FORMING PEER ADVISORY GROUPS IN AGRICULTURE: AN ALTERNATIVE APPLICATION OF CLUSTER ANALYSIS

A Thesis

by

KAYLA MARIE DOERR

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

May 2012

Major Subject: Agricultural Economics

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Approved by:

Chair of Committee,	Danny A. Klinefelter
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ABSTRACT

Forming Peer Advisory Groups in Agriculture: An Alternative Application of Cluster Analysis. (May 2012)

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A "peer advisory group" essentially melds a business advisory board with a peer group. Peer advisory groups consist of business managers who meet together for the purpose of mutual self-improvement and learning through the sharing of experiences. The entire peer advisory group concept encompasses many variations and this research focuses on groups consisting of farm managers.

Unfortunately, some farm managers who wish to participate have expressed frustration with group formation: they find it difficult to identify suitable individuals to participate in a peer advisory group with. Peer advisory groups can take many forms, and experts have suggested an individual should specifically seek out people interested in the same type of group. For example, an individual who wants to strictly focus discussion on production issues should seek out other individuals who also seek to focus on production discussions. Some individuals have suggested that some type of "clearinghouse" organizations could be beneficial in assisting individuals with the peer advisory group formation problem. Such an organization would likely need to adapt some sort of method for identifying individuals who have interest in a similar type of group.

Although this could be approached from several different angles, one possible approach involves the practice of cluster analysis—a wide set of procedures intended to break down a set of objects into "clusters" of individuals with similar attributes. Cluster analysis comes with several attractive benefits; however, literature includes countless variations in the methods and criticisms of certain aspects of the methodology. This thesis focuses on using cluster analysis to assist with peer advisory group formation. More specifically, this thesis seeks to answer the following question: how could a clearinghouse organization apply cluster analysis methods to a pool of candidates to effectively create peer advisory groups congruent to the individuals' needs and wants? An approach was proposed which differs slightly from traditional cluster analysis methods, and this was applied to a hypothetical pool of candidates, along with several control methods. The proposed approach was found to most effectively create peer advisory groups which fulfilled the desires of the individuals.

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NOMENCLATURE

ARI	Adjusted Rand index
CCC	Cubic clustering criterion
UPGMA	“Unweighted pair-group method using arithmetic averages,” also referred to as “average linkage”

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CHAPTER I

INTRODUCTION

One of the four competitive goals defined by Oxenfeldt and Schwartz is "learn from rivals" (1981). Oxenfeldt and Schwartz go on to suggest doing so through tactics such as hiring away rivals' employees, using customers to report on what rivals are offering, and scrutinizing rivals' annual reports. However, the competitive nature of agricultural production differs from that of its corporate counterparts. For example, the fast food industry has a limited number of participants who compete through the production of differentiated products; whereas, in production agriculture, a vast number of businesses produce mostly homogeneous products. If a small group of five to ten fast food restaurant CEOs gathered together to openly share advice and learn from one another's experiences, participants would risk giving away "the keys to the castle." A similar grouping of five to ten farm managers faces less drastic risk. Due to the large number of competitors, if one producer shares a piece of information that drastically improves five other producers' outputs, the effect would still not be large enough to affect the first producer's own market or price received for goods.

This thesis follows the style of the *American Journal of Agricultural Economics*.

A small group of business managers openly sharing business experiences and advice as described in the previous paragraph illustrates the essence of a “peer advisory group.” Such a group can be thought of as the combination of a peer group and a business advisory board. Peer advisory groups typically consist of less than fifteen different business managers who meet together for the purpose of mutual self-improvement and learning through the sharing of experiences (Doerr 2011). The small group setting offers the potential for more privacy and trust than offered in larger industry associations, which can lead to more detailed and useful open discussions. Peer advisory groups offer participants a unique opportunity to learn from the cumulative knowledge of others who have likely faced similar business challenges. The peer advisory group concept encompasses many different types of individual groups which have been documented in the general literature of various industries. This study deals with the formation of peer advisory groups in agriculture, specifically groups consisting of farm managers.

Statement of the problem

At a recent conference focusing on peer advisory groups in agriculture, several individuals expressed frustrations with peer advisory group formation and specifically with identifying suitable individuals to participate in a peer advisory group with (AAPEX 2011). Since peer advisory groups can take many forms, some individuals with peer advisory group experience suggested an individual should specifically seek out people interested in the same type of group (AAPEX 2011). For example, one individual might want to strictly focus on production issues; whereas, a different individual might have the desire to discuss organizational management and financial issues. Even though these two individuals might have extremely similar farming operations or management styles, a group that contains both of these people could potentially be counter-productive due to the conflicting goals for membership. Some conference participants suggested that some type of "clearinghouse" may be beneficial to assist individuals in locating potential group members (AAPEX 2011). Such an organization would likely need to adapt some sort of method for identifying individuals who have interest in a similar type of group.

Although this peer advisory group formation problem could be approached from several different angles, one possible approach involves the use of cluster analysis by the clearinghouse organization. The practice of cluster analysis includes a wide set of procedures intended to break down a set of objects into homogeneous "clusters". Fields ranging from biology to psychology use cluster analysis in research. Since one can argue that peer advisory groups should consist of individuals who have similar desires for the group (e.g. what the group will discuss, what the group makeup will look like), a clearinghouse organization could potentially employ cluster analysis methods to assist in identifying groups of candidates with similar group desires.

According to Aldenderfer and Blashfield, researchers commonly use cluster analysis to accomplish one of four goals: "development of a typology or classification, investigation of useful conceptual schemes for grouping entities, hypothesis generation through data exploration, and hypothesis testing, or the attempt to determine if types defined through other procedures are in fact present in a data set" (1984). These descriptive purposes are quite different from the creation of *functional* groups like peer advisory groups. When researchers place entities into groups for the sake of classification or description, the entities never actually *interact* with one another. A peer advisory group is only useful if members derive benefits from the interaction with these fellow members. Therefore, this special aspect will need to be considered while developing cluster analysis methodology for the creation of peer advisory groups.

Research question and objectives

This research does not seek to determine the *absolute best* means for a clearinghouse organization to create peer advisory groups. Whether or not cluster analysis is the *best* manner for solving the underlying problem cannot be determined without comparing multiple approaches. Instead, this research will focus only on cluster analysis methods and how they could best be adapted for the particular purpose of creating peer advisory groups. Cluster analysis literature includes countless variations in the methods. Also, criticisms of the methods and of previous researchers' applications of the methods have been well documented (Everitt 1979; Ketchen and Shook 1996; Punj and Stewart 1983). Taking these into consideration, this thesis seeks to answer the following question: how could a clearinghouse organization apply cluster analysis methods to a pool of candidates to effectively create peer advisory groups congruent to the individuals' needs and wants?

In order to answer this question, this thesis will look at prior criticisms of cluster analysis and examine the literature's suggestions for overcoming its challenges. Cluster analysis methods will then be selected and applied to a hypothetical "candidate pool" in attempt to create *functional* groups of farm managers who meet for the purpose of learning from one another's experiences. A final evaluation of the application will also be provided.

In undertaking the research goal, the study will also assume secondary objectives. This research will add to the literature of cluster analysis by utilizing it for a new application. Furthermore, the overarching goal of this study is to increase the awareness of peer advisory groups for agricultural producers.

Organization of the study

This thesis is presented in five chapters. Chapter II reviews the literature in two parts: peer advisory groups and cluster analysis. Chapter III provides the framework of the study: it describes the survey administration, the survey sample, and the specific cluster analysis methods to be used. Chapter IV presents the results and evaluates the results as they relate back to the research question. Chapter V summarizes the study, draws conclusions, admits the limitations of the study, and provides recommendations for further research.

CHAPTER II

LITERATURE REVIEW

This chapter presents the literature necessary to lay the foundation for the methodology of this research. In order to properly address the research question, two general areas need addressed. Peer advisory groups will first be described and then cluster analysis will be reviewed.

Peer advisory groups

A "peer advisory group" essentially melds together a peer group and a business advisory board. A peer advisory group consists of peers (typically farm managers in the case of agricultural peer advisory groups) who gather together and share business experiences for the sake of mutual self-improvement. Not only do members learn from one another's experiences, but many times they also provide motivation, support, and accountability for one another. Openly sharing business advice with fellow peers (potential competitors) may sound counter-intuitive to competitive business behavior. Therefore, this section will first examine the nature of competition and cooperation in order to illuminate why the peer advisory group concept can and does work for farm managers. Literature regarding sources of learning for farm managers will also be examined before finally developing the peer advisory group concept.

The natures of competition and cooperation

As theorized by May & Doob, “when an individual competes or cooperates with others he does it in order to close the gap between his level of achievement and that of his aspirations by achieving certain goals.” May and Doob go on to elaborate that if an individual “is aware that the goals sought in a given situation are *limited* so that they cannot be shared, or if shared will not satisfy him, he will compete; conversely if he is aware that the goals sought can be *shared* and can be reached best by working with others who are seeking them, he will cooperate” (1969).

