instances in which the calculated recommendation probability exceeds the recommendation rule, (1/# product-types) = .20. That is, we say that products of type P more strongly attract customers of type C_0 than one would expect if products of type P attracted all customer-types equally.

By observing the product-types recommended to each of the customer-types in Table 9, we can identify patterns in the recommendations across product-types. We indirectly infer product segments by grouping together product-types for which we observe the same pattern of recommendations. As such, with the results of the CS approach we indirectly infer three product segments: Management courses (which are recommended to all customer-types), Finance courses (which are recommended to all customer-types except IT Managers), and MIS courses (which are recommended to IT Managers and Brand Managers). We summarize the product segments inferred from the CS approach in the bottom half of Table 8.

TABLE 8
CUSTOMER SEGMENTATION APPROACH: SUMMARY OF CUSTOMER SEGMENTS AND PRODUCT SEGMENTS

Directly Identified Customer Segments	Customer Segment 1 "Quantitative"	Customer Segment 2 "Analytical"
Customer-types in segment	Investment bankers Corporate financiers General managers Consultants Others	Brand managers IT managers General managers Consultants Others
Product-types targeted to segment	Accounting Finance MIS	Marketing Management

Indirectly Inferred Product Segments	Product Segment 1 "Finance"	Product Segment 2 "MIS"	Product Segment 3 "Management"
Product-types in segment	Finance	MIS	Management
Customer-types to which segment is recommended	All student-types except IT managers	Brand managers IT managers	All student-types

TABLE 9
CUSTOMER SEGMENTATION APPROACH: PROBABILITY OF RECOMMENDING PRODUCTS TO CUSTOMER-TYPES

	Probability of Recommending Product-types[a, b]				
Customer-types	**Accounting**	**Finance**	**MIS**	**Management**	**Marketing**
Investment banker	.18	**.43**	.06	**.27**	.06
Corporate finance	.17	**.42**	.07	**.27**	.06
Other	.16	**.28**	.17	**.26**	.13
Consultant	.16	**.27**	.18	**.26**	.14
Brand manager	.15	**.23**	**.21**	**.25**	.15
General manager	.16	**.26**	.18	**.26**	.14
IT Manager	.15	.18	**.25**	**.25**	.18

[a] Recommendation probability = prob(P | C_0)
[b] Probabilities in bold exceed recommendation rule (1 / # product-types) = .20

Comparing Product Segmentation Approach and Customer Segmentation Approach Results

Managerial comparison of approaches' segmentations. The differences between the directly estimated product segments from the PS approach and the inferred product segments from the CS approach are illustrated by comparing the top half of Table 4 and the bottom half of Table 8. This comparison highlights the relationship between the product segmentation schemes derived from the two approaches. The inferred product segment "Management" courses is roughly analogous to directly identified Product Segment 4 "General Appeal" courses. The inferred "Finance" courses product segment is roughly analogous to directly identified Product Segment 1 "Quantitative" courses. The inferred product segments "MIS" courses is roughly analogous to directly identified Product Segments 2 and 3, "Technical" courses and "Analytical" courses. While we can see a rough equivalence, it is very likely that we will get better product recommendations from the product segments directly constructed by the PS approach since the composition of those product segments is not constrained to take "all or none" of the courses offered by a particular department as are the inferred product segments from the CS approach.

Similarly, the differences between the directly estimated customer segments from the CS approach and the inferred customer segments from the PS approach are illustrated by comparing the top half of Table 8 and the bottom half of Table 4. This comparison highlights the relationship between the customer segmentation schemes derived from the two approaches. The inferred customer segment "Financiers" is roughly analogous to directly identified Customer Segment 1 "Quantitative" students. The inferred customer segments "General Managers" and "Technology Managers" are roughly analogous to directly identified Customer Segment 2 "Analytical" students. The inferred customer segment "Consultants and Others" is split between Customer Segment 1 and Customer Segment 2. Thus, although we see a rough equivalence, it is again very likely that we will get better customer target recommendations from the customer segments directly estimated by the CS approach since the composition of those customer segments was not constrained to take "all or none" of a particular customer-type as are the inferred customer segments from the PS approach.

