Gaining Insight to B2B Relationships Through New Segmentation Approaches: Not All Relationships Are Equal

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Abstract

We propose using two market segmentation approaches: the Embedded Exchange Approach (a descriptive model) and the Predictive Satisfaction Approach (a predictive model) to study the relationship and interfirm interactions within business-to-business (B2B) market. Our segmentation methods are evolutionary based, multi-objective and generate Pareto optimal solutions, which could be applied in practice directly. We use data collected from a leading international wholesaler to illustrate and highlight the application, results, and benefits of both approaches. For each segmentation approach, the segmentation method generates a set of Pareto optimal solutions which not only gives a holistic view of possible solutions in the Pareto optimal space but also allows marketers to use solution selection algorithm based on the properties of Pareto optimal sets.

Keywords

market segmentation; B2B market; multi-objective market segmentation; Pareto optimal solution.

1. Introduction

There exists a tremendous number of factors, such as technological innovation, competitive intensity, and economic cycles, influencing the environment in which firms compete. In interfirm interactions, as opposed to retail-customer interactions, business-to-business (B2B) markets have been described as more uncertain and complex, the result of which increases the emphasis placed upon building and maintaining B2B relationships. This is demonstrated by the trend for businesses to having both fewer and closer relationships (Ulaga and Eggert 2006). Outcomes of closer relationships aim to achieve strategic and tactical outcomes such as reduced time-to-market, improved quality, and lower overall costs through such mechanisms as supplier and partner reduction, risk sharing, and value creation (Barry and Terry 2008).

While firms' efforts in relationship marketing activities do not come without costs and such costs must be balanced against potential rewards, the ultimate cost is the loss of customers. Firms that operate in B2B contexts are particularly sensitive to both customer loss and retention due to the smaller number of customers (compared to consumer markets) and the subsequent increased proportion each customer has upon sales and financial performance. Accordingly, firms are highly interested in maintaining relationships and, as such, relationship marketing plays a key role in B2B contexts. To foster improved relationships between businesses, firms often rely upon segmentation to better define, advance, and deliver value to their customers which can aid in strategic decisions such as which business (sector) to participate and how to best allocate resources (Freytag and Clarke 2001). Simkin (2008) describes some practical outcomes from effective B2B segmentation including effective target determination, focusing on customer needs, building relationships, product and service value creation through tailoring propositions, and competitive barrier creation.

While there are many ways in which consumer markets differ from B2B markets, assessing the context of the market segmentation analysis is important for understanding how such difference may influence the segmentation implementation. For example, business markets typically have fewer customers where each customer represents a larger overall proportion of sales than in consumer markets. Also, with business markets there are often sales and/or technical personnel that manage accounts so often segmentation is based on practicalities of implementing any segmentation program and thus often segments reflect geography of the customer, size of the customer and type of industry the customer represents. Further, business markets often have institutional buying structures (i.e. buying centers) that differ in size and decision-making style from individual consumers. However, it is important to acknowledge that many B2B contexts do not always differ from consumer markets in these ways. It is not uncommon for suppliers to be dealing with a large number of retailer-customers and those retailer-customers represent small business where purchasing is not performed via buying centers. For instance, this occurs often for retail lines such as giftware, furniture, jewelry, restaurants, laundry and drycleaners, and hardware where there are still many small mom and pop or independent and non-chain retailers.

Ideally, firms would attempt to understand their customers' needs on an individual level in order to best satisfy needs and wants (Hung 2005). Unfortunately, such an approach is not often practical given the resources necessary. As such, it is attractive to minimize costs in appropriately segmenting the market. Simkin (2008) notes firms often utilize little more than trade sectors or product groups as the basis for segmentation. Similarly, the three most common variables utilized in segmenting B2B markets are geographic, demographic and how often the product is used (Abratt 1993). These are the easiest and cheapest pieces of information that can be acquired by one firm about another. Results of such simplification of segmentation will categorize customers into groups, but often those are artificially derived and are inefficient and ineffective in both product and service delivery. Therefore, it is important to investigate approaches to segmentation which could overcome these deficiencies.

In this study, we study the application of two approaches that potentially offer many benefits in B2B segmentation: the embedded exchange approach and the predictive satisfaction approach. Section 2 reviews B2B segmentation literatures. The theoretical underpinnings of the two segmentation approaches are explained in details in section 3. Using the nascent but emerging methodology of evolutionary algorithms, section 4 and section 5 illustrate and highlight the application, results, and benefits of both approaches. Finally, section 6 discusses the implications and research directions.

2. Literature Review

2.1. B2B Segmentation

The literature on segmentation has traditionally focused upon segmenting consumer markets, research on industrial segmentation has tended to lag behind (Dowling et al. 1993). Dowling et al. (1993) indicate such lag of business market segmentation to have several causes including which criteria are to be selected upon, which to segment and how to best describe and reach segments through media selection. The authors also cite the difficulties business markets face such as complex buying (center) decision making, problems reaching business markets, trouble identifying the specific variables to be utilized in segmentation, and the general heterogeneity of organizations themselves.

Heterogeneity of organizations is the underlying assumption of segmentation that drives differences in preferences and behavior. Although the heterogeneity of organizations is problematic, segmentation, at its heart, is primarily concerned with identifying aspects of homogeneity within groups while maintaining a degree of appropriate heterogeneity between groups (Bonoma and Shapiro 1984). Numerous conceptual and practical definitions of segmentation exist (Mitchell and Wilson 1998) including aspects such as potential market, response to marketing mix, the strategic nature of implementing the segmentation process, or the ever changing and instable segments themselves. While our context is not strictly one of an industrial setting, our working definition of segmentation follows that of Bonoma and Shapiro (1984) where we attempt to identify organizational customers that are more similar to one another than those outside the identified group, thereby helping the firm to ‘homogenize market heterogeneity’.

2.2. Relationship Segmentation Approaches

Relationship segmentation as a field of research has received a considerable amount of attention and has been periodically reviewed in comprehensive manners (Ngai et al. 2009; Hiziroglu 2013). Emerging from this depth of literature comes two broad understandings of segmentation methods (Powers and Sterling 2008) described as the macro-micro segmentation method (Wind and Cardozo 1974) and the nested approach (Bonoma and Shapiro 1984). Briefly, Wind and Cardozo (1974) suggest that firms first utilize the macro approach by identifying segments based upon buyer characteristics such as firm size, Standard Industry Classification (SIC) category, usage rate, etc. and offered these as ‘macro’ level variables for segmentation. However, while easy to perform it suffers from both lack of differentiation for sufficient segmentation and incomplete insight. To counter, the ‘micro’ aspect is recommended when one wishes to learn more about the macro segments previously identified by delineating characteristics of the buyers’ decision making (micro) units, hence implementing a hierarchical approach (Powers and Sterling 2008). It is in combination of both the macro and micro approaches which aids significantly in the segmentation process to adding value to the firm.

The nested approach builds upon levels of management knowledge needed to implement the segmentation. Nesting ranged from the most outermost where segments are demographically based and very little is known about any specific potential buyer but more about the industry in which the buyer competes. Then, following in step, the next nested levels include greater, but general, information about the specific buyer which leads to the increasingly nested information where both specific knowledge about the habits and practices of each specific buyer is required. Accordingly, each stage, or nest, considers differing levels of information. The nested approach is seen to better delineate and parallel much of what was developed by Wind and Cardozo (1974) by moving from a macro to a micro perspective in information gathering.