Translating this to the case of peer advisory groups, an individual will likely not participate in a peer advisory group if he feels that the information he will receive from other members will not be of any use in closing “the gap between his level of achievement and that of his aspirations.” Perhaps even more importantly, an individual will likely not participate in a peer advisory group if he feels that the goals sought by group members (improvement to one’s own business) are *limited*. In other words, he will not participate if assisting fellow group members in achieving their goals ends up hindering the individual’s own goals (for example, fellow members overtaking his market share) or if the interests of the group are not consistent with his own.

In some industries, business owners may find it extremely difficult to participate cooperatively in a peer advisory group. However, production agriculture is a very unique setting where a very large number of businesses produce homogeneous commodities. For example, Braguinsky and Rose illustrated agriculture’s unique opportunity for cooperation through the “neighboring farmer effect”:

> "Consider a corn farmer who discovers that a new type of plow works extremely well with the soil in his immediate area. We know that farmers do not typically try to conceal this kind of information from their neighbors. In our view the reason why they do not conceal this kind of information is not merely a desire to be 'neighborly' for its own sake. The reason why is that while they are ostensibly competitors in that they both find themselves in the same competitive market, they are nevertheless not truly rivals. This is because they know that the output of any farmer is so small relative to the entire market that the actions of any (or even of every) farmer in the local area will not change the market price… since *A* knows that sharing such information with *B* will also leave the market price unchanged, *A* knows he can increase *B*'s profit at no cost to himself… a sufficiently competitive market structure produces price taking which, in turn, has the effect of taking rivalry out of the relationship between firms because the benefits derived by *B* from information shared by *A* do not come at *A*'s expense" (2009).

Sources of learning for farm managers

Considering the unique competitive nature of agriculture described above, one might hypothesize that cooperative learning among agricultural producers is quite common. However, a farm manager has many other outlets through which he or she might accumulate knowledge. The sources of learning for farmers are typically divided into two types: formal sources and informal sources. A formal source of learning typically refers to structured courses as offered through agricultural colleges and universities. Informal sources include things such as one's own experiences, the media, consultants, other farmers, field days, seminars, industry association meetings, etc. (Kilpatrick and Rural Industries Research and Development Corporation 1999). Kilpatrick also reiterated that the majority of farmers prefer gathering knowledge from informal sources than from formal sources. Reasons for this include: "valuing of independence and self-sufficiency, preference for contextualized learning, lack of confidence in training settings, preference for receiving information from known sources rather than unknown trainers, and a fear of new knowledge and skills which may cause them to question their existing beliefs" (1999). However, in a comparison of usage rates of informal learning sources, Kilpatrick found the Australian farmers surveyed utilized 'other farmers' (81.2%) less often than 'experts' (98.8%), 'media' (91.8%) or one's own 'experience' (91.8%).

Many farmers who have participated in "group-learning" settings, such as the Australian Prograze and Landcare programs, recognize the value of learning from the experiences of other farmers (Millar and Curtis 1997). In Kilpatrick's study on farmer learning, Prograze and Landcare programs were identified as examples of "farmer-directed groups." These types of groups were noted as being a relatively new source of informal learning. Kilpatrick also noted that "innovative and successful" farm managers were more likely to be members of such groups (1999). These groups will be further described within the peer advisory group context later in the literature review.

Developing the peer advisory group concept

The entire "peer advisory group" concept can be used to describe many different individual types of groups which might be referred to by various names such as forums, councils, boards, networks, roundtables, etc. Although each specific type of group has its own unique characteristics that differentiate it from others, they all share at least one common thread: a peer advisory group essentially combines a peer group with a business advisory board and meets for the purpose of learning and mutual self-improvement through the sharing of business experiences by all members (Doerr 2011). Therefore, this sub-section briefly reviews literature on peer groups and business advisory boards before formally defining the peer advisory group concept. Finally, examples of specific types of peer advisory groups and potential benefits of participation are given.

Peer groups

SunWolf defines peer groups as groups which "are composed of members who consider one another to be equals… Not all group members agree about the equality of all other members at all times, but there is overt consensus that members of the group are primarily equal" (Sunwolf 2008). This sameness among members in peer groups, often referred to as *homophily* (Jones M., Alexander J., and Estell D. 2010), functions as the cohesiveness of the group (Sunwolf 2008). Peer groups can naturally evolve (such as high school "cliques") or assemble purposefully (such as a book club). Researchers sometimes assume homophily "results from a process of influence in which one or more persons influence another." This is sometimes referred to as socialization. However, homophily among members can also be a product of selection, a process where "individuals with prior similarity on some attributes of mutual importance purposefully select each other as friends" (Kandel 1978). Members of a peer group also share goals, which may be socially-driven, task-driven, or sometime both (Sunwolf 2008).

Especially pertinent to the explanation of the peer advisory group concept are small groups in which members learn and self-improve though peer interactions. These are somewhat closely related to peer advisory groups—both tend to be purposefully assembled (i.e. not naturally evolved) and in both settings members exchange information in order to learn from one another. However, these peer learning groups lack the business advisory aspect of peer advisory groups.

Examples of such peer learning groups could include those such as Delphi groups, Alcoholics Anonymous, or peer review organizations. A "Delphi" approach to forecasting involves a panel of experts (peers) who all develop forecasts for a set of situations and provide reasoning for each forecast. Each member is then provided with everyone's forecasts and justifications, typically in an anonymous fashion, and each member can consider others' ideas and adjust his own forecast (Kerr and Tindale 2011). The knowledge exchange setting of Delphi groups introduces expert forecasters to new ideas (Green, Armstrong, and Graefe 2007). Alcoholics Anonymous and other similar "self-help" groups bring a peer approach to therapy. These groups foster fellowship among individuals who have faced similar struggles with addiction or inappropriate behaviors. The reciprocity of self-help therapy groups involves the sharing and learning from one another's personal experiences—members "mutually assist" one another in overcoming personal struggles (Hurvitz 1970). Peer review organizations can also stimulate self-improvement among members through the sharing of critiques, although the "group" context might be a stretch in some situations. The notion of "peer review" should not be constricted to the publication process for scientific research. Several professions (nursing, dentistry, psychology, etc.) use peer review as a way of keeping a certain level of professional standards or quality of care among peers. It also provides an outlet through which to give support to and receive support from fellow professionals (Rout and Roberts 2008).

Business advisory boards

Business advisory boards can be defined as "a panel of experts who are asked by a firm's managers to provide counsel and advice on an ongoing basis" (Barringer and Ireland 2010). Not only do these boards provide information and advice, but they also spend time listening, giving feedback, and helping "to sharpen the strategic processes of the (management) team" (2002). Not every business sets up an advisory board—instead, they tend to be utilized by start-up firms (Barringer and Ireland 2010) and by family businesses which may not have a formal board of directors (Blumentritt 2006). Advisory boards often assist CEOs or management teams in much different ways than a Board of Directors does. Since an advisory board has no legal or fiduciary responsibilities to the business's shareholders, the more relaxed setting of an advisory board allows problems to be discussed more openly (Morkel and Posner 2002).

With the exception of advisory boards established for a specific purpose (such as a customer advisory board), Barringer suggests that advisory boards consisting of members with various backgrounds (e.g. financial consultants, technical consultants, CEOs/entrepreneurs, media/advertising specialists) are preferable to boards consisting of members with very similar backgrounds (2010). Although some business advisory board members participate free-of-charge for personal stimulation or for a possible early investment opportunity (Morkel and Posner 2002), others are provided with some sort of honorarium such as a small stipend for each meeting or a small equity share of the business (Barringer and Ireland 2010).

Morkel and Posner found the effectiveness of an advisory board most often hinges on the CEO's attitude. If the CEO (or management team) is unable to listen to or act upon the constructive criticisms and guidance of the advisory board, the advisory board will obviously have little effect on the performance of the business. In addition, "marquee" boards (those assembled simply to associate the company with high profile individuals) may lend credibility to a new business; however, they are of less use as a source of business advice and mentoring (2002).

Formal definition of "peer advisory group"

By melding together a "peer group" with a "business advisory board," the concept of a peer advisory group comes to life. A "peer advisory group" consists of peers who advise and support one another on business management practices through the sharing of personal business experiences (Doerr 2011). As described by a peer advisory group member: “It’s not a social club. It’s not therapy. It’s not a fix-it group. But those are all small components that are a big part of it” (AAPEX 2011). It is very important to keep in mind that the entire peer advisory group concept is rather broad in scope. Many individual groups function quite differently from one another and often have a unique designation for themselves, as will be shown through examples of individual groups. Unfortunately, little peer-reviewed literature regarding the concept exists. Therefore, the conclusions in the following chapter mostly derive from two sources: (1) reoccurring themes in a large collection of general-audience (not peer-reviewed) literature and (2) opinions shared at the conference, “Peer Advisory Groups: Best Practices and Alternative Structures,” held in Grapevine, Texas in July of 2011.