Empirical comparison of approaches' recommendations. To assess the relative performance of the PS and CS approaches, we first apply both approaches to recommend a set of courses for a withheld student to take and compare the approaches' recommendations with the set of courses the withheld student actually took. The hit rate used in this approach comparison is the proportion of courses the withheld student actually took that the approach recommended. In a second test, we apply both approaches to recommend a set of students for a withheld course to target and compare the approaches' recommendations with the set of students who actually took the withheld course. The hit rate for this test reports the proportion of students who actually took the withheld course that the approach recommended as targets[2].

In the first test, the PS approach provided statistically significantly better recommendations of courses for a withheld student to take (PS hit rate = .63, CS hit rate = .45, $p < .01$ based on a paired sample t-test). In the second test, the CS approach provided better recommendations of students for a withheld course to target (CS hit rate = .46, PS hit rate = .41, difference not significant based on paired sample t-test). Note that the CS approach's recommendations of students for a withheld course to target were statistically significantly better than recommendations from the PS approach using the alternate recommendation rules.

DISCUSSION

We began this research with two primary objectives. Our first objective was to develop a product segmentation approach that could be applied by retailers with large multi-category product offerings to identify latent groups of products. We refer to these groupings as product segments such that the products within a segment attract the same types of customers, while products in different segments attract different types of customers. Our second objective was to examine the relationship between the product

[2] We note that both estimated models were stable through the n-fold bootstrapping procedures. Across each of the 326 withheld students in the first test, the structure of neither the best fitting PS model nor the best fitting CS model changed. Similarly there were no changes in the structure of the best fitting models across any of the 32 withheld courses in the second test. In Appendix F, we present statistics that speak to the stability of the estimated models.

segmentation approach and a parallel customer segmentation approach by comparing the segments identified by each approach and the effectiveness of each approach at addressing two managerial questions: Which products should be recommended to a customer? Which customers should a product target?

We addressed our first objective by applying the proposed product segmentation approach to identify latent product segments among courses offered by a business school. To begin estimation of the product segmentation approach, business school administrators defined seven managerially relevant customer-types based on the careers students pursue after graduating (Investment Bankers, Corporate Finance, IT Manager, Brand Manager, Consultant, and Other). Given the defined customer-types, the product segmentation approach directly identified four product segments: “Quantitative” courses, “Technical” courses, “Analytical” courses, and “General Appeal” courses, where each product segment was made up of courses from several different departments. Thus, the product segmentation approach provides a methodology for retailers with large, multi-category product and service offerings to directly identify customer-centric, cross-category product groupings.

We addressed the second objective by comparing results identified by the proposed product segmentation approach with results from a parallel customer segmentation approach. To begin estimation of the customer segmentation approach, business school administrators defined five managerially relevant product-types based on the business school’s departments (Accounting, Finance, MIS, Management, and Marketing). Given the defined product-types, the customer segmentation approach directly identified two customer segments: “Quantitative” students and “Analytical” students, where each customer segment was made up of students who pursued different types of careers.

Comparing results from the product segmentation approach and the customer segmentation approach in our illustrative application, we see the implication of representing students by only seven customer-types – the aggregation constraint that makes estimation of the product segmentation approach tractable – and the impact of representing courses by five product-types – the aggregation constraint that makes estimation of the customer segmentation approach tractable. The four product segments directly identified by the product segmentation approach are not identical to the three product segments indirectly inferred from the results of the customer segmentation approach. Similarly, the two customer segments directly identified by the customer segmentation approach are not identical to the four customer segments indirectly inferred from the results of the product segmentation approach. As such, while the proposed product segmentation approach parallels the widely applied latent class customer segmentation approach, our application illustrates the fact that the two approaches are not exactly "reverse sides of the same analysis" as suggested by Grover and Srinivasan (1987). Rather, the aggregation constraint imposed on customers in the product segmentation approach and imposed on products in the customer segmentation approach influence the product segments and customer segments that each approach identifies. Thus, we contribute to marketers' understanding of the relationship between customer segmentation and product segmentation by illustrating the implications of the aggregation constraint in the underlying models.