Inherently, the variables to describe macro, or shallowly nested, segments are more widely available and broad in scope, such as SIC code (Sudharshan and Winter 1998). However, the hierarchical nature of both of these methods implies a movement from the broad and general towards one describing the specific and including the characteristics of the decision-making unit of the purchasing organization at its most micro or nested levels. Accordingly, given the two-step methodology of the Wind and Cardozo (1974) and the five-step nested model approach (Bonoma and Shapiro 1984), variable selection for both determining and defining segments has become a topic of interest for researchers and have been delineated as micro- and macro-, product (or service) specific, those independent of product and service offering, observed vs. inferred, demographics, psychographics, behavioral characteristics, purchasing approaches, and needs and desired benefits. Foedermayr and Diamantopoulos (2008) give a good review of various studies and variables utilized.

The variables utilized for investigation aid in the distinction of macro-/micro-level and nested level analysis but also influence the method of segmentation selected. Broadly, methodologies have been classified in two manners (note, we exclude discussion of normative segmentation methods). First, they can be seen as either a-priori or post hoc methods. A priori methods determine the number and type of segments before conducting the analysis and post hoc relies upon the analysis itself to guide the type and number of segments. Second, segmentation methods can also be classified as either descriptive or predictive. Descriptive methods investigate the associations where no distinction is made between dependent and independent variables. Predictive methods investigate the relationship between independent and dependent variables. Used together, they give a more comprehensive view of the B2B relationships than what can be done using a single method.

3. Two Segmentation Approach

In this study, we offer and explain two differing approaches to segmentation in B2B markets. First, what we refer to as the embedded exchange approach, we delineate a segmentation procedure that, as mentioned above, can be classified as a post hoc, descriptive procedure. This analysis relies upon economic and social value components to provide inputs for using evolutionary algorithms in identifying segments. Second, the determinants (predicting) of satisfaction approach we posit is a post-hoc, predictive procedure where regression analysis is used to identify segments predictive of overall satisfaction. The two approaches posited in this research are intended to offer new methodologies to the B2B literature on segmentation but also provide a solution to many of the market segmentation problems currently experienced by managers. We now turn our attention to the embedded exchange approach.

3.1. Embedded Exchange Approach

The idea of embedded exchange first took hold in the marketing literature following the seminal ideas put forth by Granovetter (1992). As such, market exchanges can be seen as acting in two dimensions socially and economically. Exchanges can be seen as purely social, where exchanges are symbolic, and purely economic, where exchanges are perfectly utilitarian (Granovetter 1992; Uzzi 1997). Often, market exchanges are seen on a continuum where both of these dimensions are opposing and most market exchanges take place somewhere between the extremes of either purely social *or* purely economic. Paralleling such thought is the idea of relational vs. discrete exchanges posited by Macneil (1983) in the relational contracting literature where discrete transactions are short-lived and both begin and end sharply, almost entirely understood through economic performance. Relational exchanges, on the other hand, are those longer in term, may include multiple interactions and transactions, and the development of relational norms. Relational exchange has been investigated in the literature surrounding relationship marketing, norms, trust, alliances, networks and other forms of governance (Ivens and Blois 2004).

One of the key tenets of relationship marketing is an established relationship between exchanging entities offers additional value above the value offering of products and services themselves (Gronroos 2004). Numerous specific areas of value, such as safety, credibility, security, trust (Morgan and Hunt 1994), communication, dialogue and interaction (Gronroos 2004), dependence and satisfaction (Anderson and Narus 1990), and commitment (Dwyer, Schurr and Oh 1987), amongst others. The traditional view of markets was built upon the influential works of social exchange theory and that of neoclassical economics, where exchange transactions are often interpreted through a utilitarian lens and actors engaged in exchange do so in their own best interest to maximize value (Varman and Costa 2008). The social embeddedness approach “has established itself as an alternative discourse to neoclassical economics” (Varman and Costa 2008, p141) and is the approach we adopt here. As seen in Figure 1, we decompose the strictly utilitarian and economic approach and the strictly relational exchange approach on both axes to formulate the four quadrants.

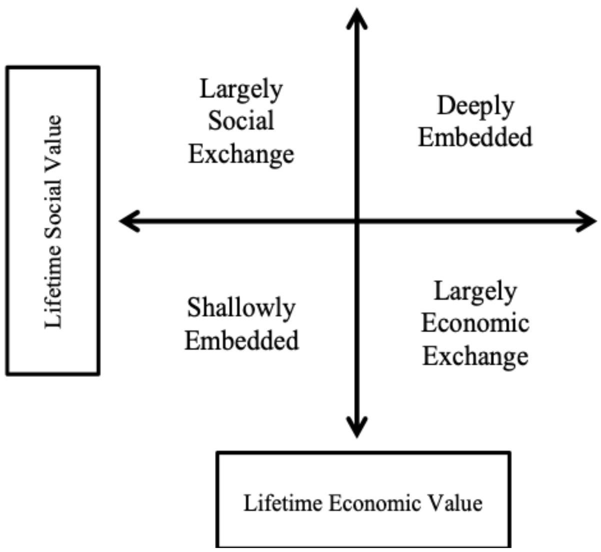

Figure 1 Embedded Exchange Segmentation Approach

As can be seen in the figure, the vertical axis demonstrates the range of lifetime social value potentially realized between exchanging entities. The horizontal axis indicates the range of lifetime economic value potentially realized between entities. In addition, we have identified some key variables associated with each axis. Anderson and Narus (1990) have suggested trust aids in joint efforts in achieving results that could not have been achieved alone. Mody (1993) have indicated that trust will influence exchange partners willingness and ability to adjust agreements in the face of uncertain or turbulent circumstances and, over time, those relationships that have developed trust are likely to survive for longer periods and both trust and commitment have been central to relationship marketing theory development (Morgan and Hunt 1994). Social identification, or merely identification, is the self, classifying into social categories (Ashforth and Mael 1989) and denotes a sense of connectedness or belongingness with others. Identification leads to supporting partners and has been extended to the inter-organizational level and has been shown to moderate the effect of exiting channel relationships (Lusch, Brown, and O'Brien 2011).

Procedural justice centers on the procedures and processes utilized to reach the outcome or result of an exchange whereas distributive justice refers to the resources associated with the outcome itself (Organ and Ryan 1995). Both distributive and procedural justice which indicate firms, when sensing justice, are willing to go above and beyond what is explicit or traditionally expected. On the horizontal axis we have indicated the variables of percent of purchases from supplier, overall sales volume, and loyalty. These variables are economic indicators and all demonstrate the degree and strength of financial linkages between two exchanging entities. For example, the size of the customer (indicated by store volume here) and total amount of purchases have been linked as customer characteristics to the degree of contribution margin in total profit in determining overall customer lifetime value (Venkatesan and Kumar 2004) and loyalty is hypothesized to lead to more profitable relationships as a natural consequence of exchange efficiencies.

The result of proposed framework indicated in Figure 1 is four potential market segments. While we theoretically expect these four classifications of potential B2B customers, the purpose of our investigation is whether post hoc descriptive segmentation methods can be used to identify and profile these predicted segments. Through our analyses, we will address whether in fact we can identify these differing patterns of lifetime economic and social value. After, we will investigate some of the interesting tradeoffs between these two criteria of lifetime economic and social value in segmenting B2B customers and try to understand if these segments differ in how suppliers can serve them.