In the examination of many different individual groups, a few common themes among peer advisory groups have been identified:

- Active participation: Everyone gives as well as takes. As described by an individual who participates in two different agricultural peer advisory groups, “If you don’t share, you hit the highway. And that’s, to me, one of the big distinctions of a peer (advisory) group… you need to participate” (AAPEX 2011).
- Equality: One of the defining aspects of any peer group is the lack of an authoritative hierarchy—no one member of a peer group has greater power than any other member (Sunwolf 2008). Although members may not necessarily come from equally-sized businesses, members should regard one another as “equal” in the ability to manage a business (AAPEX 2011). Some peer advisory

groups might have certain roles (treasurer, facilities organizer, etc.) for a task-sharing structure (Barrett 1998), however this does not necessitate such individuals to exert greater influence over other members in discussion. Many groups also utilize a “facilitator” to moderate discussion; however, this individual usually does not participate in discussions (AAPEX 2011).

- Confidentiality: Many peer advisory group participants have expressed the need for trust and confidentiality among members in order for open and candid discussions to take place. Recalling back to the earlier discussion on the natures of competition and cooperation, an individual will not cooperate with others if he feels that doing so will “cost” more than he will receive. This is why confidentiality is imperative for peer advisory groups: it fosters cooperation among members by easing any concerns about risk of exposing private business matters to anyone outside the group. In order to establish this foundation of trust, many advocate the discussion of “ground rules” (and possibly even signing a “confidentiality agreement”) at onset. The small size of most peer advisory groups (most tend to be less than 15 members) also lends itself to camaraderie among members. Furthermore, assuring that none of the members are direct competitors or have conflict of interest builds trust and confidentiality more quickly (AAPEX 2011).

Examples of different types of peer advisory groups

To reiterate, the peer advisory group concept is somewhat broad in scope. Many individual groups which fall under the general definition given above operate quite differently from one another. To illustrate this, table 1 provides a few examples of non-agricultural peer advisory groups.

Table 1. Examples of Non-Agricultural Peer Advisory Groups

Designation	Comments	Source
Performance roundtables	Homogeneous in industry and business size Members are geographically dispersed to prevent direct competitors Biannual meetings Put entire focus on one individual business per meeting and discuss the issues that business is facing in very great detail	The Family Business Institute 2007
CEO Roundtable	Slightly homogeneous: businesses are “comparable but not competitors” Locally-based Monthly meetings Put focus on one member for a portion of the meeting. The other portion of the meeting involves the “roundtable” where each member is allowed to briefly discuss a current concern or problem with fellow members. Also have “half-day seminars” every few months where members from multiple groups gather to network and listen to a speaker	CEO Roundtable
20 Group	Homogeneous in industry and business size Members are geographically dispersed to prevent direct competitors Meet at members’ businesses, but spend time discussing issues from all members (don’t necessarily focus all the attention on the “host”) Meetings include financial consulting from Spader and benchmarking with other members	Spader Business Management 2011
Peer Advisory Group	Homogeneous in business size (annual revenue minimum to join) Very diverse in business industry Locally-based Monthly meetings, allow each member to discuss a current issue facing his or her business with other members Also includes a “one-to-one” meeting between each member and the facilitator between meetings	Vistage International 2011
YPO Forum	Homogeneous in age (under 45) and business size Very diverse in business industry Offers a few alternative set-ups (a forum for couples, an international forum)	Young Presidents’ Organization

As illustrated in table 1, many groups are “facilitated” by a consulting firm (Fusaro 2000). Some are special-purpose firms specifically for peer advisory groups (such as CEO Roundtable) and others provide business consulting outside of peer advisory groups (such as Family Business Institute). Although many individuals with peer advisory group experience support the use of a professional facilitator, groups can also be self-facilitated (AAPEX 2011). A distinction should also be noted regarding the designation for Vistage’s facilitation services. Although Vistage refers to their groups specifically as “peer advisory groups,” the reader should not assume the Vistage model of conducting groups is the *only* model for the entire peer advisory group concept.

Table 2 provides a few examples of agricultural peer advisory groups. The first three examples are all examples of large networks of smaller groups. The final five examples are individual groups which do not operate as part of a larger network. These final five examples do not have specific designations and are simply noted numerically. Information regarding these five individual groups (none of which are a part of a larger network of groups) was presented by a member of the group or the group facilitator at the conference

Table 2. Examples of Agricultural Peer Advisory Groups

Designation	Comments	Source
Dairy profit discussion groups	Homogeneous in commodity (dairy) Locally-based Focus mostly on production topics, and education/skills development for members, but may discuss financial issues in very trusting groups Works through the Cornell University ProDairy Program and the New York Center for Dairy Excellence Approximately 35 small groups	Barrett 1998
CREA (Regional consortiums for agricultural experiment-tation)	Mostly crop farms Local groups Production and education/skills development focused, but also includes benchmarking financial information Approximately 200 groups. Very well-structured network of groups throughout Argentina. Even though the entire organization is very structured, it is still "organic" in the sense that the members themselves dictate what goes on in meeting and group activities. Monthly meetings, held at a member's farm. The group spends time discussion a problem the "host" member is currently facing Groups conduct cooperative experimentation	AACREA 2007
Farmer-directed groups	Examples are "Landcare" or "Prograze." Both of these are networks of small groups facilitated through Australian extension services. Local groups Mostly education/skills development and problem-solving focused Groups may also include non-farmers	Kilpatrick and Rural Industries Research and Development Corporation 1999; Millar and Curtis 1997
1	Somewhat geographically dispersed Diverse commodities and sizes Focus on organizational management Meet twice per year—bring in a speaker (consultant, expert, etc.) for a few hours, remainder of the day is entirely member discussion	AAPEX 2011
2	Not extremely geographically dispersed, but no members are neighbors Meets irregularly (whenever members feel the need to meet) Mostly production-oriented topics, but also discusses financial issues Discuss one specific problem (suggested by members) per meeting	AAPEX 2011
3	Relatively small geographic area Strictly dairy farms, relatively homogeneous in sizes of operations Focuses on production/industry issues, does a lot of production benchmarking and may begin to benchmark financial figures as the group continues to build trust	AAPEX 2011

Table 2. Continued

Designation	Comments	Source
4	Small geographic area Mostly row crop producers Production and education/skills development issues, especially precision agriculture topics	AAPEX 2011
5	Very geographically dispersed Meets 2-3 times per year and holds monthly conference calls Focuses on education/skills development and financial issues Several individuals from each operation participate	AAPEX 2011

By looking at the examples in table 1, the reader can see that the non-agricultural groups ensure members are not direct competitors. For locally-based groups, members represent different industries. For groups where members represent the same industry, members are geographically dispersed to prevent direct competition. As previously illustrated in the “neighboring farmer effect,” agricultural peer advisory groups do not necessarily need to adhere to this separation of competitors. However, some farm managers may feel more comfortable discussing sensitive topics (e.g. business-related family problems, financial issues) with individuals who do not live in a close proximity, due to the “rumor mill” of rural areas (AAPEX 2011).

Potential benefits of participation

In reviewing a vast number of general-audience articles and the aggregation of opinions provided during the conference on peer advisory groups, a few common benefits most members procured were identified. These include, but are not limited to: (1) open and objective observations, (2) exposure to diversity, (3) a support structure, (4) assistance in identifying blind spots and prioritizing issues, (5) accountability, and (6) a sounding board (Doerr 2011). The exact benefits that an individual derives might depend on the specific peer advisory group structure and chemistry, to some extent. For example, groups which focus on education and skill development might not help members in prioritizing specific business issues.

Some of the benefits received from participation in an effective peer advisory group stem from the combination of the peer group and business advisory board aspects. For example, some groups participate in benchmarking in order to identify blindspots or areas for improvement. According to the social comparison theory, "people continually compare themselves to others that they believe are similar (or slightly better.)" This theory has been used to assist in describing behaviors in peer groups (Sunwolf 2008). Adding to the benefits derived from peer-interactions, Kilpatrick noted some farm managers expressed preference "to learn from other farmers because they had experienced difficult times themselves and were better able to understand the problems faced by farmers and to suggest workable management strategies for dealing with problems" (1999).

Receiving open and objective observations is a key reason why business advisory boards are beneficial for family-operated businesses, such as farms. As described by Jaffe, family-run businesses face a unique set of issues:

> *"The family's goal is to develop self-esteem and to nurture the children so they grow into responsible adults. The focus of the business, on the other hand, is to generate profits and be economically successful. When these goals get mixed, problems almost always develop. Since the*

> *family's goals usually take precedence over those of the business, the business suffers from family-oriented decisions... the family must begin to see the need to add some order to dealings between the family and the business"* (Jaffe et al. 1997).

In addition, Morkel and Posner noted in their evaluation of business advisory boards, "the CEO is a lonely position—(the CEO) need someone to talk to where the relationship is not clouded by other relationships" (2002).

