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Segmenting the Commercial Producer Marketplace for Agricultural Inputs

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ABSTRACT: A cluster analysis procedure was used to develop a market segmentation of U.S. crop and livestock farms with annual sales in excess of $100,000. The segments were developed based on the importance of six factors that producers evaluate when selecting input suppliers. The results indicate that four distinct segments exist: Convenience buyers, Balance buyers, Price buyers, and Performance buyers. Differences in preferences across these segments have important implications for the marketing strategies of agricultural input suppliers.

INTRODUCTION

The farm producer is an important customer of virtually all agricultural input suppliers, including equipment manufacturers and dealers, financial institutions, fertilizer and chemical companies, seed companies, and feed companies. Because the revenue of these industries is generated by purchases made by farm producers, knowledge producers' preferences for products, services, and information are important to these industries. This knowledge helps input suppliers better match their product, service, and information offerings to the needs of their customers. By better serving their customers, agricultural input suppliers can potentially increase sales and profits.

However, the farm sector is not homogeneous. Farms differ on dimensions

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Table 1. Farms by Sales Class, 1997

Sales Class	*$1,000,000 +*	*$500,000–$999,999*	*$250,000–$499,999*	*$100,000–$249,000*	*$50,000–$99,999*	*less than $50,000*
Percent of						
Farms	0.9	1.7	4	10.1	9.1	74.2
Livestock receipts	35.9	14.6	14.5	16.4	8.9	9.7
Crop receipts	29.8	13.7	17.5	21.4	8.8	8.7
Cash expenses	29.9	12.8	15.9	18.7	8.4	14.2
Cash ($)						
Gross income per farm	3,788,565	900,357	437,434	210,086	110,205	16,432
Expenses per farm	2,664,251	615,579	320,544	151,165	75,067	15,581

Notes Source: Appendix Tables 5 and 6 *Agricultural Income and Finance Situation and Outlook Report,* September 1998.

such as size, management style, location, production practices, and so forth. In efforts to segment the farm market, farms are often grouped by criteria such as crops grown, type of technology employed, and region of production (Rosenberg and Turvey, 1991). Grouping farms by sales classes is one of the most common of these segmentation schemes. According to the *Agricultural Income and Finance Situation and Outlook Report,* in 1997 there were 2.06 million farms in the United States (Resource Economics Division, Economic Research Service, 1998). The information in Table 1, which is taken from the September 1998 report, indicates how farms vary by sales class. One of the important features of these data is that 83.3% of the farms in the United States had sales less than $100,000. At the same time, these smaller farms accounted for only 18.6% of the livestock receipts and 17.5% of the crop receipts in the United States. On the other hand, farms with sales over $1,000,000 accounted for only 0.9% of farms, but produced 35.9% and 29.8% of livestock and crop receipts, respectively. This means that much of the economic activity associated with agricultural production is concentrated in the nation’s largest farms. Therefore, by marketing to 16.7% of the nation’s farms (those with sales in excess of $100,000) marketers can gain access to farms that produce 81.4% of the livestock, 82.5% of the crops, and 77.3% of cash farm expenses in the United States. Because farms with sales over $100,000, hereafter called commercial producers, represent such a large portion of cash expenses and thus input supplier revenues, it is worthwhile to examine this segment in greater detail.

Market researchers have professed the value of market segmentation for many years. The central purpose of market segmentation is to identify segments, or groups of buyers that react differently to marketing choices (Riquier et al., 1997). The main assumptions of the segmentation concept are 1) buyers can be grouped into segments such that preferences are homogeneous within segments and heterogeneous across segments and 2) marketing offerings that are matched to the segments will outperform unmatched offerings (Green and Krieger, 1991).

Market segmentation frequently consists of grouping buyers into segments according to sales classes and then developing marketing strategies to serve the different segments. Clearly, if factors other than, or in addition to, sales define the true market segments, market segments based only on sales classes will be misleading. As more information about buyers becomes available, marketers have advocated more rigorous, data-intensive segmentation schemes. Under this methodology, many factors thought to influence buying preferences are considered and used to form market segments. This approach to segmentation is often implemented through cluster analysis (Punj and Stewart, 1983).