Further, the aggregation constraints degrade model performance. Specifically, we see that the aggregation constraint imposed on customers in the product segmentation approach degrades that approach's recommendations of students for a course to target. Similarly, we see that the aggregation constraint imposed on products in the customer segmentation approach degrades that approach's recommendations of courses for a student to take. Thus, the decision of whether to apply the product segmentation approach or the customer segmentation approach should be based on the particular managerial objectives involved in aligning a retailer's product offerings with its target customers.

Having demonstrated the usefulness of the proposed product segmentation approach in a service provider context, the potential for further application is clear. Retailers with large multi-category product or service offerings that have customer management systems can use the power of latent class analysis coupled with the simplicity and flexibility of the multinomial logit-like structure of the proposed product segmentation approach to extract insights from their data and to guide managerial action. For example, Wal-Mart, having already identified "Hispanics, " "African-Americans," "Suburbanites," "Rural Residents," "Affluent," and "Empty-nesters" as its target customer-types, could use this methodology to design store layouts that organize products into groups that attract a particular customer-type. Direct retailers such as Amazon and Dell could apply the methodology to dynamic website design whereby, when a customer of a particular customer-type logs on to the website, the web page features the set of products most likely to attract that customer-type. Retailers such as Best Buy could apply the approach to develop targeted direct mail campaigns that offer promotions on products from the set of items that is most likely to attract a particular customer-type. The product segmentation approach could help retailers cross-merchandise by identifying which products to display together or for salespeople to recommend to particular customer-types.

Limitations and Future Research

While the proposed product segmentation approach presents a parsimonious approach for identifying product segments from large numbers of products in multiple categories, it also has limitations that invite further model development opportunities. First, analogous to the IIA assumption in logit choice models, the attraction model that underlies the product segmentation approach implicitly assumes that adding a new customer-type to a product's customer mix will not change the relative strength of attraction that the product has for existing customer-types. It is easy to imagine a scenario in which such an assumption will not hold. Consider the case in which a product becomes attractive to a new customer-type that is an opinion leader (e.g. media personalities). The arrival of that new customer-type in a product's customer mix might increase the product's relative strength of attraction for existing, impressionable customer-types and might decrease the product's relative strength of attraction for existing customer-types who tend to avoid fads. Models that relax the IIA assumption could be applied to remedy this limitation.

Second, analogous to the assumption in logit choice models that repeated choices over time are independent, the attraction model that underlies the product segmentation approach assumes that a product's strength of attraction for a particular customer-type is independent of the other customer-types attracted. It is also possible to imagine a scenario in which this will not hold. Customer-types that are closely related to each other may influence each other's attraction probability in a way not captured by the attraction model. Again, this limitation could be addressed by incorporating model developments designed to relax this assumption.

Key results in this research rest on the impact of imposing the aggregation constraint on customers in the proposed product segmentation approach and imposing the aggregation constraint on products in the customer segmentation approach. Since imposing the product-type aggregation constraint has become standard procedure in estimating choice models, the implications of the constraint has received little consideration. In this research, we demonstrate some of the implications of imposing the product-type aggregation constraint and highlight the need for marketers to give wider consideration to the impact of the a priori assumptions used to impose product-types. It would be valuable to compare this approach of identifying product segments and customer segments with approaches that do not impose an aggregation constraint on either customers or products, such as non-parametric methods.

Finally, the characteristics of the data in our illustrative application also entail limitations that open opportunities for future research. In our application, we had no record of customers' responses to marketing interventions. As such, we were unable to capture the impact of marketing interventions on the strength with which a product attracts different customer-types and the impact of changes in that attraction strength on product segmentation. It would be interesting to apply the proposed product segmentation approach in a context that incorporates marketing activities to assess their impact on product segmentation. In general, we invite application of the proposed approach in additional contexts that involve other large, multi-category collections of products, as well as observations of the interventions used to market those items.