Cluster analysis

Before attempting to use cluster analysis to create peer advisory groups, cluster analysis methods need to first be thoroughly described. Cluster analysis refers to a wide-ranging set of procedures which attempt to group entities (i.e. persons, businesses, plants, animals, etc.) into smaller, nearly homogeneous clusters. Authors characterize "cluster" in a variety of ways, the most widely recognized of these being the summary given by Cormack, which involves two parts: internal cohesion and external separation (Cormack 1971). Cluster analysis literature currently offers no perfect method of determining an ideal balance of this cohesion and separation. This choice is many times a subjective decision made by the researcher. Romesburg's definition of a cluster illustrates this subjectiveness:

> *"A cluster is a set of one or more objects that we are willing to call similar to each other. A cluster can be as few as one object, if we are willing to call no other objects similar to that object. Or it can be as*

> *many as all of the objects in the data matrix, if we are willing to call all of them similar to each other. It may seem strange to use the word 'willing,' but that is exactly the right word. To call two or more objects similar, we must be willing to neglect some of the detail that makes them nonidentical. We must be tolerant of some of their differences"* (1984)

The development of clustering methods mostly began after 1963 when biologists Robert Sokal and Peter Sneath proposed classifying organisms by comparing "degrees of similarity" between organisms and grouping according to relative similarity (Aldenderfer and Blashfield 1984). The advent of computers further pushed the development of cluster analysis since computing large matrices became less time consuming. According to Aldenderfer and Blashfield, cluster analysis most commonly accomplishes one of the four following goals:

1. "development of a typology of classification"
2. "investigation of useful conceptual schemes for grouping entities"
3. "hypothesis generation through data exploration"
4. "hypothesis testing, or the attempt to determine if types defined through other procedures are in fact present in a data set" (1984).

The literature provides many applications of cluster analysis in a wide variety of fields. For example, the applications described by Everitt—biology, botany, medicine, psychology, geography, marketing, image processing, psychiatry, archaeology (1979)—are some of the possible fields in which researchers have found usefulness in the application of cluster analysis techniques. Since many different fields utilize cluster analysis methods, the literature includes a wide variety of notations and terminology (Aldenderfer and Blashfield 1984).

Perhaps one of the greatest features of cluster analysis is its ability to create classifications involving multiple variables. Ketchen and Shook reviewed and analyzed applications of cluster analysis in the field of strategic management research and pointed out that prior to the popularization of cluster analysis, strategic management groups were mostly constructed with a very small set of attributes. The implementation of cluster analysis provides the ability to handle a larger number of variables and therefore "can provide very rich descriptions of configurations without overspecifying the model" (Ketchen and Shook 1996). Researchers in applied fields also find cluster analysis to be an intuitive and straightforward method of identifying groupings; most methods require only simple algebraic algorithms (Romesburg 1984).

Unfortunately, the benefits of cluster analysis also come with some drawbacks. Several authors have provided thorough investigations into the problems plaguing cluster analysis applications in certain fields, such as market research (Punj and Stewart 1983) and strategic management research (Ketchen and Shook 1996). Many criticisms revolve around the subjective nature of cluster analysis methods. The usefulness of cluster analysis groupings can also be questioned at times, since the methods have the potential to "impose groupings where none exist" (Ketchen and Shook 1996). Punj and Stewart note, however, that similar problems can also be encountered in several other multivariate statistical procedures (1983).

Before proceeding, a distinction should be noted. Cluster analysis commonly refers to clustering of *objects* or *cases*. Although some early cluster analysis literature used this to trait alone to differentiate from factor analysis's classification or grouping of attributes, a researcher can utilize cluster analysis to accomplish this, as well (Everitt 1979). A Q-analysis refers to the clustering of *objects*; whereas, an R-analysis refers to the clustering of *attributes* (Romesburg 1984). The primary difference between an R-type cluster analysis and factor analysis concerns the linearity of factor analysis's model, which is not found in the majority of cluster analysis methods (Everitt 1979). Furthermore, cluster analysis differentiates itself from other statistical classification methods by avoiding *a priori* assumptions about the population differences among its members (Punj and Stewart 1983). R-analysis, although very useful in some situations, will not be used in this thesis; therefore, the remainder of this literature review will be written and notated in accordance with Q-analysis. Also, the terms "variable" and "attribute" may be used interchangeably.

Although many variations in cluster analysis methodology exist, the most common steps researchers follow are as given here. Cluster analysis usually begins with a $n \times p$ data matrix, **X**, which includes n objects described by p attributes:

$$\boldsymbol{X} = \begin{bmatrix} x_{11} & \cdots & x_{1p} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{np} \end{bmatrix}. \tag{1}$$

The designation of this data matrix involves both identification of the sample of objects to be used and the careful selection of attributes to cluster these objects by. After designation of the data matrix, the researcher usually must choose an appropriate proximity measure and apply it to the data matrix in order to calculate the proximity matrix, **P** $(n \times n)$, which shows the level of similarity or dissimilarity (the proximity, p) between every pair of objects (Jobson 1992):

$$(2) \qquad \boldsymbol{P} = \begin{bmatrix} 0 & - & - & - & - \\ p_{2,1} & 0 & - & - & - \\ p_{3,1} & p_{3,2} & \ddots & - & - \\ \vdots & \vdots & \ddots & 0 & - \\ p_{n,1} & p_{n,2} & \cdots & p_{n,(n-1)} & 0 \end{bmatrix}.$$

The selection of proximity measure and calculation of the proximity matrix is sometimes bypassed, however, depending on clustering method which the researcher plans to use. The researcher next applies his or her chosen clustering method, generally a simple algebraic algorithm, to the proximity matrix, **P**, (or sometimes to the original data matrix, **X**) in order to determine possible cluster solutions.

A researcher who chooses to use cluster analysis has many different ways that he or she can customize the analysis in each of the above steps in order to best fit the particular objectives of the research and the nature of the data. Although the general concept behind cluster analysis is intuitive and straightforward, there are countless variations in cluster analysis methods. The following literature review of cluster analysis is not intended to provide the reader a compendium of all available cluster analysis methods. Instead, it will provide the sufficient information necessary for the reader to understand the criticisms of different practices and to understand the methods used in this study. Specifically, this section looks at each common step of cluster analysis individually and relates some of the literature's criticisms regarding each. This includes data selection, the determination of proximity measure, the choice of clustering method, and the evaluation of cluster solutions.

Data selection and related criticisms

As with most types of statistical analysis, improper variable selection in cluster analysis can potentially lead to very misleading results. Researchers tend to follow one of three methods for variable selection. The inductive approach throws a large number of variables into the analysis without making *a priori* choices of which variables are likely to be most important. The opposite approach to this would be the deductive approach, which carefully selects variables based on theoretical reasoning. The final method of variable selection, the cognitive approach, uses the views of "experts" in the field to determine which attributes to include in the analysis.

Multiple authors stressed the significance of variable selection. Ketchen and Shook suggest that a researcher should carefully consider the nature of his or her study before determining a variable selection approach to follow. Although some strategic management research is exploratory to some extent, they felt that far too many of the prior applications of cluster analysis in strategic management research used an inductive approach to variable selection (1996). Calling it a "shotgun" approach, Punj and Stewart strongly advised against the use of inductive variable selection due to the "marked decremental effect on the performance of all clustering methods" when spurious attributes are included in the analysis (1983). Aldenderfer and Blashfield also recommended avoiding the inductive approach whenever possible, referring to its use as "naïve empiricism" (1984).

In some instances, researchers might alter the data by identifying and removing outliers before moving forward with the analysis. An extreme observation can cause distortion in cluster solutions, especially when using certain methods for clustering, an issue which will be further explored later in the literature review. In fact, the SAS User's Guide recommends users to include the TRIM option with certain clustering methods. This option withholds from the analysis a user-defined percentage of objects with low estimated probability densities (SAS Institute Inc. 2008a). Others, however, advise that only "erroneous" outliers (objects with incorrect observations for attribute values) should be removed from a data set and "natural abnormalities" should be allowed to remain (Romesburg 1984). Keeping his or her study objectives in mind, a researcher should use his or her best judgment before removing what he or she considers to be an outlier from a dataset.

Multivariate statistics offers a general approach for identifying the outliers of any multivariate dataset by measuring the Mahalanobis distance between each observation and the center of the data (Jobson 1992). This classical distance equation is usually squared and given as

(3) $$h_i^2 = (x_i - \bar{x})' S^{-1} (x_i - \bar{x}),$$

where $\bar{x}$ is the arithmetic mean and S is the sample covariance matrix (Jobson 1992). An outlier is then indicated by a relatively large value ofh_i^2. Some argue, however, that this measure should be utilized with caution due to its susceptibility to two problems: masking and swamping. Masking refers to the situation in which true outliers fall into a small cluster. In this case, the small cluster can augment the covariance matrix in the direction of it and pull the arithmetic mean towards it—outliers "mask" one another and result in a small Manalanobis distance for each. The swamping problem refers to how the same small cluster of outliers pulls the arithmetic mean and covariance matrix *away* from other observations which are *not* outliers, resulting in misleading large values of the Manalanobis distance (Hadi 1992).