3.2. Predictive Satisfaction Approach

In this approach we utilize a predictive method for distinguishing market segments. Predictive statistical methods differ from descriptive methods in that predictive methods analyze the relationship between a collection of independent (predictor or determinant) variables and one (or more) identified dependent variable. While the methods differ in statistical operation, they also differ in their purpose where descriptive methods are ideally suited for profiling segments and predictive methods are better in segmenting markets in regards to their responsiveness. If portions of the market react differently from one another to marketing efforts, they meet the responsiveness criterion of segmentation. The other, traditionally recognized, criteria of good segmentation solutions include substantiality (size of the segment is sufficiently large to provide profitable returns), identifiability (the degree of homogeneity within a segment), accessibility (how easily segments can be communicated to), stability (the make-up of the segment is not so fleeting as to not be able to market to), and the ability to proceed and act upon the segmentation results, or actionability. Here, our expectation is that segments of B2B customers will differ in their responsiveness to a number of marketing efforts of a supplier, namely the supplier's service provision. Accordingly, the approach specified here will utilize service elements as determinants or predictors of B2B customers' satisfaction.

There have been different ways to conceptualize the breadth of both product and service offerings in B2B contexts. For example, Chakraborty et al. (2007) glean eight generalized areas (reliability, delivery, technical products, breadth of products, pricing, credit policy, return policy, and warranty coverage) from both prior research and their qualitative investigation, while Homburg and Rudolph (2001) delineate seven (products, salespeople, product information, ordering, technical services, internal personnel, and complaint handling). Like Chakraborty et al.

(2007) we have utilized both the past research and qualitative exploratory research to validate our eight identified areas of product and service offering. They are products, pricing, ordering, delivery, invoice processing, advice/consulting, marketing, and salespeople). As one can see, these measures are similar to those identified in other studies.

We define satisfaction as the positive affective state resulting from the appraisal of all aspects of firm's relationship with another (Anderson and Narus 1990; Dwyer, Schurr and Oh 1987). As Chakraborty et al. (2007) argue, satisfaction is believed to be influenced by the perceptions with each of the identified component elements and can be viewed as the drivers or determinants of overall satisfaction. Further, like that of Homburg and Rudolph (2001) who indicate it is 'common practice' to relate dimensions of a construct to an overall assessment of the construct, we suggest the identified elements of overall offering influence general satisfaction.

The purpose of employing the determinants (predictors) of satisfaction approach is to answer the question of what is the overall relationship between product and service provision and overall satisfaction. Additionally, we seek to investigate such relationships at the segment level and attempt to understand if different segments have different determinants of satisfaction and if satisfaction is differentially responsive to determinants of satisfaction across the segments

4. Embedded Exchange Segmentation

4.1. Sample Data

An international wholesaler whose sales represent over US $5 Billion was contacted for participation in this study. The wholesale organization provided a full list of customer contacts where the supplier provided sales and service to three distinct brands at the retail level. The list of retail customers identified owner/operators of the retail locations as key informants for the sample. After eliminating the very small percentage of international retailers and identifying those owner/operators who run multiple locations (both less than 5% of the total sample combined), 6302 surveys were distributed. Of the distributed surveys, completed questionnaires utilized for analysis here totaled 828. Respondent bias was determined to be negligible as we compared both early and late respondents and complete versus incomplete respondents (where possible) using demographic information (e.g. years conducting business with supplier, sales volume, supplier percentage of sales penetration) with no significant differences.

A structured questionnaire was designed to measure the constructs. The development of the questionnaire was based upon both a review of the relevant literature as well as interviews with executives of the wholesale organization and retail owner/managers. Further, most items were pre-tested prior to this data collection. Finally, a small sample of the respondents was interviewed after the data collection to ensure validity. Consequently, the sample data demonstrate good validation values. Most multi-point measures use Likert type scale similar to what are used by Morgan and Hunt (1994) and have a Cronbach alpha between 0.8 and 0.95.

4.2. Measures

The embedded exchange market segmentation has two bases: the lifetime social value basis and the lifetime economic value basis. This is joint descriptive market segmentation because it uses two bases to identify and profile segments. The variables used in the embedded exchange approach are delineated in the following paragraphs beginning with those variables associated with the lifetime social value basis.

Commitment was measured using a scale previously used by Morgan and Hunt (1994) and adapted for use here. The Commitment scale was a nine item Likert type scale. The

Identification scale for measuring the retailer's identification with their supplier intended to tap the perception to which the retailer has a sense of belongingness with the supplier. The measurement scale was used five items where respondents were asked to indicate their level of agreement with the items.

Trust was measured by asking respondents to rate their trust in the supplier with seven Likert-type statements. Responses were recorded on a five-point scale where higher scores represent higher trust in the cooperative. The justice scales of *Procedural Justice* have the three subscales of *Fairness, Interactional Justice, and Open Communication*). *Distributive Justice* are measured by asking how retailers are pleased with the economic rewards then have received from the supplier.

Dealer Satisfaction asked the retailer to report on items that reflected their levels of satisfaction with the supplier. This variable represents a global satisfaction of the retailer with their focal supplier, here the cooperative. This scale utilized two items that were very similar to items used previously in channels research (Dwyer, Schurr and Oh 1987); however, these items only represented satisfaction with the entity as a whole and not any specific aspect. *Member Orientation* assessed the belief of how much the supplier is aware of and attended to the needs of the retailers.

Turning to the variables associated with the lifetime economic value basis, *Store Performance* was assessed by the retailer responding to seven items comparing their store's performance to similar retailers (measured on a 1-7 scale with 7 being Significantly Better Performance). This scale produced a Cronbach alpha of 0.911. The variable *Continue*, representing the expectation of continuing to exchange with the supplier in the future, was measured via a 7-point three item scale ranging from (0%) definitely will not continue to (100%)

definitely will continue was utilized across three-time measures. This measure was adapted from a similar measure for propensity to leave used by Morgan and Hunt (1994) where it was defined as the perceived likelihood that a partner would terminate the relationship. The *Dependence* measure was a three-item scale (Lusch et al. 2011) demonstrating a Cronbach Alpha of 0.843.

A number of single item measures were also used in aiding the measurement of the lifetime economic value basis. *Percentage Purchased* was measured from 1-100 where the questionnaire asked respondents to estimate annual purchase percentage % with the focal supplier. *Years Associated* (*YrsAssoc*) simply asked the number of years the retailer had been associated with the focal supplier. Finally, *Store Size* is a ten-point coded variable where we used the retailer's approximate sales volume to determine size where the anchors were under $100,000 (1) to over $20,000,000 (10).

Each of the embedded exchange approach variables were subsequently standardized for analysis. All variables are standardized using z-scores for the segmentation process because the standardized data performs well in clustering algorithms.

4.3. Procedure

In this joint descriptive segmentation, we want to segment firms into 4 segments and to minimize the within-segment heterogeneity of both segmentation bases. This is multi-objective optimization problem that can be solved by so-called MMSEA algorithm (Liu et al. 2012). MMSEA stands for Multi-objective Market Segmentation using Evolutionary Algorithm. The within cluster omega squared (WCOS) was used to measure the quality of segment homogeneity for each segmentation basis. It is based on Euclidean distance and is defined as following:

Let $x_{ij} =$ the value of attribute *j* for firm i; $i = 1,...,I$, I is the number of firms; $j = 1,...,J$, J is the number of attributes in the segmentation basis; $I(c) =$ the set of firms in the cluster c;

$\bar{x}_{j_c}$ = the mean of attribute j of cluster c : $\bar{x}_{j_c} = \frac{1}{|I(c)|}\sum_{i\in I(c)} x_{ij}$;

$\bar{x}_j$ = the mean of attribute j for all customers: $\bar{x}_j = \frac{1}{I}\sum_{i=1}^{I} x_{ij}$;

$$\text{Within Cluster Omega Squared (WCOS)} = \frac{\sum_{c=1}^{K}\sum_{j=1}^{J}\sum_{i\in I(c)}(x_{ij}-\bar{x}_{j_c})^2}{\sum_{j=1}^{J}\sum_{i=1}^{I}(x_{ij}-\bar{x}_j)^2}$$

A smaller WCOS value means a better segment homogeneity. The goal is to minimize the WCOS of both segmentation bases. The segmentation is a multiobjective optimization problem that has many Pareto optimal solutions.