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APPENDIX A
COMPARISON OF PRODUCT SEGMENTATION APPROACH AND CUSTOMER SEGMENTATION APPROACH SPECIFICATION AND ESTIMATION

		Product Segmentation Approach	**Customer Segmentation Approach**
	Notation	c = Index of individual customers n_c = Total number of individual customers C = Index of customer-types N_C = Total number of customer-types Π = Index of product segments N_Π = Total number of product segments $t_{p,C}$ = Index of all transactions including product p that were made by customers of type C (sometimes represented without subscripts to ease reading) $T_{p,C}$ = Total number of transactions including product p that were made by customers of type C	p = Index of individual products n_p = Total number of individual products P = Index of product-types N_P = Total number of product-types χ = Index of customer segments N_χ = Total number of customer segments $t_{c,P}$ = Index of all transactions including a product of type P made by customer c (sometimes represented without subscripts to ease reading) $T_{c,P}$ =Total number of transactions including a product of type P made by customer c
a)	Objective	Reveal segments of products that are related in terms of the strength with which they attract different customer-types	Reveal segments of customers that are related in terms of the strength with which they prefer different product-types
b)	Impose the aggregation constraint on	Customers. Define customer-types $C = 1,2,\ldots N_C$, such that every individual customer, c, is of one, and only one, customer-type	Products. Define product-types $P = 1,2,\ldots,N_P$ such that every individual product, p, is of one, and only one, product-type
c)	Directly identify	Product segments: $\Pi = 1,2,\ldots, N_\Pi$	Customer segments: $\chi = 1,2,\ldots,N_\chi$

d)	Model Assumptions	The strength with which product p attracts customer-type C, relative to the strength with which p attracts other customer-types: $a_{p,C,t} = \alpha_{p,C,t} + \varepsilon_{p,C,t}$	The strength with which customer c prefers product-type P, relative to the strength with which c prefers other product-types: $u_{c,P,t} = v_{c,P,t} + \varepsilon_{c,P,t}$
e)		For a given purchase of product p, the probability that the purchase was made by a customer of type C_0 is the probability that product p attracted customer-type C_0 more strongly than it attracted any other customer-type $prob[\alpha_{p,C_0,t} \geq \alpha_{p,C,t}, \forall C \neq C_0]$	For a given choice by customer c, the probability that the purchase was of product-type P_0 is the probability that customer c prefers product-type P_0 more strongly than he/she prefers any other product-type $P[v_{c,P_0,t} \geq v_{c,P,t}, \forall P \neq P_0]$
f)		$\varepsilon_{p,C,t}$ are iid Gumbel type II extreme value	$\varepsilon_{c,P,t}$ are iid Gumbel type II extreme value
g)	Model	Attraction Model: $prob(C_0,t \mid p) = \exp\{\alpha_{p,C_0,t}\} \Big/ \sum_{C=1}^{N_C} \exp\{\alpha_{p,C,t}\}$ We refer to these probabilities as product p's customer mix since, all else equal, $prob(C_0,t \mid p)$ is the expected proportion of product p's customers who are customer-type C_0	Choice Model: $prob(P_0,t \mid c) = \exp\{v_{c,P_0,t}\} \Big/ \sum_{P=1}^{N_P} \exp\{v_{c,P,t}\}$ We refer to these probabilities as customer c's product choice shares since, all else equal, $prob(P_0,t \mid c)$ is the expected proportion of customer c's purchases that are product-type P_0
h)		$\alpha_{p,C,t} = \sum_{m=1}^{M} w_m x_{p,C,t}$ where w_m = attraction weight of characteristic m and $x_{p,C,t}$ = observed value of characteristic m for customer-type C and product p on the t^{th} transaction	$v_{c,P,t} = \sum_{j=1}^{J} z_j y_{c,P,t}$ where z_j = preference weight of characteristic j and $y_{c,P,t}$ = observed value of characteristic j for customer c and product-type P on the t^{th} transaction
i)	Latent class analysis	Infer product segments by identifying products that have similar customer mixes. $prob(C,t \mid p\varepsilon\Pi) = Q_\Pi * prob(C,t \mid p)$ where $Q_\Pi = \exp\{\theta_\Pi\} \Big/ \sum_{\Pi=1}^{N_\Pi} \exp\{\theta_\Pi\}$	Infer customer segments by identifying customers that have similar product choice shares. $prob(P,t \mid c\varepsilon\chi) = R_\chi * prob(P,t \mid c)$