This study uses a clustering methodology to segment the commercial farm population according to this population's preferences for elements of the bundle of products, services, and information that could be provided by a farm input supplier. The commercial farm population is defined as farm producers with annual sales from at least one enterprise (corn/soybeans, wheat/barley, cotton, dairy, beef, or hogs) in excess of $100,000. Survey returns from a sample of commercial producers are used to segment the population according to the importance of six factors producers evaluate when selecting a supplier: convenience/location, customer services/information (e.g., responsiveness, follow-up, advice), personal factors (e.g., trust, working relationships), price, product performance (e.g., yield, durability, rate of gain), and support services (e.g., delivery, repair, application). The results of the segmentation are then used to characterize the various segments along dimensions thought to influence the input purchase decision.

Background: Market Segmentation

Market segmentation can be used to determine how different groups of buyers respond to changes in the firm's marketing strategies—price, product introductions, product changes, promotional activities, among others (Wind, 1978). Once these responses have been determined, the firm may divide the market into distinct groups of buyers where any group can be chosen as a target market to be reached with a distinctive marketing mix (Kotler, 1978).

The three basic ways to segment a market are the a priori approach, cluster-based methods, and through combinations of the two methods. The a priori approach, or the prespecified method in Rosenberg and Turvey's (1991) terms, is the most subjective. With the a priori approach, researchers use their knowledge of the marketplace to identify characteristics that define market segments. For instance, researchers might conclude that all farms of 1,000 acres or more will be placed in one group and farms of 999 acres or less will be placed in another group. Clearly, if the researcher makes poor choices when defining the segments, the segments will not consist of groups that have homogeneous attitudes toward the firm's marketing strategies. This segmentation method can be very useful, in part because of its simplicity, but it does not make full use of the information contained in the data available to many marketers.

In cluster-based segmentation the researcher selects a series of variables that are thought to characterize buying behavior. Next, observations on these variables are submitted to an algorithm that places respondents with similar responses in distinct groups. Because this method is capable of considering many more segmentation variables than the a priori approach, it makes better use of the information gathered on the population being segmented.

The reliance of market segmentation research on clustering methods becomes apparent when one considers the interpretation of clustering given by researchers such as Anderberg (1973), who identified the objective of cluster analysis as grouping observations so that the level of natural association is high among group members and low across groups. Thorough, methodological reviews of cluster analysis are offered by Punj and Stewart (1983; marketing), Milligan and Cooper (1987; psychology), Ketchen and Shook (1996; strategic management), and Larson (1993; agricultural economics). Three of a number of general textbooks on the subject include Anderberg (1973), Everitt (1980), and Aldenderfer and Blashfield (1984).

Several studies have specifically attempted to segment various farm populations (Mwangi, 1991; Rosenberg and Turvey, 1991; Hooper, 1994; Bernhardt et al., 1996; Gloy et al., 1997). Mwangi (1991) used cluster analysis to identify four segments of Illinois farms that desired different benefits from fertilizer and chemical suppliers. Gloy et al. (1997) used an a priori segmentation scheme to segment the retail petroleum customers of two Midwestern cooperatives according to the profitability that the customers generated for the cooperative. Rosenberg and Turvey (1991) used cluster analysis to segment Ontario swine producers with the goal of determining segments that responded differently to extension offerings. Bernhardt et al. (1996) used cluster analysis to identify farm segments, ranging from commercial to alternative, for the purpose of guiding interdisciplinary research efforts. These studies varied widely with respect to the population segmented, goals of the segmentation, segmentation bases used, quantitative methods used, and validation procedures. It appears that there have been no published attempts to segment the commercial farm population of the United States by using a clustering methodology for the purpose of defining market segments for agricultural input suppliers.

Method

The basic steps in cluster analysis include choosing variables to cluster or segment on, selecting the clustering algorithm, choosing the solution, and validating the solution (Bernhardt et al., 1996). The method used in this study is outlined below.

1. Randomly split the sample in half.
2. Select the clustering variables.
3. Choose the hierarchical clustering algorithm and identify the number of clusters.
4. Combine samples and use a nonhierarchical k-means clustering algorithm with the means of the clustering variables conditional on hierarchical cluster membership as starting seeds.
5. Validate the segmentation with tests for significant group differences on nonclustering variables.
6. Interpret the solution; develop marketing strategies; and assess factors, such as segment size.

The first step of the method allows for concurrent analyses on the split samples and the entire sample. This provides an additional opportunity to examine the choice of the number of clusters present in the data and helps insure that the solution is not a function of artifacts such as the ordering of the data. This step was accomplished by assigning a uniformly distributed, random variable to each observation, sorting the observations by this variable, and dividing the data set in half.