Data manipulations and related criticisms

The measurement of variables can in some instances have an impact on a cluster solution. If one attribute is measured on a very wide range compared to all other attributes, the former can arbitrarily carry more "weight" in the formation of clusters. In select instances this may be a desired characteristic; however, the "standardization" of variables has become a relatively routine practice in order to circumvent this unintentional variable-weighting (Aldenderfer and Blashfield 1984). Standardization essentially "strips the identity from each attribute, changes its numerical value, and recasts it in dimensionless form" (Romesburg 1984). Aldenderfer and Blashfield caution readers that standardization should not necessarily be a routine that all cluster analyses implement and the need to standardize should instead be evaluated on a case-by-case basis. When a data matrix necessitates standardization, the researcher must choose the best means of doing so. For example, many studies use a common standardizing function which uses the standard deviation as in Equation 4 (Romesburg 1984). Equation 4 is applied to each observation in the original data matrix, **X**, with *n* objects (*j*=1, 2, …, *n*) measured by *p* attributes (*i*=1, 2, …, *p*) and results in the standardized data matrix, **Z** $(n \times p)$.

(4) $$Z_{ij} = \frac{X_{ij} - \overline{X_i}}{S_i}$$ where

(5) $$\overline{X_i} = \frac{\sum_{j=1}^{n} X_{ij}}{n},$$ and

(6) $$S_i = \left(\frac{\sum_{j=1}^{n} \left(X_{ij} - \overline{X_i}\right)^2}{n-1}\right)^{1/2}.$$

After standardizing the data, the values in the resulting standardized data matrix, **Z**, are unitless (Romesburg 1984). Several other options for standardizing data exist. Certain functions may only be used in instances where the entire original data matrix is nonnegative and no attribute carries all zeros. In select instances, researchers might choose to use data *transformation* rather than standardization. This involves functions such as $Z_{ij} = \log(X_{ij})$ or $Z_{ij} = \sqrt{X_{ij}}$. Using transformation causes attributes to be more closely "weighted," but this method is used much less in research applications than common standardization (Romesburg 1984). Transformation can also involve methods such as principal component analysis or factor analysis (Aldenderfer and Blashfield 1984). Researchers may use transformations as a means of dealing with correlations among variables; however, in some situations, these interdependencies are necessary and should not be corrected (Punj and Stewart 1983). When considering standardization or transformation of data, two questions arise: (1) Should this data be standardized or

transformed? (2) If so, what method should be used? Some argue standardization does not strongly impact final cluster solutions, except in the presence of outliers (Punj and Stewart 1983). Others, however, recommend a cautious approach, such as completing the analysis with both standardized and raw data and comparing the results (Ketchen and Shook 1996). For an interesting illustration of the effects standardization can have on proximity measures, the reader is referred to Aldenderfer and Blashfield (1984).
Since the methodology in this thesis does not necessitate standardization or transformation of the data, the review of these will not be detailed any further and the reader is guided to cluster analysis texts such as Romesburg (1984) for more detailed information.

Proximity measures

After a researcher has arrived at a satisfactory data set, the next step in cluster analysis typically involves the choice of a proximity measure, although this step is bypassed when using certain clustering methods. Proximity measures, which may also be referred to as a similarity/dissimilarity measures or a resemblance coefficients, numerically represent the similarity or dissimilarity between each pair of objects in the dataset. When a proximity measure is considered a "similarity" measure, a large value indicates a high level of similarity; whereas, a large value for a "dissimilarity" measure indicates a low level of similarity. A multitude of proximity measures exist, and the determination of which measure to use can depend on the scales of measurement in the data and the types of data profile similarities the researcher is specifically interested in.

For further illustration regarding data profiles, refer to the example in figure 1. Here, Series 2 and Series 3 exhibit an additive translation: the two data profiles are separated by a constant amount. A proportional translation can be seen between Series 1 and 2 or Series 1 and 3—both sets vary by a constant multiplier (Romesburg 1984).

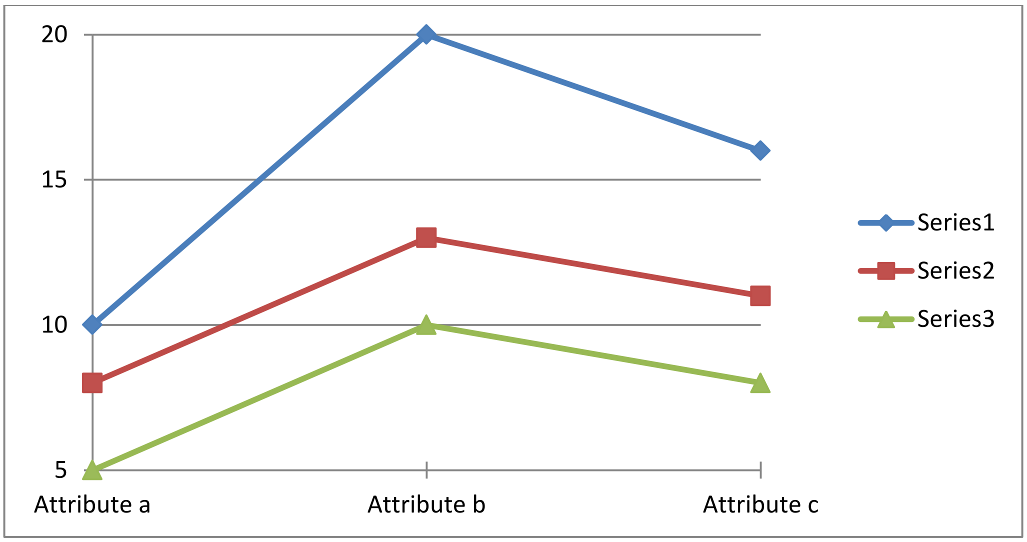

Figure 1. Data profile relationship example

Some proximity measures purposely ignore the additive and/or proportional translation. Therefore, a researcher must carefully determine if each of these data profile properties are important in the determination of similarity between objects. In certain research situations, the shape ("the pattern of dips and rises across variables") relationship between two data profiles may be of more importance than the elevation ("level or size") or scatter ("dispersion of the scores around their average") relationships (Aldenderfer and Blashfield 1984). The choice of proximity measure also depends on the scale of measurement used for attributes. Qualitative attributes are measured on a nominal scale which includes binary variables (e.g. attribute present/attribute not present) and unordered categorical variables (e.g. eye color or state of residence). Quantitative attributes are measured on ordinal, interval, or ratio measurement scales. An ordinal measurement scale involves ordered categories; whereas, interval and ratio measurement scales are continuous (Romesburg 1984). Since certain proximity measures specifically deal with particular types of measurement scales, a researcher needs to consider what scale attributes are measured with when selecting an appropriate proximity measure.

The remainder of this sub-section will describe the proximity measure which this study will utilize, as well as briefly touch on a few others commonly used in the social sciences for the sake of comparison. For a more in-depth view of specific proximity measures the reader may consult cluster analysis texts such as Everitt (1993), Romesburg (1984) or Aldenderfer and Blashfield (1984). The conclusion of this sub-section also provides some of the literature's criticisms and suggestions relating to proximity measures.

Proximity measures for quantitative attributes

Many proximity measures for quantitative attributes fall into what Aldenderfer and Blashfield call "distance measures." These are generally dissimilarity metrics and represent the separation between two objects, j and k, as measured by the distance between the attributes of each pair of observations, X_{ij} and X_{ik}. Distance measures are especially useful when the researcher does not want to ignore additive or proportional translations between data profiles. Distance measures include different variations of the popular Euclidean distance coefficient. The Euclidean distance coefficient, e_{jk}, finds the square root of the sum of squared differences between the two objects among p attributes (Romesburg 1984). It is defined on $0 \leq e_{jk} < \infty$ and is calculated by

(7) $$e_{jk} = \sqrt{\sum_{i=1}^{p}\left(X_{ij} - X_{ik}\right)^2}.$$

An alternative version, the squared Euclidean distance, e_{jk}^2, squares the entire expression in order to do away with the square root function (Aldenderfer and Blashfield 1984):

(8) $$e_{jk}^2 = \sum_{i=1}^{p}(X_{ij} - X_{ik})^2.$$

Another common distance measure is referred to as the "city-block" or Manhattan distance. It can show less sensitivity to outliers than the Euclidean distances (Jobson 1992). This coefficient is also defined on $0.0 \leq m_{jk} < \infty$ and is calculated by

(9) $$m_{jk} = \sum_{i=1}^{p}\left|X_{ij} - X_{ik}\right|.$$

The Mahalanobis distance (as defined by Equation 3) may also be adapted for use as a distance-type proximity measure. The incorporation of the covariance matrix in the Mahalanobis distance differentiates it from other distance measures (Aldenderfer and Blashfield 1984).