4.4. Segmentation Solutions and Solution Selection

The MMSEA algorithm generates 300 solutions depicted in Figure 2. The two axes are the two optimization objectives. Each data point is a segmentation solution that assigns all firms to different segments.

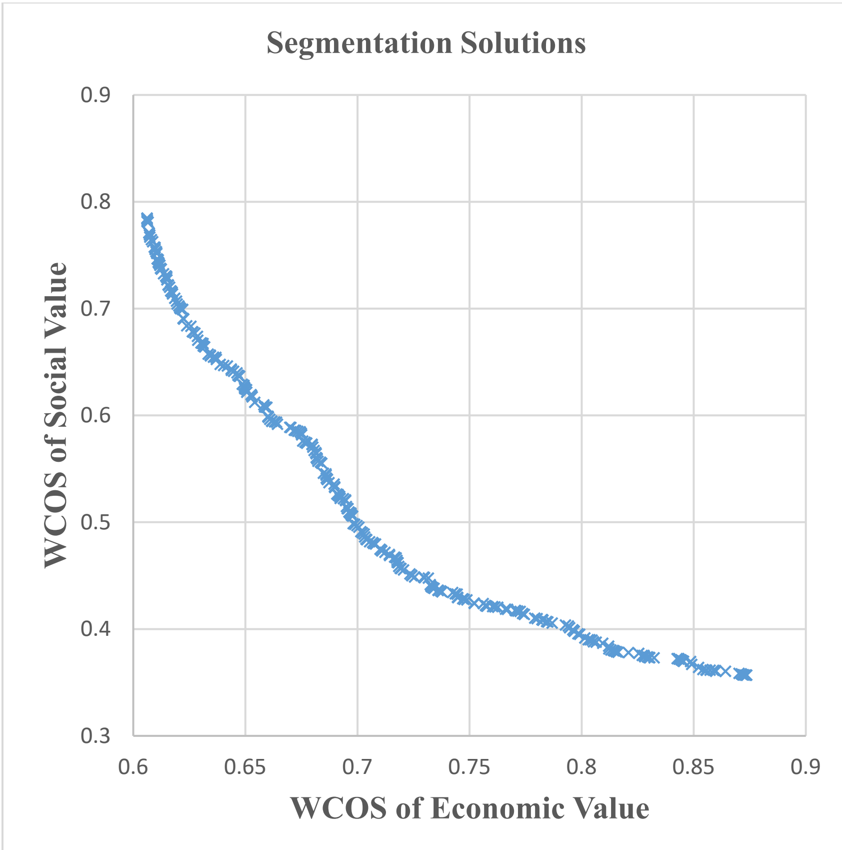

Figure 2 Embedded Exchange Segmentation

Given the set of Pareto optimal solutions, we have a holistic view of the solutions in the objective space. Technically these solutions are equally acceptable because no solution has better segment homogeneity in both bases than another solution. Nonetheless, our segmentation model suggests that we want to find a solution whose 4 segments sit in different quadrants of the embedded exchange matrix and the 4 segments should be as distinguishable as possible. Though each segment can be represented by its centroid, the question of determining the quadrant of a segment is not an easy one. Each segment is measured by two bases and each basis consists of multiple descriptive variables that have different scales and statistical attributes. The weighted product model (WPM) (Triantaphyllou 2000) is a simple and popular method to compare objects with multiple attributes. To determine the quadrant of a segment centroid, the

WPM method first calculates the ratio of each centroid attribute and the sample mean of that attribute. If all attributes have the same weight, the product (multiplication) of ratios of all attributes of a segmentation basis shows the position of the segment. If the production is bigger than 1, the segment position is above the sample mean. However, our experiment showed that the product is every sensitive to the variable variance and failed to identify a solution that has 4 segments located in different quadrants.

To solve this problem, we decided to use the average of the Z-scores (standardized value) of the segment centroid to determine its location. First, for each solution, we calculate the Z-scores of each attribute of the segment centroid. Because the Z-score removes the scale of each variable, we are able to use the average of Z-scores of all variables of a segmentation basis to determine its position in that dimension. We call the average of Z-scores of variables of a segmentation basis as basis score. The two basis scores of a segment centroid represent the centroid in the segmentation matrix. If the basis score is bigger than 0, the centroid is posited above the corresponding dimension. This method allows us to find some solutions whose 4 segments are located in the 4 quadrants. Moreover, we want to select the solution that has the most distinguishable segments. The distance of the segment centroid to the origin approximates the deviation of the segment from the sample mean. The segment is more identifiable if the distance is bigger. Consequently, we sum up the distances of the 4 segments and select the solution that has the biggest summation of distances. The basis scores of the selected solution are shown in the following figure. The segments are named by the quadrant number that they sit in.