Variable selection for cluster analysis directly corresponds to segmentation-base selection. Most authors, notably Anderberg (1973), point to variable selection as one of the most important steps in cluster analysis because appropriate variable choices increase the likelihood of recovering the true market segments. Algorithm selection is important because the clustering solution is sensitive to characteristics of the data and type of algorithm used. There are two primary classes of clustering algorithms, hierarchical algorithms and nonhierarchical algorithms.

Agglomerative hierarchical algorithms join observations or clusters until instructed to stop. These methods are often criticized because observations joined early in the process cannot be separated (Aldenderfer and Blashfield, 1984; Ketchen and Shook, 1996). Nonhierarchical algorithms require the researcher to specify the number of clusters in the data and the cluster centroids, or seeds. Nonhierarchical methods are dependent on the initial arrangement of the observations or the starting point of the analysis (Ketchen and Shook, 1996). Some authors have stated that a preferred approach is to first use a hierarchical procedure to find the number of clusters and then use the hierarchical solution as the seeds, or starting point, for the nonhierarchical, k-means procedure (Larson, 1993; Ketchen and Shook, 1996).

In this research, Ward's hierarchical clustering method was used to identify the number of clusters and to provide the seed values for the k-means, nonhierarchical algorithm. Both the split sample results and the entire sample results were taken into account to determine the number of clusters in the data. Then, the data were combined and the entire sample results used to calculate the seeds for the k-means algorithm. The procedure of using the hierarchical cluster means as seeds for the k-means algorithm is equivalent to accepting the hierarchical clustering variable means conditional on cluster membership as the prior belief for the final conditional cluster means. Next, the k-means algorithm rearranges the observations optimally given the seeds, or the prior belief about the cluster means. Then, the cluster means are recomputed, and observations are reassigned to the nearest cluster mean. The means are then recalculated and observations reassigned. The process repeats until no observation changes clusters (SAS Institute, Inc., 1989). The k-means solution is then the updated prior belief of the conditional clustering variable means. The belief in the updated prior can then be strengthened or weakened by tests of group differences on nonclustering variables.

Data

Sudman and Blair (1999) pointed out that when sampling subgroups (commercial producers) that are a small proportion of a much larger group (all producers), the first step is to determine whether a good list of subgroup members is available. The farms in this sample were identified from a proprietary database that contained information on farm size, enterprise type, and location. Based on the estimated response rates, 10,500 surveys were mailed to farms believed to have sales in excess of $100,000. The six enterprises targeted were corn/soybeans, wheat/barley, cotton, dairy, beef, and hogs. Geographic targeting by enterprise class was accomplished by sampling producers from the states that accounted for 75% of total production/inventory of one of the six commodities.

The survey instrument was designed with the input of academics, representatives from several large agricultural input firms, and the firm in charge of administering the survey. The initial survey instrument was pretested with farmers in February 1998. After incorporating suggested changes, we mailed the final survey instrument and a postage paid reply envelope in March 1998. Because providing a meaningful financial incentive for completion of the questionnaire was not feasible given the budget for the project, respondents were offered a summary of the results as an incentive for participation. A follow-up reminder card was sent approximately two weeks after the initial mailing. Next, calls were made to nonrespondents in late March. Data collection ended in April 1998. Of the 10,500 surveys mailed, 1,721 usable questionnaires were returned, for a response rate of 16.4%. Although the response rate appears low, it was in line with our expectation of 20% given the size of the farms sampled and the length of the survey instrument. [A copy of the survey instrument, which provided data on the 256 response variables, can be found in Gloy (1999.)]

Respondents that operated farms with sales between $100,000 and $499,999 made up 39% of the sample, whereas the remainder had sales of $500,000 or more. With respect to enterprise type, corn/soybean farms accounted for the largest percentage of respondents (27.5%), and wheat/barley growers made up the smallest percentage of total respondents (11.6%). Additional detail on the sampling procedure and the response rate can be found in Gloy (1999) or Akridge et al., (forthcoming).

Results

The results were developed by using various routines in SAS release 6.12 (SAS Institute, Inc., 1989). For example, the hierarchical clustering was implemented with the CLUSTER procedure, and the k-means clustering algorithm was implemented with the FASTCLUS procedure. Twelve questions, measured on a forced sum scale, served as ideal segmentation bases (clustering variables). The questions asked respondents to assign a percentage to the influence of several factors toward their choice of input suppliers for capital goods and expendable goods. The question was stated as

> When you choose a supplier for either capital items like equipment or expendable items like pesticides or feed, how is your decision influenced by the following factors? Assign a percentage value to each factor based on its importance in the decision. Each column should sum to 100. [There was a column for expendables and a column for capital items.]