If the additive relationship between data profiles are not of interest to the researcher, he or she may want to consider a "shape" measure, such as the Pearson product-moment correlation coefficient (Aldenderfer and Blashfield 1984) or the coefficient of shape difference (Romesburg 1984). These are both sensitive to shape, but slightly differ in execution. The correlation coefficient is a similarity measure defined on $-1 \leq c_{jk} \leq 1$, where $c_{jk} = 1$ considers j and k to be "maximally similar" but not necessarily identical. The coefficient of shape difference, on the other hand, is a dissimilarity measure defined on $0 \leq s_{jk} \leq \infty$, where $s_{jk} = 0$ considers j and k to be "maximally similar" but not necessarily identical (Romesburg 1984).

Proximity measures for qualitative attributes

Since the measurement scales for qualitative attributes cannot be "ordered," the measurement of similarity/dissimilarity between objects must take a slightly different approach. Referred to by Aldenderfer and Blashfield as "association coefficients," these proximity measures for binary variables are plentiful and mostly defined in biology literature (1984).

Romesburg suggests converting unordered categorical variables into multiple binary variables in order to satisfy the binary condition for these proximity measures (Romesburg 1984). For example, instead of using one variable for eye color with three unordered categories (blue, green, brown), a researcher can create a mutually exclusive set of three binary variables, one for each eye color (1=color present, 0=color not present). These proximity measures are mostly written using the notation in table 3, where a represents the number of 1-1 matches of attributes between the two objects and so on.

Table 3. Notation for Association Coefficient Equations

	Object j	
Object k	1	0
1	a	b
0	c	d

The key to determining an appropriate association coefficient involves determining how the researcher wants to treat 0-0 matches—should these add to similarity or should only 1-1 matches carry significance? To illustrate the different ways in which these coefficients might consider 0-0 matches, compare Equations 10 and 11 given below which are two of the most popular association coefficients, written in accordance with the notation given in table 3.

The Jaccard coefficient is defined on $0 \leq c_{jk} \leq 1$ and is written as

(10) $$c_{jk} = \frac{a}{a+b+c},$$

which completely ignores the negative matches (d) between the objects j and k. This means that the Jaccard coefficient is sensitive to the direction of coding. This is intended for use with "asymmetrical" nominal scales—those in which one category carries more importance (SAS Institute Inc. 2008b). The SAS User's manual provides an example of the presence or absence of a very rare gene or trait—a researcher may not be particularly interested in those cases where the gene or trait is similarly absent (2008b).

Conversely, the simple matching coefficient, which is also defined on $0 \leq p_{jk} \leq 1$, gives equal significance to 1-1 and 0-0 matches:

(11) $$p_{jk} = \frac{a+d}{a+b+c+d}\ .$$

This type of coefficient is appropriate for “symmetrical” nominal scales—those in which the researcher equally values the presence and absence of each attribute (SAS Institute Inc. 2008b). This proximity measure is therefore insensitive to the direction of coding (Romesburg 1984).

The final proximity measure which deserves acknowledgment is Gower’s coefficient of similarity. This special measure handles data measured on any scale simultaneously. This unique proximity measure is defined on $0 \leq g_{jk} \leq 1$, with $g_{jk} = 1$ indicating maximum similarity of two objects. Equation 12 (and the subsequent conditions given in Equations 13, 14, 15, and 16) was adapted from the SAS User’s Guide (2008b) to fit with the previous notations used in this literature review where objects *j* and *k* are compared along *p* attributes:

(12) $$g_{jk} = \frac{\sum_{i=1}^{p} \delta_{j,k}^{i} d_{j,k}^{i}}{\sum_{i=1}^{p} \delta_{j,k}^{i}}\ .$$

For asymmetric nominal attributes,

(13) $$\delta_{j,k}^{i} = \begin{cases} 1\ where\ either\ j_i\ or\ k_i\ is\ present \\ 0\ where\ both\ j_i\ and\ k_i\ are\ absent \end{cases}.$$

For all symmetric nominal, ordinal, interval, or ratio attributes;

(14) $$\delta_{j,k}^{i} = 1\ .$$

For nominal attributes (symmetric or asymmetric),

(15) $$d_{j,k}^{i} = \begin{cases} 1 \ where \ j_i = k_i \\ 0 \ where \ j_i \neq k_i \end{cases}.$$

For ordinal, interval, or ratio attributes;

(16) $$d_{j,k}^{i} = 1 - |j_i - k_i| .$$

The Gower metric can be converted to a dissimilarity measure simply by subtracting g_{jk} from 1 (SAS Institute Inc. 2008b). It essentially melds together different coefficients: if all data are quantitative, the result will equal that of the Manhattan (city-block) distance; if all data are binary, the result will equal that of the Jaccard coefficient (Romesburg 1984). Romesburg also suggests a few other methods for dealing with mixed data measurement scales without using the Gower coefficient, such as treat qualitative variables as if they are quantitative or convert quantitative attributes into binary attributes using ranges of values (1984).

Criticisms relating to proximity measures

Although selecting the "correct" proximity measure from a multitude of options may seem a daunting task, some literature regards it as one of the less critical decisions a researcher must make when implementing cluster analysis. In fact, Ketchen and Shook make no mention of the choice of proximity measure in their analysis of applications of cluster analysis in the field of strategic management research (1996). In their analysis of applications of cluster analysis in marketing research, Punj and Stewart suggested:

> *"To the extent that a particular measure of similarity… reduces the extremity of outliers, the performance of some algorithms which are sensitive to outliers may be improved. Otherwise the selection of a similarity measure… appears to have minimal effect. We do not suggest that the choice of a similarity measure should be indiscriminant; the measure should be appropriate for the type of data being considered"* (1983).

A few early researchers argued that additive translations between data profiles should never be ignored and therefore distance-type proximity measures should always be used. However, Lorr reasons that some research applications have no interest in the elevation differences between objects. Lorr goes on to provide a possible approach where the researcher might differentiate elevation, scatter, and shape of data profiles in order to see how each contributes individually to a given hierarchical clustering (1983).

Clustering methods

Just as the researcher must select a proximity measures from many alternatives, a wide variety of clustering methods also exist from which to choose. Although Aldenderfer and Blashfield categorized the methods into seven families (1984), the most commonly applied methods fall into two categories, hierarchical methods and partitioning methods, each of which comes with advantages and disadvantages.

Hierarchical methods use an algorithm to either combine small clusters into larger ones or divide large clusters into smaller ones in a sequential "step-by-step" fashion. A partitioning method, on the other hand, begins with a specified number of clusters and "sweeps" through the original data, rearranging cluster membership until the partitioning is optimized according to a certain criterion.

The following review of clustering methods is in no way comprehensive. Instead, it focuses on the most commonly used methods and summarizes the literature's criticisms on these. For a more in-depth look at clustering methods, the reader is referred to more detailed cluster analysis texts, such as Everitt (1993).

Hierarchical methods

Hierarchical clustering methods may be further divided into two subgroups: agglomerative methods and divisive methods. The two are virtually opposites of one another, but agglomerative methods are more widely-used. An agglomerative method begins with n clusters, each cluster consisting of exactly one object, and combines the clusters one-by-one until the process finally ends with one cluster consisting of n objects. A divisive method conversely begins with one cluster consisting of n objects and splits clusters step-by-step until the process finally ends with n clusters, each consisting of one object. The process of either therefore requires exactly $n - 1$ steps to complete (Aldenderfer and Blashfield 1984). Although the remainder of the review of hierarchical methods will focus on agglomerative methods as they are the most popular, the reader should keep in mind divisive methods theoretically work in reverse.

Hierarchical agglomerative methods use “linkage rules” in order to determine which two clusters to combine in each step. Following each step, the clustering algorithm recalculates the proximity matrix to account for the new cluster. For example, in the original proximity matrix$(n \times n)$, *j* and *k* are two objects. If the first step combines *j* and *k*, they essentially become one new object, the cluster *jk*. The new proximity matrix $[(n-1) \times (n-1)]$ reflects the proximity of every other object in the sample to the new cluster, *jk*, instead of the proximity of every other object to *j* and *k* individually. Therefore, with each subsequent step, the proximity matrix becomes smaller and smaller (Romesburg 1984).

“Single linkage” and “complete linkage” represent opposite approaches to linkage rules. To illustrate the difference between the two, refer to the simplified example illustrated in two-dimensional attribute space in figure 2. Both single linkage and complete linkage merge clusters based on the nearest proximity; however, the difference is how each calculates the proximity between clusters. Single linkage measures the proximity between two clusters as the proximity between the two *nearest* objects of each cluster. Conversely, complete linkage measures the proximity between two clusters as the proximity between the two *furthest* objects of each cluster. After using these rules to recalculate the proximity matrices, two clusters are merged based on the smallest proximity. In figure 2, the single linkage method would therefore merge clusters B and C; whereas, the complete linkage method would merge clusters A and B.