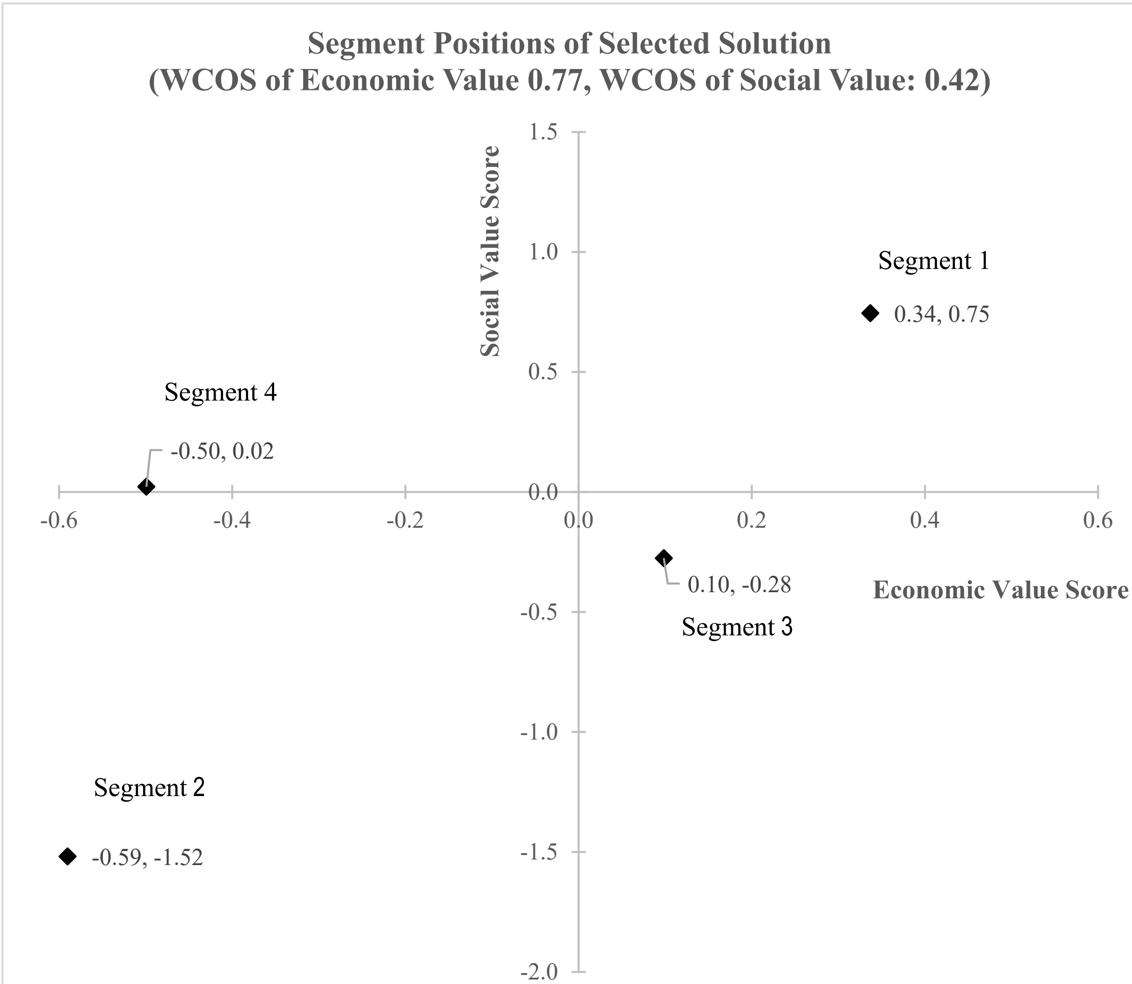

Figure 3 Segments of the Selected Solution

Segment 1 and segment 2 are more identifiable than segment 3 and segment 4 because they are far away from origin. Segment 1 is the deeply embedded segment that has the largest economic and largest social values. Segment 2 is the shallowly embedded segment that has the smallest economic and smallest social values. Segment 3 is the largely economic exchange segment that has slightly above average economic values and below average social values. Segment 4 is the largely social exchange segment that has average social values and below average economic values.

4.5. Solution Description and Segment Profile Analysis

The segment descriptive statistics are shown in Table 1. The largest of the four segments constitutes approximately 39% (323 of 828) of the total whereas the smallest represents over 12% (102 of 828).

Table 1 Embedded Exchange Approach Segment Summary Profile

	Shallowly Embedded N 102	Deeply Embedded N 323	Largely Social N 193	Largely Economic N 210	Total N 828
COMMIT[a]	2.71[b]	4.45	3.77	3.75	3.90
	0.70[c]	0.42	0.49	0.54	0.75
IDENT[a]	2.54	4.38	3.78	3.64	3.83
	0.66	0.50	0.48	0.56	0.78
TRUST	2.19	4.10	3.54	2.90	3.43
	0.63	0.48	0.42	0.52	0.83
PJ[a]	2.17	3.90	3.40	2.69	3.26
	0.63	0.53	0.48	0.50	0.82
INTPJ[a]	1.95	3.86	3.34	2.65	3.20
	0.62	0.48	0.48	0.52	0.84
DJ[a]	2.19	4.02	3.64	3.01	3.45
	0.75	0.49	0.47	0.51	0.81
SAT[a]	1.95	4.33	3.80	3.22	3.63
	0.68	0.50	0.55	0.60	0.95
MEMBORT[a]	2.32	3.57	3.21	3.12	3.22
	0.49	0.48	0.42	5.35	2.74
%PURCH[a]	73.95	85.63	57.44	84.41	77.31
	24.23	15.12	25.84	16.71	22.80
YRSASSOC[a]	16.32	19.81	17.48	15.15	17.66
	11.46	11.69	9.93	9.84	10.97
STOREPERF[a]	3.63	4.34	4.26	4.51	4.28
	1.26	0.94	0.91	6.36	3.32
CONTINUE[a]	60.34	98.61	92.23	87.61	89.62
	24.96	3.77	12.72	16.95	18.21
SIZE[a]	6.45	6.28	4.84	6.83	6.10
	1.66	1.69	1.54	1.50	1.76
DEPEND[a]	2.27	4.27	3.31	3.35	3.57
	0.89	0.66	0.78	0.84	1.01

[a] *COMMIT*: Commitment; *IDENT*: Identification; *PJ*: Procedural Justice; *INTPJ*: Interactional subscale of Procedural Justice; *DJ*: Distributive Justice; *SAT*: Satisfaction; *MEMBORT*: Member Orientation; *%PURCH*: % of store's total purchases from supplier; *YRSASSOC:* Number of Years Associated with relationship; *STOREPERF:* Store Performance; *CONTINUE:* Expectation of continuing relationship; *SIZE:* Size of sales volume; *DEPEND:* Dependence upon supplier.
[b] Mean
[c] Std. Deviation

The segment centroid values of each basis are depicted in the following figures (Figure 4 and Figure 5). As expected, the values are consistent with the segment names. Deeply exchanged segment has the biggest values in both social and economic dimensions. Shallowly embedded exchange segment has the smallest values in social dimension. Most of its economic values are also the smallest among the four segments. The largely social exchange segment has the smallest percent purchased (%PURCH) value.