The response categories included convenience/location, customer services/ information (e.g., responsiveness, follow-up, advice), personal factors (e.g., trust, working relationships), price, product performance (e.g., yield, durability, rate of gain), and support services (e.g., delivery, repair, application). The customer segments derived from this segmentation base will reflect the respondents' differing attitudes toward the possible benefits that input suppliers can provide. The responses to these questions were submitted to Ward's hierarchical algorithm. The results produced by Ward's algorithm were then used to identify the number of clusters, or segments, in the marketplace. The average linkage clustering algorithm was also considered, but Ward's method produced the most sensible results.

Both Ward's and the k-means clustering algorithms use Euclidean distance as the similarity measure. The use of this similarity measure made it important to

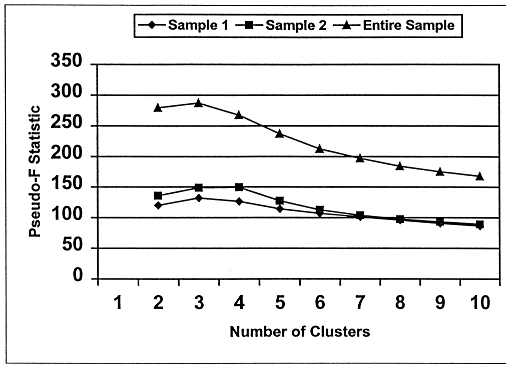

Figure 1. The Pseudo-F Statistic for Ward's Hierarchical Clustering Algorithm.

consider the scale of the variables submitted to a clustering algorithm. Because the variables were measured on a ratio scale, the relative differences between them were important, and it was not necessary to adjust the scale of the variables. Although variables such as age, education, and other demographic characteristics may be related to each group's preferences for different input supplier offerings, these factors were not used to derive the segments. Such demographic data tend to be indirectly related to buying preferences. Here, the goal was to develop groups of respondents, whose ratings of input supplier offerings were similar, by directly focusing on preferences. Then, demographic data were used to characterize the members of the different groups.

Several measures were evaluated to determine the number of clusters. The cubic clustering criterion failed to produce a reasonable solution in this case and is not reported. The pseudo-F statistic is a ratio of the between-cluster variation to the within-cluster variation (Milligan and Cooper, 1985). Fig. 1 shows the pseudo-F statistic, for both halves of the sample (Sample 1 and Sample 2) and for the entire sample. Local maxima in the pseudo-F statistic indicate potential cluster solutions (Larson, 1993). The pseudo-F statistic has a local peak at three clusters for the entire sample and a flat top at three and four clusters for both of the split samples. This would indicate that the data likely contains three or four clusters.

The second measure used to identify the number of clusters was the pseudo-T^2 statistic. This statistic is a ratio of the sum of squared errors when the merging clusters remain separate to the sum of squared errors when the merging clusters are joined. The pseudo-T^2 statistic indicates a cluster solution when the value of the statistic falls or has a trough (Larson, 1993). The pseudo-T^2 statistic falls sharply when going from three clusters to four clusters in Sample 2, and the entire sample also shows a trough forming at four clusters. Sample 1 shows a slight trough at seven clusters. These results indicate a four cluster solution in the entire sample and in Sample 2.

Taken together, these statistics point to a four cluster solution. Unrealistic assumptions are necessary to guarantee that these statistics possess well-known distributions. Therefore, no reliable statistical tests are available to directly identify the solution. However, these statistics and the general rules of thumb discussed are widely used in the literature. What is more important is that in Monte Carlo experiments these methods have been shown to be very effective at recovering the true group structure of the data (Milligan and Cooper, 1985). Once a potential solution has been identified, statistical tests for differences across clusters on nonclustering variables can be carried out to examine differences in segment characteristics and attitudes. (Statistical tests of mean differences by clusters on the clustering variables would be strongly biased because the clustering algorithms are designed to maximize these differences.)

The four cluster solution produced by Ward's method contained one large cluster, 32–42% of the respondents in the samples, and three moderate sized clusters, 13–27% of the respondents in the various samples. In general, Ward's method appears to produce a sensible solution whose properties did not vary drastically from sample to sample. This suggests that there are four segments in the population of commercial producers, and these segments desire different attributes from their input suppliers. Because hierarchical methods only make one pass through the data, they are often criticized (Aldenderfer and Blashfield, 1984; Ketchen and Shook, 1996). To account for these failings, the hierarchical results from the entire sample were used as a starting point for the k-means clustering procedure.