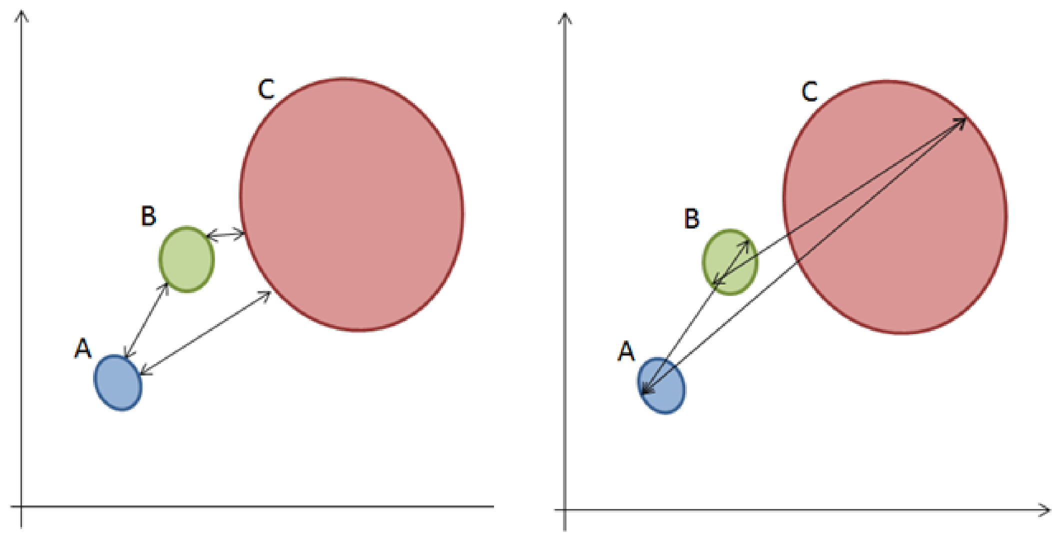

Figure 2. Comparison of single linkage (left) and complete linkage (right)

Two other popular hierarchical methods are average linkage and Ward's method. The "average linkage" method, sometimes referred to as the "unweighted pair-group method using arithmetic averages" (UPGMA), lessens the single and complete linkage extremities. Instead of calculating the proximity between two clusters, *g* and *h*, as the proximity between one object from each cluster, average linkage uses the proximity between the average of all objects in *g* and the average of all objects in *h* (Aldenderfer and Blashfield 1984). Rather than merging clusters based on nearest proximity, Ward's method seeks to merge clusters based on within-cluster variance. In order to optimize this, a Ward's method algorithm will calculate the error sum of squares of each potential grouping and select the grouping with the minimum value (Aldenderfer and Blashfield 1984). Single, complete, and average linkage methods merge clusters based on similarity and therefore typically begin with the proximity matrix; however, Ward's method merges clusters based on the minimization of error sum of squares and therefore begins with the raw data matrix rather than a proximity matrix (Romesburg 1984).

All four of the aforementioned methods continue repeating the algorithm until all objects are merged into one cluster. The entire step-by-step process is commonly shown graphically on a tree-like structure called a "dendrogram." Figure 3 displays an example of a dendrogram—the y-axis represents the identification numbers of the objects and the x-axis represents the "agglomeration coefficient." Although different statistical programs use different terminology for this coefficient, it essentially represents the proximity between two clusters at the point which they were merged. The responsibility then lies with the researcher to determine where to "cut" the tree. For example, if the dendrogram in figure 3 were cut at the agglomeration coefficient of 10, the resulting "cluster solution" would have three clusters: one consisting of objects 7, 8, 9, and 10; one consisting of only object 4; and one consisting of objects 1, 2, 3, 5, and 6. Decisions regarding the number of clusters in the "cluster solution" will be discussed later in the literature review.

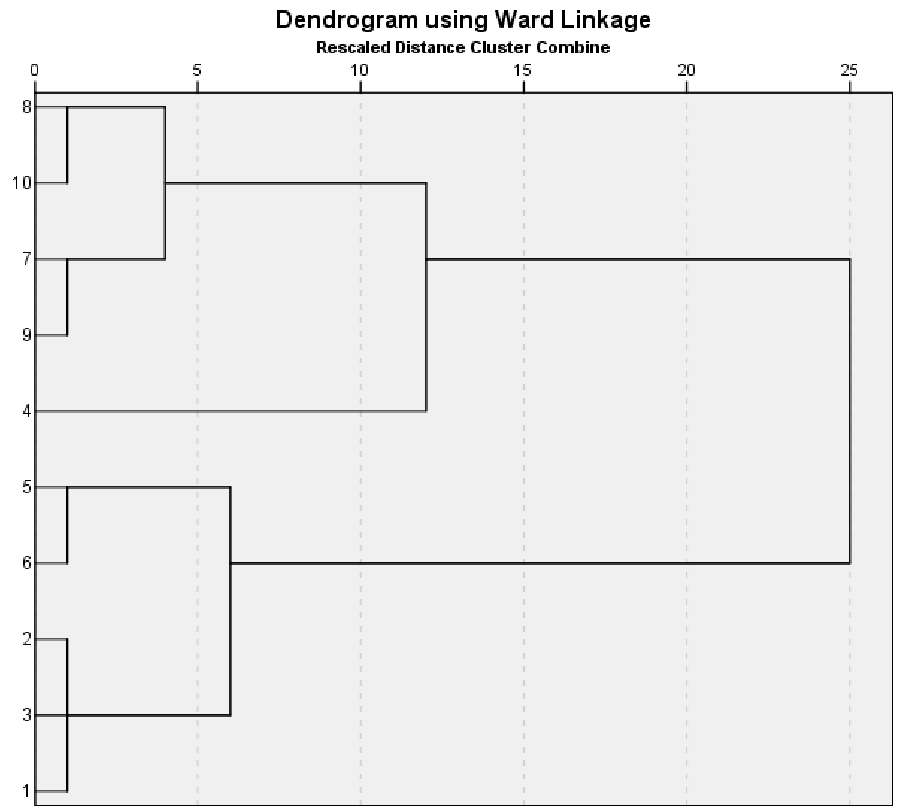

Figure 3. Example of a dendrogram

Partitioning methods

Partitioning methods (sometimes referred to as iterative methods) operate quite differently than hierarchical methods. Partitioning requires a defined number of clusters prior to the initialization of the algorithm (Lorr 1983). Compared to the common hierarchical clustering methods, iterative partitioning of data is less straightforward and may not even be fully understood by some researchers who apply it (Aldenderfer and Blashfield 1984). Partitioning algorithms make repetitive "passes" through the data, reconfiguring the cluster arrangements to optimize a certain criterion function. (Aldenderfer and Blashfield 1984; Lorr 1983). The literature offers several suggestions for statistical criteria with which to optimize the cluster solutions of iterative partitioning methods.

The "k-means" method is the most commonly used partitioning method and is generally described here, following the notation used by Hamerly and Elkan (2002). K-means, as well as other partitioning methods, works directly from the original data matrix, **X** (consisting of *n* objects in *p*-dimensions), and bypasses the calculation of the proximity matrix. An initial set of *p*-dimensional cluster centers is then defined as $C = \{c_1, \ldots, c_k\}$, where *k* represents the number of clusters designated by the researcher. The "membership function" $m(c_j|x_i)$ then determines the membership of each data point to each cluster, notating each cluster by its cluster center, c_j. Some partitioning algorithms use a "soft" membership function, where the membership may be a proportion, constrained by $(c_j|x_i) \geq 0$; $\sum_{j=1}^{k} m(c_j|x_i) = 1$; and $0 \leq m(c_j|x_i) \leq 1$. K-means, however, uses a "hard" membership function, where $m(c_j|x_i) \in \{0,1\}$. In any iterative method, a weight function, $w(x_i)$, describes the "influence" that x_i exerts on the determination of the new cluster centers in the subsequent iteration. This weight, constrained by $w(x_i) > 0$, can give additional influence to objects which the current clustering does not cover well. After the membership and weight have been computed for each data point, x_i, in each cluster, c_j, the location of each cluster center, c_j, is recalculated using the following equation:

(17)
$$c_j = \frac{\sum_{i=1}^{n} m(c_j|x_i)w(x_i)x_i}{\sum_{i=1}^{n} m(c_j|x_i)w(x_i)}.$$

The k-means (K) algorithm continues to repeat these steps until the optimization of

(18) $$K(X,C) = \sum_{i=1}^{n} \min_{j\in\{1\ldots k\}} \left\|x_i - c_j\right\|^2,$$ where

(19) $$m_K(c_j|x_i) = \begin{cases} 1 \ \ if\ l = argmin_j \left\|x_i - c_j\right\|^2 \\ 0 \ \ otherwise \end{cases}$$ and

(20) $$w_K(x_i) = 1.$$

In summary, the k-means algorithm uses a constant weight for every data point and a hard membership function in order to "minimize the within-cluster variance" (Hamerly and Elkan 2002). Several authors refer to the objective function of a k-means algorithm as the minimization of trace(**W**), where **W** is the pooled within-group dispersion matrix (Lorr 1983; Everitt 1993). For a more in-depth look at this and other partitioning algorithms, the reader is directed to more comprehensive cluster analysis texts, such as Anderberg (1973) or Everitt (Everitt 1993).