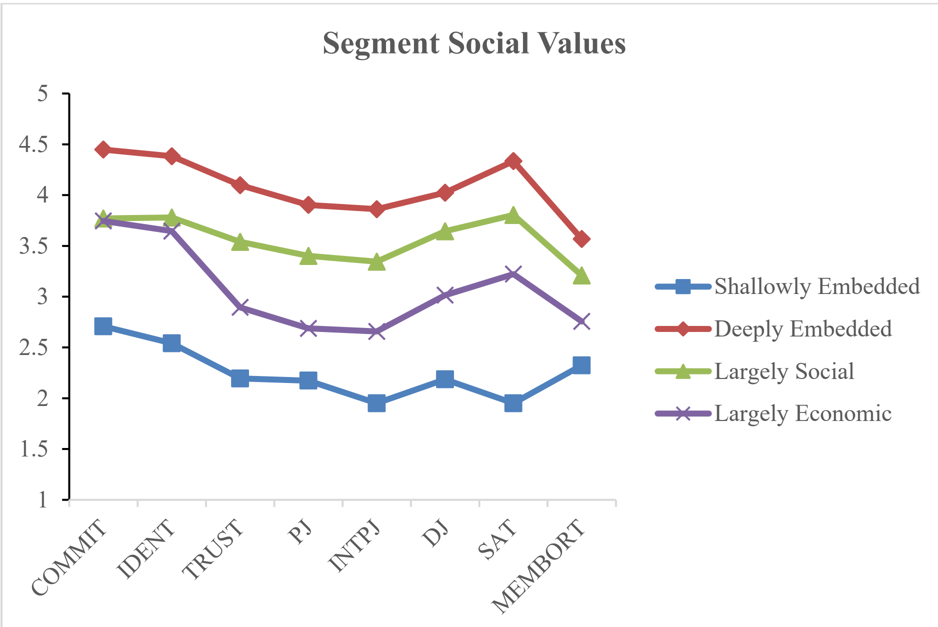

Figure 4 Segment Social Values

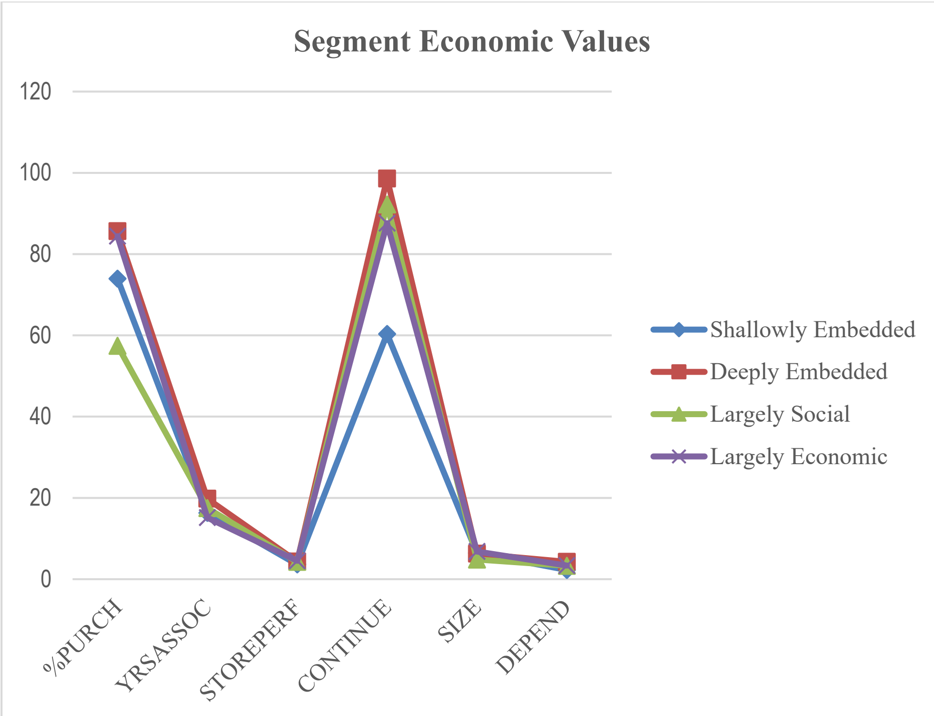

Figure 5 Segment Economic Values

Decision makers may want to transform the other three segments into the deeply embedded segment. For example, marketers should socially interact with largely economic exchange segment or try up-sell and cross-sell with the largely social exchange segment.

5. Predictive Satisfaction Approach

Same sample data are used in predictive satisfaction segmentation. Measures for the predictive segmentation model are chosen based on the above theoretical analysis.

5.1. Measures

Dealer Satisfaction is unchanged from the previous analysis where it represents a global satisfaction of the retailer with their focal supplier. The remaining variables (Products, Pricing, Ordering, Delivery, Invoices, Advice, and Marketing) utilized in the predictive satisfaction approach were measured at the attribute level. The attributes listed were to represent the total offering of the supplier to the retailer across a number of areas. Meaningful attributes were of both products and services provided were identified across numerous meetings with management. The broad categories, each with multiple measures were decided upon and represent the holistic offering. Further, the boundary spanning position of the retail consultants (RC) who work for the supplier but serve the retailer was assessed. Here, four main areas of consulting were again assessed by the retailer's using formative scales which were summated and averaged. The overall variable average (RCAVG) is a formative scale summated and averaged across the following four subscales.

- *RCServ*: Included assessments on overall service including overall preparation, accessibility, and adding value.
- *RCInfo*: Included assessments on information provision including vendor programs, product lines, and supplier specific news.
- *RCPlan*: Included assessments on store planning elements including store improvement, competition, financial planning, and benchmarking.
- *RCDemand*: Included assessments on demand stimulation efforts including assortment planning, layout, signage, and promotional effectiveness.

The four subscales capture how has the supplier's retail consultant performed on each area over the last 12 months. We use the average because the four variables have strong correlations. The descriptive statistics of the segmentation bases are also shown in Table 2.

Table 2 Descriptive Statistics of Measures of Predictive Satisfaction Approach

Variable N 838	Mean	Std. Dev.
DealrSat	3.45	0.84
Products	2.80	0.60
Pricing	3.11	0.67
Ordering	2.79	0.61
Delivery	2.78	0.69
Invoices	2.87	0.81
Advice	2.79	0.68
Mkting	2.70	0.73
RCavg	2.67	0.92

5.2. Procedure

In order to better emphasize the value of the predictive satisfaction approach we first run a linear regression using all sample data to establish a baseline for comparison. The following equation indicates the model of the predictive satisfaction segmentation approach.

DealrSat = B0 + B1*Products + B2* Pricing + B3*Ordering + B4*Delivery +

B5*Invoices + B6*Advice + B7*Mkting + B8*RCavg

The results of the baseline model are shown in Table 3. In this model we detect no strong collinearity as the highest VIF value is 2.712. The Adjusted R Squared value of 0.422 shows a relationship between satisfaction and the predictors. Delivery, Invoices, Advice, and Marketing are not significant at 0.01 level. Because of the firm heterogeneity, the segment level predictive model should produce strong relationship between satisfaction and the predictors.

Table 3 Baseline Regression Parameter Estimates for Predictive Satisfaction Approach

Dependent Variable DealrSat Estimate			
Parameter	Unstd.	Std.	t-Value
(Constant)	0.426	0.000	3.286[a]
Products	0.149	0.106	2.940[a]
Pricing	0.218	0.173	4.773[a]
Ordering	0.309	0.222	5.119[a]
Delivery	0.042	0.034	0.981
Invoices	0.092	0.088	2.456[b]
Advice	0.080	0.064	1.600
Marketing	0.096	0.083	2.391[b]
RCavg	0.113	0.123	3.790[a]
Adj. R-Square	0.424		
Largest VIF	2.706		

$^a p \leq 0.01$. $^b p \leq 0.05$.

Both the embedded exchange and predictive satisfaction segmentation approaches are multiobjective optimization problems. The embedded exchange segmentation minimizes the WCOS of both segment descriptive bases. The predictive satisfaction segmentation minimizes the total RSS of segment-level regression model and the WCOS of independent variables. Additionally, the predictive model has a constraint of minimum segment size. The multiobjective nature of market segmentation raises many issues that cannot be addressed appropriately with traditional market segmentation methods such as K-means and clusterwise regression because they only optimize one objective. As a result, many methods have been proposed to address the multiobjective requirement of market segmentation. These methods can be classified into three types: multistage approach, transformation approach and Pareto optimal approach (Liu et al. 2012). The multi-stage approach allows researchers to deal with one objective at one time. The transformation approach transforms the multiobjective problem into a single-objective problem. The Pareto optimal approach directly optimizes multiple segmentation objectives and generates a set of Pareto optimal solutions. Compared with the other two approaches, the Pareto optimal approach does not change the segmentation problem definition and gives a holistic view of possible solutions. The multi-criteria evolutionary market segmentation algorithm is such a Pareto optimal approach. The evolutionary algorithm is a meta-heurist method and can be easily adapted to different segmentation problems. We use the MMSEA for our segmentation problems. Nonetheless, there are two questions that are not answered by the MMSEA algorithm: 1) how to determine the number of segments? 2) how to select the best solution from a set of Pareto optimal solutions? We extend the MMSEA algorithm to answer the questions for the proposed B2B segmentation approaches. The extension details are described in the segmentation solution discussion.

5.3. Segmentation Solutions and Solution Selection

To address the first of these MMSEA extensions, we investigate 3-segment, 4-segment and 5-segment predictive segmentation solutions. These numbers of segments were chosen because the results produce both good predictive performance and good segment homogeneity. The predictive performance is measured by the total residual sum of squares (RSS) of segment level regression models. A smaller total RSS means better predictive performance. The within cluster omega squared (WCOS) of all independent variables is used to measure segment homogeneity. A smaller WCOS value means a better segment homogeneity. Additionally, in order to produce valid segment level regression models as well as meet the substantiality criterion of market segment, we add a constraint to the segmentation model that the segment size should be greater or equal to 30. Accordingly, the segmentation is a multiobjective optimization problem that has many acceptable solutions.

Applying the above constraints, the MMSEA algorithm generates 200 solutions for each number-of-segments that are depicted in Figure 6. The two axes are the two optimization objectives. Each data point is a segmentation solution that assigns all firms to different segments. Due to the computational complexity of the problem and the heuristic solution procedure, it is very difficult, if not impossible, to obtain the real Pareto optimal solution set. The set of solutions of each number-of-segments approximate the real Pareto optimal front.