The k-Means Results

The clustering-variable means conditional on membership in each of the four Ward's clusters from the entire sample analysis were input to the FASTCLUS procedure in SAS (SAS Institute, Inc., 1989) as initial seeds. The algorithm then assigned observations to the nearest seeds. Next, it recalculated the cluster means (drift option) and reassigned observations. This procedure repeated until no observation changed clusters. The k-means algorithm altered Ward's solution by enlarging the largest cluster produced by Ward's method and reducing the size of the other three clusters.

Although significant differences between the segment means of the clustering variables are expected, and not statistically meaningful, these means can be used to name the segments. The total sample means of the six expendable clustering variables are presented for each cluster in Table 2. (The six capital clustering variable results were very similar.) The entries in Table 2 are the average percentage influence that each expendable factor had on the supplier choice in

Table 2. Relative Importance of Each Factor in the Input Supplier Decision

Factor	*Balance*	*Convenience*	*Performance*	*Price*
Convenience/location	16	56	8	13
Service/information	16	8	7	6
Personal factors	17	9	8	7
Price	20	14	20	54
Product performance	16	6	50	14
Support services	15	6	8	7
Percent of sample	47	15	16	21

each segment. Therefore, each entry represents the average of the relative importance that segment members placed on each factor.

The members of the Balance segment represented 47% of the respondents. Table 2 shows that members of this segment weighted the various factors very evenly when selecting an input supplier. Price, 20% of the choice, was the most important factor when selecting a supplier, but the least important, support services, was only 5% smaller. This segment was looking for an input supplier who can provide a wide array of services and information, reasonable prices, and products that perform well. The Balance segment was by far the largest segment in the commercial producer marketplace.

The Convenience segment was 15% of the marketplace. Convenience segment members placed a great deal of importance (over half of the weight in the supplier choice decision) on convenience and location factors. As can be seen in Table 2, members of this segment placed a lower weight on price than did members of any other segment. This segment also weighted personal factors more heavily than did all segments except the Balance segment. Finally, they placed less weight on performance factors than did any other segment.

The Performance segment was approximately 16% of the sample. Its members based half of their supplier choice decision on product performance factors. Price was the next most important feature. Performance members weighted the other factors almost evenly, on average. Thus, the segment contains buyers who were very focused on obtaining products that perform well and were at least as price conscious as members of the Balance segment.

The final segment identified was the Price segment. Members of this segment accounted for 21% of the commercial producers in the sample. Table 2 clearly shows that these producers placed a great deal of weight (54%) on price factors when selecting an input supplier. This is over twice the weight placed on price by members of the other segments. The low ranking of personal factors indicates that members of this segment placed little value in working relationships when choosing their supplier. This makes it likely that members of this segment change input suppliers frequently. The ability of the supplier to provide service and

Table 3. Demographics and General Farm Characteristics

Demographic Characteristics	*Balance*	*Convenience*	*Performance*	*Price*	χ^2 *Statistic*[a]
College Graduate	36	33	43	38	6.188
Age < 45	38	28	37	37	7.893*
Age 45–64	52	56	54	53	1.029
Age > 64	10	16	9	10	8.274*
Percent of large Frams	60	52	61	68	14.449**

Notes [a]χ^2 statistic to test null hypothesis of no association between row and column variables of cross tabulation between segment membership and the attribute.
$^*p \leq .05$, $^{**}p \leq .01$.

information was rated as low. Supporting services, such as delivery and custom application, were also relatively unimportant to members of this segment.

Characterizing the Segments

Four segments of the commercial producer marketplace were identified. These segments varied with respect to the marketing factors they valued most when selecting an input supplier. The goal of the segmentation was not to suggest that one segment is the most desirable segment for all suppliers. Rather, the purpose was to help marketers identify groups of producers that would be most likely to desire their products or services. The results of the segmentation can also be used to assist marketers in determining how resources should be targeted in customer retention, acquisition, and recovery efforts. It is believed that any segment (of sufficient size) can be profitably served with the correct product/service mix. To help suppliers assess which segment represents the best target market or markets, the segments were examined with respect to many of the factors that characterize the decision makers and their farm business and the product/service/information mix that they are likely to desire. For this reason, responses related to the demographics, management practices/tools used, off-farm influences on the purchase decision, brand preferences, loyalty, and preferences for salespeople were considered.