		is the relative size of each product segment in terms of the unconditional probability that a given product p is included in product segment Π, and θ_Π is the estimated product segment size parameter	where $R_\chi = \exp\{\gamma_\chi\} \Big/ \sum_{\chi=1}^{N_\chi} \exp\{\gamma_\chi\}$ is the relative size of each customer segment in terms of the unconditional probability that a given customer c is included in customer segment χ, and γ_χ is the estimated customer segment size parameter
j)	Likelihood function	Letting H_p be the collection of all transactions in which product p was chosen, $L(H_p) = \sum_{\Pi=1}^{N_\Pi} Q_\Pi * L(H_p \mid \Pi)$ $= \sum_{\Pi=1}^{N_\Pi} [Q_\Pi * (\prod_{C=1}^{N_C} \prod_{t_{p,C}=1}^{T_{p,C}} prob(C, t_{p,C} \mid p\varepsilon\Pi))]$	Letting H_c be the collection of all transactions made by customers c, $L(H_c) = \sum_{\chi=1}^{N\chi} R_\chi * L(H_c \mid \chi)$ $= \sum_{\chi=1}^{N\chi} [R_\chi * (\prod_{P=1}^{N_p} \prod_{t_{c,P}=1}^{T_{c,P}} prob(P, t_{c,P} \mid c\varepsilon\chi))]$
k)	Results of MLE	Relative size of each product segment, Q_π and w_m^Π = attraction weight of characteristic m for products in product segment Π	Relative size of each customer segment, R_χ and z_j^χ = preference weight of characteristic j for customers in customer segment χ
l)	Bayesian calculation for set assignment	$prob(p\varepsilon\Pi \mid H_p) = L(H_p \mid \Pi) * Q_\Pi \Big/ \sum_{\Pi=1}^{N_\Pi} [L(H_p \mid \Pi) * Q_\Pi]$	$prob(c\varepsilon\chi \mid H_c) = L(H_c \mid \chi) * R_\chi \Big/ \sum_{\chi=1}^{N\chi} [L(H_c \mid \chi) * R_\chi]$

APPENDIX B
CONDITIONAL PROBABILITIES USED TO COMPARE RECOMMENDATIONS

	Product Segmentation Approach	**Customer Segmentation Approach**
Test 1: Objective of test	Recommend products in product segment Π for a customer of type C_0 to purchase	Recommend products of type P for a customer for a customer of type C_0 to purchase
Quantities estimated with approach	prob(C_0|Π) = probability, given a product in segment Π was chosen, the choice was made by a customer of type C_0 Q_Π = size of product segment Π ; i.e., unconditional probability product p is included in product segment Π	$prob(P \mid \chi)$ = probability, given the choice was made by a customer in segment χ , a product of type P was chosen
Quantities observed from sample	prob(C_0) = proportion of customers that are of type C_0, i.e., unconditional probability customer c is of customer type C_0	$prob(\chi \mid C_0)$ = probability a customer of type C_0 is a member of customer segment χ[a]
Conditional probabilities on which recommendations are based	$prob(\Pi \mid C_0) = prob(C_0 \mid \Pi) * Q_\Pi / prob(C_0)$ = probability, given a customer of type C_0 did the choosing, a product from segment Π was chosen	$prob(P \mid C_0) = prob(P \mid \chi) * prob(\chi \mid C_0)$ = probability, given a customer of type C_0 did the choosing, a product of type P was chosen