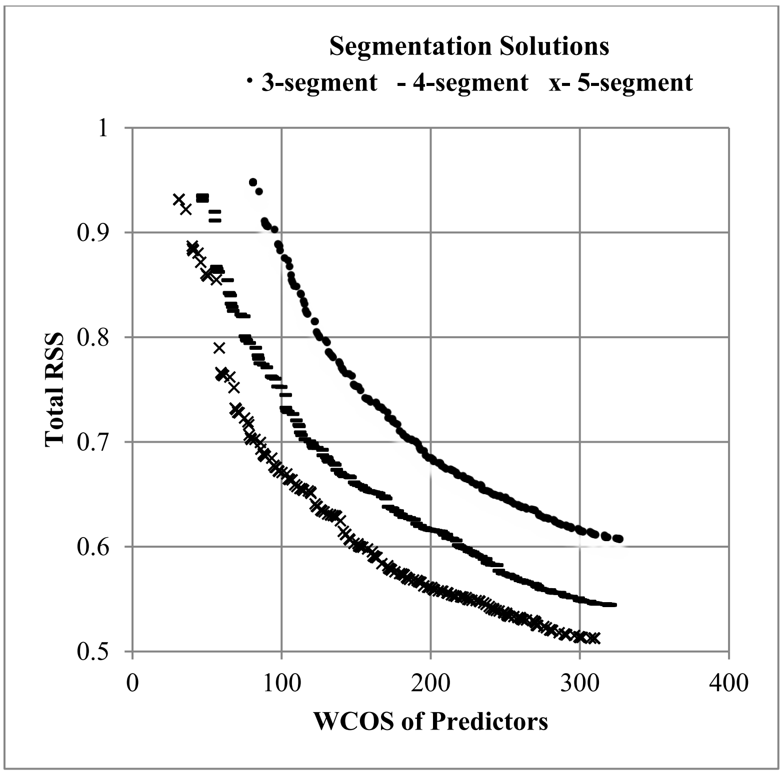

Figure 6 Predictive Segmentation Solutions

The set of Pareto optimal solutions of each number-of-segments give a holistic view of the solutions in the objective space. Based on the segmentation model and research questions, we want to find a solution that best fit our segmentation goal. The definition of the "best" is ambiguous because of the complexity and the multiple optimization objectives of the market segmentation problem. Additionally, identifying the number of segments is a problem without a satisfactory statistical solution. Nonetheless, the Pareto front characteristics make some solutions more interesting than the others. We use a two-stage approach to select the solution for this segmentation problem. First, we choose a solution from each number-of-segments solution set based on the shape of the Pareto front. Second, from the three selected solutions, we determine the number of segments based on the segment profiles and predictive models of the solution.

If the solutions are evenly distributed in the solution space, an angle-based algorithm (Branke et al. 2004) could be used to find the knee of the Pareto front. The algorithm uses the angle formed by one point and its neighbors to find the knee of the Pareto front. The knee is the point that has the biggest angle. Figure 7 shows the possible shape for a two-objective Pareto front with 9 solutions that are not distributed evenly in the solution space.

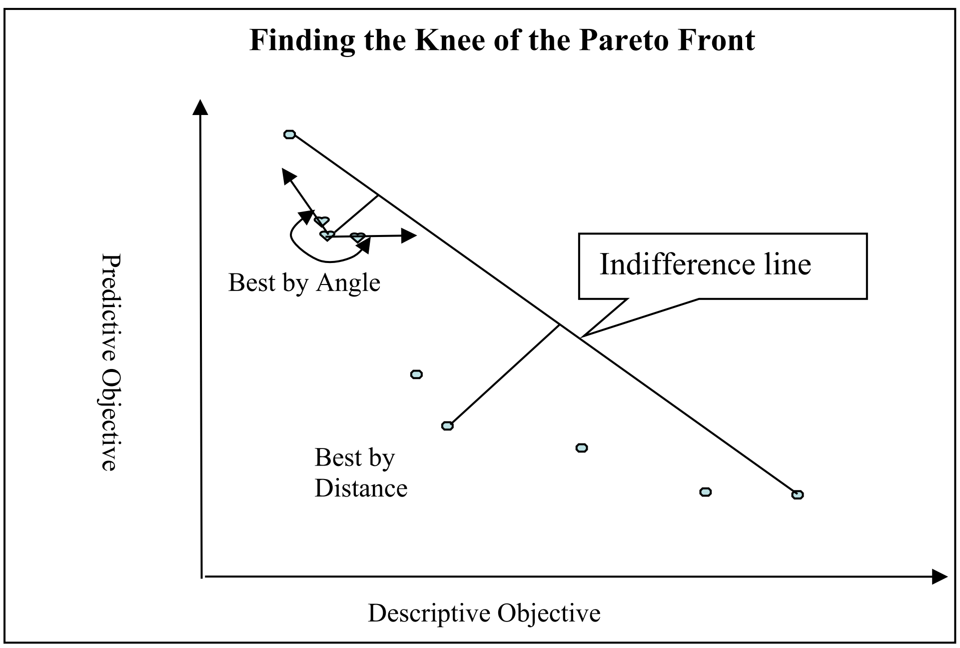

Figure 7 Finding the Knee of the Pareto Front

As illustrated by the upper-left part of Figure 7, the algorithm fails to find the global optimal knee because of the local maximum formed by the three points clustered together. We developed a maximum distance algorithm to find the knee of the Pareto front whose solutions are not evenly distributed in the solution space. If we assume that the line between two extreme solutions forms an indifference line, i.e., solutions in this line are equally good, solutions sitting below this indifference line are better solutions because they represent a set of solutions that have better gain/loss rate. Then the distance from each intermediate solution to the line is calculated. The solution that (i) is below the reference line and (ii) has the maximum distance is the suggested solution for this Pareto front. Figure 7 depicts the process of finding maximum distance solution. The suggested 4-segment solution is depicted in Figure 8.

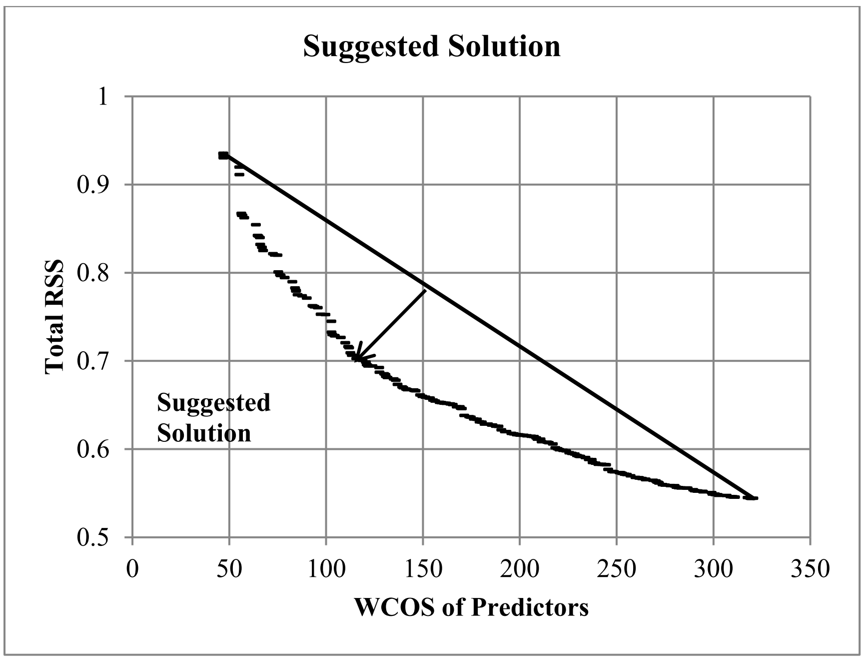

Figure 8 4-segment Maximum-distance Solution

The suggested 4-segment solution sits in the middle of the Pareto front and represents a better tradeoff between the segment predictability and identifiability. We use this method to find a 3-segment solution and a 5-segment solution from their corresponding Pareto fronts. Table 4 summarizes the selected 3-segment, 4-segment and 5-segment solutions.