Demographics and General Business Characteristics

The demographic and general business characteristics considered were education, age, and farm size. These characteristics are generally observable and assist marketers in building a demographic profile of the segments. The entries in Table 3 show the percentage of members in each segment that possessed the characteristic shown in the left column of the table. The probability of no association between group membership and the characteristic was estimated from the χ^2 statistic of the cross tabulation between the possession of the characteristic and segment membership.

The results show that relatively strong, significant differences emerged across

Table 4. Percent of Members Using Management Practices/Tools

Practice	*Balance*	*Convenience*	*Performance*	*Price*	χ^2 *Statistic*[a]
Custom fertilizer application	65	61	65	57	5.795
Custom perticide application	61	55	58	49	12.215***
Custom seeding	13	7	9	11	7.80**
Use computer for financial records	70	63	72	67	6.945*
Use a computer for production planning	43	32	39	40	10.284**
Use computer for communication	43	32	36	39	10.258**
Do not own computer on my farm	16	22	15	15	6.262*
Own a computer but do not use for farm business	9	9	10	12	1.610

Notes [a]χ^2 statistic to test null hypothesis of no association between row and column variables of cross tabulation between segment membership and the attribute.
*$p \leq .10$, **$p \leq .05$, ***$p \leq .01$.

the segments on these demographic characteristics. For instance, the Performance segment contained the largest proportion of college graduates, and the Convenience segment contained the smallest proportion of college graduates. Convenience members also tended to be older producers and operated a smaller proportion of large farms (primary enterprise sales greater than $500,000). The Price segment had the largest proportion of large farms.

Management Practices/Tools

Information about the management practices/tools that producers were currently using was collected. Significant differences with respect to the usage of custom services, computers, and the Internet emerged.

Table 4 shows the percentage of each segment that used the management practices/tools in the left column and the χ^2 statistic for the test of no association between group membership and the use of the practices/tool. Several general trends emerged from the results presented in Table 4.

The use of custom application services is important for many local fertilizer and chemical dealers. The results show that nearly half of all the segments used custom fertilizer or pesticide application services on some of their acres. The heaviest users were Balance members, whereas members of the Price segment were the least likely to be using these services.

The respondents were asked if they owned a computer and what purposes it was used for. The results show that Convenience members were the most likely to not own a computer, whereas the other segments had approximately equal proportions of computer users. Many producers used the computer for financial record keeping. Performance members were the most likely to use the computer

Table 5. Relative Influence of Off-Farm Sources in Capital and Expendable Purchase Decisions

Off Farm Influence	*Balance*	*Convenience*	*Performance*	*Price*	*F statistic*[a]
Capital items	26	21	22	23	4.354**
Expendable items	31	26	28	29	3.357*

Notes [a]*F* statistic for test of regression significance.
*$p \le .05$, **$p \le .01$.

for financial record keeping. Price and Convenience members tended to use the computer for these purposes at a lower rate. Interestingly, 32-43% of the respondents indicated that they used the computer for communication. The Balance segment members were the most likely to use the computer for this purpose, whereas convenience members were the least likely.

Key Influences of the Purchase Decision

When purchasing products, producers rely on their own judgment and the judgment of those outside their operations. For example, agronomic consultants likely have an impact on the specific crop protection products that a producer uses. Of course, the producer makes the final decision on the specific product, but the ability of off-farm parties to influence this decision is of great interest to many input suppliers. Of specific interest was the amount of influence that off-farm parties had on the purchase decision relative to the producers' own opinions. Furthermore, it was important to determine which specific off-farm parties had the most influence on the purchase decision. These results have many implications for marketing strategies that manufacturers and distributors use when selling to the commercial producer. For instance, if consulting agronomists were perceived to be an extremely important source of information to producers, chemical manufactures would want to undertake efforts to educate these individuals about the value of their products.

Respondents were asked to assign a percentage value to on-farm and off-farm sources based on their contribution to the purchase decision. Table 5 shows the relative influence of all off-farm parties on the purchase decision for capital and expendable items by the different segments. The *F* statistic for the test of no difference across the segments is shown in the final column of Table 5.[1] The numbers in Table 5 represent the relative importance of off-farm sources on the purchase decision. One can see that producers attribute about one fifth of the total purchase decision to off-farm sources. The Balance segment placed the most reliance on outside sources, whereas the Convenience segment was the least reliant on these sources. The results also show that a larger percentage influence was awarded to off-farm influence for the purchase of expendable items, such as feed, seed, and fertilizer, relative to capital items, such as equipment.