Test 2: Objective of test	Recommend customers of type C for a product of product type P_0 to target	Recommend customers from customer segment χ for a product of product type P_0 to target
Quantities estimated with model	$prob(C \mid \Pi)$ = probability, given a product in segment Π was chosen, the choice was made by a customer of type C	$prob(P_0 \mid \chi)$ = probability, given a customer from customer segment χ did the choosing, a product of type P_0 was chosen R_χ = size of customer segment χ, i.e., unconditional probability customer c is included in customer segment χ
Quantities observed from sample	prob($\Pi \mid P_0$) = probability a product of type P_0 is a member of product segment Π [b]	prob(P_0) = proportion of all products that are of type P_0, i.e., unconditional probability product p is of type P_0
Conditional probabilities on which recommendations are based	$prob(C \mid P_0) = prob(C \mid \Pi)\, prob(\Pi \mid P_0)$ = probability, given a product of type P_0 was chosen, a customer of type C made the choice.	$prob(\chi \mid P_0) = prob(P_0 \mid \chi) * {R\chi}/{prob(P_0)}$ = probability, given a product of type P_0 was chosen, a customer from customer segment χ made the choice.

[a] This is the method we used to estimate prob(χ|C_0), however, since the model gives no guidance on how to calculate this, other methods could be used

[b] This is the method we used to estimate prob(Π|P_0), however, since the model gives no guidance on how to calculate this, other methods could be used

APPENDIX C
ADDITIONAL RULES USED TO COMPARE RECOMMENDATIONS

Rule for Recommendations	Product Segmentation Approach	Customer Segmentation Approach
Test 1:		
Recommendation	Recommend products in product segment Π to a customer of type C_0 if:	Recommend products of product-type P to a customer of type C_0 if:
Fixed threshold	$prob(\Pi \mid C_0) > .50$	$prob(P \mid C_0) > .50$
Relative threshold	Π has highest $prob(\Pi \mid C_0)$	P has highest $prob(P \mid C_0)$
Better than chance I:	$prob(\Pi \mid C_0) >$ [1 / number of product segments]	$prob(P \mid C_0) >$[1 / number of product-types]
Better than chance II:	$prob(\Pi \mid C_0) >$ [number of products in product segment Π / total number of products]	$prob(P \mid C_0) >$ [number of products of type P / total number of products]
Test 2:		
Recommendation	Recommend that a product of type P_0 target customers of customer-type C if:	Recommend that a product of type P_0 target customers in customer segment χ if:
Fixed threshold:	$prob(C \mid P_0) > .50$	$prob(\chi \mid P_0) > .50$
Relative threshold:	C with highest $prob(C \mid P_0)$	χ with highest $prob(\chi \mid P_0)$
Better than chance I:	$prob(C \mid P_0) >$ [1 / number of customer-types]	$prob(\chi \mid P_0) >$ [1 / number of customer segments]
Better than chance II:	$prob(C \mid P_0) >$ [number of customers of type C / total number of customers	$prob(\chi \mid P_0) >$ [number of customers in customer segment χ/ total number of customers]

APPENDIX D
COMPARISON OF MEAN HIT RATES FOR ADDITIONAL RECOMMENDATION RULES

	PS Mean Hit Rates	CS Mean Hit Rates	Comparison of PS Mean Hit Rate & CS Mean Hit Rate (p-value)
Test 1:			
For withheld student of type C_0, what percent of the courses actually taken by the student were recommended by the approach			
Recommend if probability of product segment (PS) or product-type (CS) is:			
Greater than .50	.15	.00	< .01
The highest	.51	.39	< .01
Greater than [1/no. of sets of courses]	.69	.46	< .01
Greater than [no. of courses in set / total no. of courses]	.56	.31	< .01
Test 2:			
For withheld course of type P_0, what percent of the students who took the course were identified as being in the target segment			
Recommend if probability of customer-type (PS) or customer segment (CS) is:			
Greater than .50	.00	.45	< .01
The highest	.23	.40	.02
Greater than [1 / no. of sets of students]	.41	.45	.41
Greater than [no. of students in set / total no. of students]	.30	.43	.05