Table 4 Predictive Satisfaction Approach Model Regression

Number of Segments	One-way ANOVA	Adjusted R Squared Values of Segment-level Regression
3-Segment Solution	All variable means are significantly different	Segment 1: 0.40 Segment 2: 0.52 Segment 3: 0.36
4-Segment Solution	All variable means are significantly different	Segment 1: 0.55 Segment 2: 0.66 Segment 3: 0.47 Segment 4: 0.63
5-Segment Solution	Only dependent variable mean is significantly different	Segment 1: 0.45 Segment 2: 0.51 Segment 3: 0.42 Segment 4: 0.40 Segment 5: 0.39

We use One-way ANOVA to compare the segment means. If the means are significantly different, the segments have good identifiability. The R squared values are used to measure the predictive model performance. Bigger R squared value means better prediction performance. The above table shows that the 4-segment solution has good segment identifiability and all its predictive models have good R squared values. Therefore, we use the 4-segment solution. Below is the segment level descriptive statistics of the 4-segment solution.

5.4. Solution Description/Segment Profile Analysis

The segment level descriptive statistics of the 4-segment solution are in Table 5. At the segment level, the relationship between service provision and satisfaction is stronger than the overall relationship. The R squared value of four segment level regression models are 0.576, 0.676, 0.496 and 0.636. There are different patterns for each segment level regression models. Importantly, the number of significant predictors and predictor coefficients are different for different regression segment models. Additionally, because we optimize both predictive and identification objectives, the segment profiles are different from each other and the one-way

ANOVA results are significant for dependent variable and all predictors. The following table, Table 6, summarizes the segment-level regression models.

Table 5 Predictive Satisfaction Approach Segment Summary Profile

	Segment 1 N 143	Segment 2 N 190	Segment 3 N 198	Segment 4 N 297	Total N 828
DealrSat	2.24 [a]	3.81	3.59	3.96	3.54
	0.65 [b]	0.56	0.63	0.51	0.84
Products	2.54	3.24	2.43	2.90	2.80
	0.64	0.56	0.51	0.42	0.60
Pricing	2.75	3.65	2.76	3.18	3.11
	0.68	0.60	0.57	0.49	0.67
Ordering	2.39	3.36	2.49	2.82	2.79
	0.59	0.49	0.51	0.43	0.61
Delivery	2.41	3.31	2.49	2.81	2.78
	0.72	0.66	0.61	0.52	0.69
Invoices	2.40	3.58	2.58	2.85	2.87
	0.83	0.62	0.77	0.60	0.81
Advice	2.35	3.35	2.29	2.96	2.78
	0.64	0.57	0.59	0.39	0.68
Mkting	2.37	3.24	2.21	2.84	2.70
	0.73	0.71	0.57	0.52	0.73
RCavg	2.14	3.10	1.94	3.10	2.66
	0.84	0.84	0.66	0.68	0.92

[a] Mean [b] Std. Deviation

Table 6 Segmentation Level Regression Models Summary

	Segment 1			Segment 2			Segment 3			Segment 4		
	Estimate			Estimate			Estimate			Estimate		
Parameter	Unstd.	Std.	t-Value	Unstd.	Std.	t-Value	Unstd	Std.	t-Value	Unstd.	Std.	t-Value
(Constant)	-0.257		-1.202	-0.324		-1.460	0.434		1.760	-0.596		-2.710[a]
Products	0.245	0.241	3.809[a]	0.221	0.220	4.001[a]	0.264	0.214	3.588[a]	0.240	0.200	5.006[a]
Pricing	0.075	0.078	1.017	0.317	0.340	6.603[a]	0.194	0.174	2.844[a]	0.229	0.220	5.795[a]
Ordering	0.305	0.277	3.466[a]	0.251	0.218	3.647[a]	0.330	0.266	3.913[a]	0.221	0.187	3.948[a]
Delivery	0.093	0.103	1.534	-0.013	-0.016	-0.299	-0.054	-0.053	-0.836	0.183	0.188	4.677[a]
Invoices	0.012	0.015	0.220	0.188	0.208	4.096[a]	0.072	0.088	1.360	0.254	0.303	7.372[a]
Advice	0.174	0.172	2.230[b]	0.126	0.127	2.336[b]	0.023	0.021	0.342	0.161	0.126	3.057[a]
Marketing	0.184	0.208	2.903[a]	0.020	0.026	0.486	0.283	0.255	4.320[a]	0.163	0.168	4.478[a]
RCavg	-0.074	-0.096	-1.447	0.098	0.146	3.267[a]	0.224	0.235	4.110[a]	0.107	0.144	3.569[a]
Adj. R-Square		0.551			0.662			0.469			0.627	

[a]$p \leq 0.01$. [b]$p \leq 0.05$.

Many managerial implications can be derived from the segment level models. For example, Segment 1 has the lowest satisfaction value. While the sample average mean of satisfaction is 3.55, the segment 1 mean is only 2.23. Actually, it is the only segment that is below the sample average. Ordering, Products and Marketing are significant predictors. All three predictors are below the sample averages: ordering mean is 2.39 vs. 2.79; products mean is 2.54 vs. 2.80; and marketing mean is 2.37 vs. 2.69.

Segment 4 has the highest satisfaction level with a segment mean of 3.97 (The sample mean is 3.54). All predictors are important. All segment predictors except invoices have above average mean values. The segment mean of invoices is very close to the sample mean. Invoices, Products, ordering and pricing have big impacts on the satisfaction result because of their large coefficient values.

6. Implications and Future Research

The meta-heuristic nature of the evolutionary algorithm allows one to quickly adapt the MMSEA algorithm to a specific B2B segmentation application, in both descriptive and predictive models. Much of our effort is spent on designing and defining the two B2B segmentation approaches and pre-process firm data. Because it is a Pareto optimal method, there is no need to use multiple process stages or transform multiple objectives to a single optimization objective. The transformation function is not easy to define for two reasons. First, the two optimization objectives may have different scales or semantics. In the predictive satisfaction approach, the total residual sum of square and the within cluster omega square have different scales and different semantics. Even when they can use the same scale after normalization, there is no clear meaning to assign the weight of each objective in a transformation function.

The Pareto optimal segmentation method generates a set of Pareto optimal solutions for each of our B2B segmentation approach. Those solutions not only give a holistic view of possible solutions in the optimization objective space but also allow marketers to develop solution selection algorithm based on the context of a specific segmentation problem. In this study, we select the best solution whose segments are located in the four quadrants of the embedded exchange segmentation model. The selected solution gives many insights of the B2B relationships. In the predictive satisfaction approach, the Pareto optimal solutions set helps to select the best solution that represents good tradeoffs between two optimization objectives. The selected solutions also help to decide the number of segments, an unsolved issue in market segmentation, in a heuristic and intuitive way.

Variable selection and determining the number of clusters are two basic tasks in segmentation, these two tasks are often driven by managerial theories, not driven by data (Liu and Ong 2008). Selecting the best solution using maximum distance method is based on the geometric shape of the Pareto optimal solution front. However, its properties are not fully investigated in this study. Giving that the two dimensions may not have the same weight in business decision, a possible extension is to include weight in calculation, both in the searching process and in the solution selection. Finally, more quantitative comparisons of the multi-objective Pareto optimal segmentation solutions to traditional single-objective segmentation solutions may bring more insights about both methods. These are future research topics.

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