Respondents were asked to allocate 100% of the total off-farm influence to

Table 6. Sources of Off-Farm Influence in the Expendable Purchase Decision

Influences	*Balance*	*Convenience*	*Performance*	*Price*	*F statistic*[a]
Local Dealers	35.6	37.4	35.8	30.4	4.580*
Other farmers	21.0	21.2	22.0	22.7	0.623
Manufacturer sales/technical reps	17.0	14.9	15.9	16.7	1.016
Independent paid consultants	10.6	11.8	11.1	11.6	0.286
Extension service	9.8	9.7	10.1	11.9	1.306
Others outside your farm business	5.9	5.0	5.1	6.8	1.410

Notes [a]*F* statistic for test of regression significance.
*$p \leq .01$.

specific outside sources. Table 6 shows the relative importance of various off-farm sources of influence for the purchase of expendable items. The results show that the local dealer was the most important source of outside information for all farmers. However, significant differences with respect to how highly the segments valued the local dealer emerged. The local dealer scored exceptionally high with members of the Convenience segment and relatively low with the Price segment. Extension was generally the lowest rated off-farm source of influence. Manufacturer salespeople and technical representatives rated about half as important as local dealers. Other farmers were also important influences in all segments.

Brands and Loyalty

Producers are able to choose from many different product offerings. Most of these products are branded to some extent, each having various quality and price characteristics. The producer must evaluate the actual quality of the brands and then evaluate whether any price differentials are appropriate. To generally assess how producers perceived brands, respondents were asked to signify their level of agreement with a series of statements measured on a five-point Likert-type scale (5 = *strongly agree*, 1 = *strongly disagree*). The average segment responses for these questions are shown in Table 7 along with the probability of no difference in response across the segments.

The perception of brands differed across the segments. The Performance segment disagreed the most strongly that there were no differences across brands, whereas the Convenience segment showed the least disagreement. Because some generic or private label options are available to producers, they were also asked to indicate agreement with the statement that generic products represent a good trade-off between price and quality. All segments weakly agreed with this statement. The Balance segment showed the least agreement with this statement. Price segment members agreed most strongly that they planned to increase their use of generic products in the future.

Because the segments did not believe that brands were the same across

Table 7. Average Agreement with Attitude Statements Related to Brands and Loyalty to Suppliers

Statement	*Balance*	*Convenience*	*Performance*	*Price*	*F statistic*[a]
Product Quality					
Capital brands are the more or less the same	2.68	2.81	2.46	2.68	3.316*
Expendable brands are more or less the same	2.65	2.87	2.52	2.76	4.937**
Generic items represent good trade-off between price and quality	3.23	3.36	3.36	3.43	4.128**
Will increase use of generic products in the next 5 years	3.30	3.34	3.30	3.44	1.755
Usually purchase lowest priced expendable products	2.85	2.87	2.73	3.31	17.936**
Usually purchase lowest priced capital products	2.36	2.42	2.25	2.69	11.655**
Loyalty Factors					
Prefer to buy expendable items from one supplier	3.25	3.51	3.15	2.98	10.662**
Prefer to buy capital items from one supplier	3.05	3.23	2.82	2.70	12.565**
Willing to pay slightly more to buy inputs from locally owned suppliers	3.64	3.66	3.52	3.19	12.895**

Notes [a]F statistic for test of regression significance.
$p \leq .05$, $^{**}p \leq .01$.

products, one would expect that most producers would not simply purchase the lowest priced products. Table 7 shows that producers tended to disagree more strongly that they always purchased the lowest priced capital products relative to expendable products. Members of the Price segment tended to agree with the statement that they always purchased the lowest priced expendable products and were least likely to disagree that they purchase the lowest priced capital products. Performance members disagreed the most strongly that they purchased the lowest priced products, indicating that they perceive value differentials among all products, but more among capital goods.