APPENDIX E
PRODUCT SEGMENTATION AND CUSTOMER SEGMENTATION APPROACH SPECIFICATIONS

PS Approach	Deterministic Component of Attraction Weight for Product *p*	Examples of Student-type Attraction Weights
Model 1	$a^p_{C,t} = w_1 D_{inv\ bank,t} + w_2 D_{corp\ fin,t} + w_3 D_{tech\ mgr,t} + w_4 D_{gen\ mgr,t} + w_5 D_{product\ mgr,t} + w_6 D_{cons,t}$ where $D_{C,t}$ is a dummy variable that takes on a value equal to 1 if the customer making the t^{th} transaction is of customer-type C, (i.e., took a job of type C) and takes on a value of 0 otherwise, and where w_m is the attraction weight for characteristic m	$a^p_{inv.bank,t} = w_1$ $a^p_{corp.\ fin,t} = w_2$
Model 2	$a^p_{C,t} = w_1 D_{inv\ bank,t} + w_2 D_{corp\ fin,t} + w_3 D_{tech\ mg,tr} + w_4 D_{gen\ mgr,t} + w_5 D_{product\ mgr,t} + w_6 D_{cons,t} + w_7 D_{tech\ degree,t}$ where $D_{tech\ degree,t}$ is a dummy variable that takes on a value of 1 if the customer making the t^{th} transaction has a technical undergraduate degree and takes on a value of 0 otherwise	$a^p_{inv.bank,t} = w_1 + w_7 D_{tech\ degree,t}$ $a^p_{corp.\ fin,t} = w_2 + w_7 D_{tech\ degree,t}$
Model 3	$a^p_{C,t} = w_1 D_{inv\ bank,t} + w_2 D_{corp\ fin,t} + w_3 D_{tech\ mgr,t} + w_4 D_{gen\ mgr,t} + w_5 D_{product\ mgr,t} + w_6 D_{cons,t} + w_7 D_{tech\ degree,t} + w_8 X_{eval,t} {*} D_{inv\ bank,t} + w_9 X_{eval,t} {*} D_{corp\ fin,t} + w_{10} X_{eval,t} {*} D_{tech\ mgr,t} + w_{11} X_{eval,t} {*} D_{gen\ mgr,t} + w_{12} X_{eval,t} {*} D_{product\ mgr,t} + w_{13} X_{eval,t} {*} D_{cons,t}$ where $X_{eval,t}$ is a continuous variable representing the average evaluation score for the product chosen on the t^{th} transaction, normalized on a scale ranging from 1 to 5	$a^p_{inv.bank,t} = w_1 + w_7 D_{tech\ degree,t} + w_8 X_{eval,t}$ $a^p_{corp.\ fin,t} = w_2 + w_7 D_{tech\ degree,t} + w_9 X_{eval,t}$

CS Approach	**Deterministic Component of Preference Weight for Customer *c***	**Examples of Course-type Preference Weights**
Model 4	$v^{c}_{P,t} = z_1 D_{FIN,t} + z_2 D_{MIS,t} + z_3 D_{MAN,t} + z_4 D_{MKT,t}$ where $D_{P,t}$ is a dummy variable that takes on a value equal to 1 if the product chosen on the t^{th} transaction is of product-type P and takes on a value of 0 otherwise, and where z_j is the importance weight for characteristic j	$v^{c}_{FIN,t} = z_1$ $v^{c}_{MIS,t} = z_2$
Model 5	$v^{c}_{P,t} = z_1 D_{FIN,t} + z_2 D_{MIS,t} + z_3 D_{MAN,t} + z_4 D_{MKT,t} + z_5 X_{eval,t}$	$v^{c}_{FIN,t} = z_1 + z_5 X_{eval,t}$ $v^{c}_{MIS,t} = z_2 + z_5 X_{eval,t}$
Model 6	$v^{c}_{P,t} = z_1 D_{FIN,t} + z_2 D_{MIS,t} + z_3 D_{MAN,t} + z_4 D_{MKT,t} + z_5 X_{eval,t} + z_6 D_{FIN,t} * D_{tech\ degree,t}$ $+ z_7 D_{MIS,t} * D_{tech\ degree,t} + z_8 D_{MAN,t} * D_{tech\ degree,t} + z_9 D_{MKT,t} * D_{tech\ degree,t}$	$v^{c}_{FIN,t} =$ $z_1 + z_5 X_{eval,t} + z_6 D_{tech\ degree,t}$ $v^{c}_{MIS,t} =$ $z_2 + z_5 X_{eval,t} + z_7 D_{tech\ degree,t}$