All segments agreed more strongly that they preferred to buy expendable items from one supplier than agreed that they preferred to buy capital items from one supplier. Convenience members tended to agree the most strongly that they

Table 8. Percent of Members Selecting Each Characteristic as One of the Three Most Important Characteristics of a Sales Representative

Most Desirable Characteristics of a Sales Representative	*Balance*	*Convenience*	*Performance*	*Price*	*χ^2 Statistic*[a]
Brings company resources to deal with my problems	28	31	27	28	0.976
Brings me the best price	20	21	22	44	65.386**
Brings me new ideas	26	26	26	24	0.600
Calls on me frequently	6	12	5	7	9.564*
Follows up on orders/ problems	36	38	35	34	0.986
Is a good communicator	12	14	9	11	2.691
Has a very high level of technical competence	37	27	46	32	20.521**
Is honest	54	46	50	49	5.659
Is a friend	8	9	7	8	0.786
Is fair	13	16	11	12	2.309
Provides relevant information	29	31	37	30	5.829
Is a consultant to my operation	9	9	8	8	0.420
Knows my operation well	21	14	16	9	22.478**

Notes [a]χ^2 statistic to test null hypothesis of no association between row and column variables of cross tabulation between segment membership and the attribute.
*$p \leq .05$; **$p \leq .01$.

preferred to buy products from one supplier and that they were willing to pay more to buy products from locally owned suppliers.

Sales Representatives

Most agricultural input suppliers have established sales networks staffed with field salespeople. To assess what characteristics segment members found most important in salespeople, respondents were asked to think of the best agricultural sales representative that they knew. They were then presented thirteen characteristics and asked to check the three characteristics that they viewed as this salesperson's most desirable characteristics. The results shown in Table 8 indicate some general characteristics of good salespeople as well as areas where the segment's opinions of good salespeople differed.

All segments indicated that honesty was the most important characteristic of a good salesperson. The ability to bring the best price was more frequently checked by members of the Price segment than by members of any other segment. Members of the Price segment found familiarity with their operation much less important than did members of other segments, and Balance members found familiarity with their operation significantly more important than did the other segments. Convenience members were more likely to desire a representative that called frequently and were less likely to be concerned with the level of technical competence possessed by the salesperson. Performance members indicated that a high degree of technical competence was important to them.

CONCLUSION

This study identified four market segments in the commercial producer marketplace. Some of the key characteristics of the segments and implications for agricultural input marketers are discussed below.

The Balance segment was the largest segment of commercial producers. These producers were some of the most sophisticated users of technologies such as computers and the Internet. They were also sophisticated buyers who, although they had the most favorable view of generic products, did not frequently purchase the lowest priced items. These buyers were the most reliant on off-farm sources of information when making purchase decisions. Of special importance in their decision process was the local dealer and local sales representative. Balance buyers were the most focused on finding sales representatives and dealers who were familiar with their operations. These producers also made heavy use of custom services. This segment is likely to be a lucrative market for suppliers offering sophisticated technologies and services. The likelihood of selling these products will be improved by tailoring services and technologies to these producers' specific operations.

The Convenience segment was the smallest market segment in the commercial producer marketplace. These producers tended to be older individuals operating smaller farms. They also preferred to buy products from one supplier and agreed that they were willing pay more to buy products from locally owned suppliers. These producers valued the information and services of the local dealer a great deal more than the information and services provided by manufacturer technical representatives and salespeople. With respect to salespeople, the convenience segment was much more impressed than were other segments by a sales representative who calls frequently. Members of this segment were highly reliant on local influences. Any product marketed to them will be more likely to be successful if local dealers are involved in the process. Likewise, brand positioning is most effectively done by local suppliers.

Performance buyers made up about 16% of the market. Members of this segment were the most educated farm producers. Performance buyers were focused on the performance of the products that they bought. They saw clear distinctions between brands and were unlikely to buy simply on the basis of price. These producers required a sales representative who was technically competent. This segment is an ideal market segment for suppliers marketing premium branded products differentiated by performance features.

The Price segment was the second largest segment. Its members operated the largest farms and were the lightest users of custom services. A large percentage of Price segment members owned computers. Members were not likely to care if the sales representative was familiar with their operation, but were very interested in whether the representative could negotiate prices. They were the least likely to prefer to buy products from one supplier and rated the influence of the local dealer lower than members of other segments. They were interested in increasing their use of generic products in the future. An important characteristic of this segment is that members were intent on purchasing the lower priced of two alternative products. It is likely that they would switch input suppliers frequently to realize lower prices. These producers also had the least favorable view of local dealers. This implies that manufacturers selling products without a local dealer network would likely find this an appealing target market.

These results illustrate the complexity of marketing to commercial agricultural producers. Although all of the farming operations considered here are "commercial" by definition, their buying preferences were not homogeneous. Successful agribusiness marketers should focus on the unique buying preferences of individual segments as they develop and deliver product-service-information bundles to commercial producers.

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Notes

1. The probability of no difference across group means was estimated by conducting an *F* test of regression significance in a model where the dependent variable was the response to the question, and the independent variables were an intercept and three dummy variables indicating segment membership.

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