APPENDIX F
PARAMETER STABILITY ACROSS N-FOLD BOOTSTRAP ESTIMATION

	Product Segmentation Model 1 4-Product Segment Solution				**Customer Segmentation Model 5 2-Customer Segment Solution**		
Test 1	The mean and the standard deviation[a] of the value for each parameter, estimating model 326 times, holding out one student each time.						
Customer-Types	**Product Seg 1**	**Product Seg 2**	**Product Seg 3**	**Product Seg 4**	**Product-Types**	**Customer Seg 1**	**Customer Seg 2**
Inv Banker	.93	-1.94	-.95	-.10	FIN	.88	-.09
	(.01)	(.05)	(.05)	(.03)		(.01)	(.01)
Corp Finance	.25	-.99	-.98	-.57	MIS	-.56	.67
	(.01)	(.01)	(.04)	(.01)		(.05)	(.05)
IT Manager	-1.34	.61	-.95	-.69	MAN	-.06	.56
	(.02)	(.01)	(.02)	(.03)		(.02)	(.02)
General Mgr	-.61	-.51	-.08	-.15	MKT	-.09	.33
	(.01)	(.01)	(.02)	(.01)		(.03)	(.03)
Product Mgr	-.99	-.36	.48	.07	Course	4.53	3.52
	(.02)	(.01)	(.04)	(.01)	Eval	(.00)	(.00)
Consultant	.06	.44	.22	.17			
	(.01)	(.01)	(.01)	(.01)			
Product	.29	.16	.17	.38	Customer	.46	.54
Seg Size	(.02)	(.02)	(.03)	(.03)	Seg Size	(.00)	(.01)

	Product Segmentation Model 1 4-Product Segment Solution				**Customer Segmentation Model 5 2-Customer Segment Solution**		
Test 2	The mean and the standard deviation[a] of the value for each parameter, estimating model 32 times, holding out one course each time.						
Customer-Types	**Product Seg 1**	**Product Seg 2**	**Product Seg 3**	**Product Seg 4**	**Product-Types**	**Customer Seg 1**	**Customer Seg 2**
Inv Banker	.92	-1.88	-1.40	-.19	FIN	.99	-.12
	(.01)	(.08)	(.18)	(.01)		(.03)	(.08)
Corp Finance	.23	-.99	-1.18	-.60	MIS	-.57	.66
	(.01)	(.03)	(.21)	(.01)		(.04)	(.04)
IT Manager	-1.37	.63	-.91	-.65	MAN	-.04	.52
	(.05)	(.04)	(.14)	(.01)		(.03)	(.04)
General Mgr	-.64	-.52	-.19	-.15	MKT	-.01	.34
	(.01)	(.01)	(.09)	(.01)		(.04)	(.05)
Product Mgr	-1.05	-.39	.34	.10	Course	4.57	3.50
	(.02)	(.01)	(.27)	(.01)	Eval	(.02)	(.02)
Consultant	.04	.45	-.02	.20			
	(.01)	(.01)	(.25)	(.01)			
Product	.28	.16	.13	.43	Customer	.50	.50
Seg Size	(.04)	(.06)	(.10)	(.08)	Seg Size	(.03)	(.00)

[a] Standard deviation in parentheses
Note: variation in estimated parameters for Product Segment 3 in Test 2 did not impact product groupings in a way that changed calculated recommendation probabilities made