Criticisms relating to clustering methods

Everitt gives the following advice pertaining to the selection of a clustering method: "methods should be designed to recover the types of clusters suspected, effective at recovering them, insensitive to error, and available in the software" (1993). In order to compare the ability of each clustering method in identifying underlying group structures, empirical studies have utilized Monte Carlo methods. In these studies, the researcher creates artificial data with a specified structure and looks at how well the clustering method “recovers” the known structure. In a thorough review of six Monte Carlo studies, Milligan noted that Ward’s method did not seem to perform as well as some researchers had previously suggested. In fact, the average linkage method resulted in equal or better structure recovery than Ward’s method in five of the studies. Milligan also found non-hierarchical methods out-performed all of the hierarchical methods used in two of the studies (Milligan 1981). Milligan’s review of clustering methods was conducted several decades ago and many new non-hierarchical methods have been developed since.

As iterated by Everitt, “no one clustering method can be judged to be ‘best’ in all circumstances” (1993). Table 4 compiles information from several different sources including Romesburg (1984), Aldenderfer and Blashfield (1984), Ketchen and Shook (1996), Jobson (1992), Everitt (1993), and Hamerly and Elkan (2002); in order to compare some of the most commonly referred-to methods.

Table 4. Comparison of Most Popular Clustering Methods

Method	Type	Comments
Single linkage	Hierarchical, agglomerative	Typically results in "compacted" hierarchical trees. Clusters tend to be "chained" and unbalanced. Outliers can have substantial impact on solution.
Complete linkage	Hierarchical, agglomerative	Typically results in "extended" hierarchical trees. Clusters tend to be compact and spherical with similar diameters. Outliers can have substantial impact on solution, but less than single linkage.
Average linkage (UPGMA)	Hierarchical, agglomerative	Hierarchical trees tend to fall between the "compact" or "extended" nature of single/complete linkages. Relatively robust compared to single/complete linkages. Tends to create "spherical" clusters. Tends to merge clusters with small variances. Relatively insensitive to outliers.
Ward's method	Hierarchical, agglomerative	Tends to create "spherical" clusters. Tends to create groups of nearly equal sizes. Outliers can have substantial impact on solution.
K-means	Iterative partitioning	May only find a "local" optimum for partitioning; solution can be dependent on the initial "seed" Must have prior determination of number of clusters Due to the hard membership rule, can produce poor solutions at times Tends to create "spherical" clusters Appears least affected by outliers and spurious attributes

The hierarchical methods can produce very different outcomes for the same data (Everitt 1979). Milligan recommended always including average linkage and Ward's method in any study—since both "have been found to give good recovery on several occasions, the relative performance of other methods can be established" (1981). The one-pass nature of hierarchical methods creates rigid clusters which cannot be modified—once an object is assigned to a cluster, hierarchical methods do not allow it to be removed from that cluster (Ketchen and Shook 1996). Partitioning methods, on the other hand, are less rigid and allow for a poor initial clustering to "correct" itself (Lorr 1983).

When using the k-means or other iterative partitioning methods, the determination of a global solution would require examining billions of iterations, even for a small data set and only a small number of clusters (Aldenderfer and Blashfield 1984). Therefore, the algorithms search for a local solution, instead. Many different local solutions can exist for the same dataset, depending on what the algorithm uses as the initial set of cluster centroids. Rather than repeating the algorithm thousands of times to compare local solutions, some researchers promote initialization with a set of "intelligent" cluster centroids, also referred to as the use of "seeds" (Steinley and Brusco 2007). In Steinley and Brusco's review and comparison of twelve different initialization methods, Milligan's two-stage method drastically outperformed other strategies. This approach, also promoted in the literature by Ketchen and Shook (1996) and Punj and Stewart (1983), uses hierarchical and partitioning methods in conjunction with one another (Steinley and Brusco 2007). Although variations of this "two-stage" method have been proposed, the basic idea is to first implement Ward's method or average linkage to determine a set of "preliminary clusters," which are used to estimate the number of clusters and estimate the centroids of each cluster. These determinations are then used to initialize the partitioning algorithm which leads to the final cluster solution (Punj and Stewart 1983). Ketchen and Shook argued that using both hierarchical and partitioning methods in tandem enhances the validity of a solution since they do not share the same biases (1996). K-means algorithms with well-chosen seeds have been shown in several studies to produce clusters superior to those generated by average linkage and Ward's method; whereas, k-means algorithms with random seeds sometimes (but not always) produce results inferior to average linkage and Ward's method (Punj and Stewart 1983).

The presence of outliers or extreme observations should also be considered when choosing a clustering method. In fact, the SAS User's manual suggests using the TRIM option to detect outliers and withhold them from the cluster analysis when using single linkage, complete linkage, or Ward's method. The TRIM option identifies outliers as a user-defined percentage of objects with low estimated probability densities (SAS Institute Inc. 2008a). Everitt points out that single linkage might also be used to attempt to identify outliers, as they are often the "singletons" merged in the final steps (1979).

Number of clusters and related criticisms

An application of cluster analysis is only as useful as the final "cluster solution." With the exception of some biology studies, the researcher typically does not find use in an entire hierarchical tree and instead needs to determine how many groups are present (Everitt 1993).

The determination of the number of clusters can many times involve subjective decisions by the researcher (Aldenderfer and Blashfield 1984; Everitt 1993). The simplest method involves a simple visual inspection of the dendrogram—the researcher simply "cuts" the tree wherever it appears to have relatively elongated branches. The use of this method alone is mostly frowned upon by critics (Ketchen and Shook 1996; Aldenderfer and Blashfield 1984). Another rather subjective method uses the agglomeration coefficient (the numerical representation of the distance between the two clusters being combined). The entire range of coefficients (from 1 cluster to *n* clusters) can be examined for a relatively large incremental change or a graph using this coefficient and the number of clusters as axes can be examined for a distinct elbow. Unfortunately, there are usually multiple instances of a drastic change in the agglomeration coefficient in the entire range of possible cluster solutions (Aldenderfer and Blashfield 1984).

In attempt to mitigate some of this subjectiveness, several authors have developed "stopping rules" for determining the number of clusters. Milligan and Cooper provide a comprehensive review and evaluation of thirty of these stopping rules (1985). Of these, three can be easily calculated in SAS: the cubic clustering criterion (CCC), the Calinski and Harabasz index (referred to by SAS as the "pseudo F"), and the Duda and Hart statistic (referred to by SAS as the "pseudo T-Squared") (SAS Institute Inc. 2008a). Before giving the equations for the calculation of these three indices, some SAS notation should be clarified. As notated previously, *k* refers to the total number of clusters. C_k then refers to the *k*-th cluster and N_k is the number of observations in the *k*-th cluster. Furthermore,

(21) $$W_k = \sum_{i \in C_k} \|x_i - \bar{x}\|^2$$

represents the within-cluster dispersion. Between-cluster dispersion is given by

(22) $$B_{kl} = W_m - W_k - W_l \text{ when } C_m = C_k \cup C_l \text{ .}$$

Finally, the total dispersion is represented by

(23) $$T = \sum_{i=1}^{n} \|x_i - \bar{x}\|^2$$

and P_G is equal to $\sum W_J$, where summation is over the G clusters at the Gth level of the hierarchy (SAS Institute Inc. 2008a). Given this, the CCC is calculated in SAS using

(24) $$CCC = \ln\left[\frac{1-E(R^2)}{1-R^2}\right] \times k$$ where

(25) $$R^2 = 1 - \frac{B_{KL}}{T}\,.$$

A peak in the CCC with a value greater than two indicates a good number of clusters. If the peak is at a positive value, but less than two, it can indicate a *possible* number of clusters. A large negative CCC may suggest the presence of outliers (SAS Institute Inc. 2008a). The "pseudo F" statistic calculated in SAS is based on the Calinski and Harabasz index:

(26) $$PSF = \frac{\frac{T-P_G}{G-1}}{\frac{P_G}{n-G}}\,.$$

A good number of clusters is indicated by a relatively large number for the pseudo-F (SAS Institute Inc. 2008a). The "pseudo T-squared" statistic calculated in SAS derives from the Duda and Hart statistic:

(27) $$PST^2 = \frac{B_{KL}}{\frac{W_K+W_L}{N_K+N_L-2}}\,.$$

The pseudo T-squared is interpreted by moving from n individual clusters towards one cluster. When a steep incremental jump occurs, the prior value (one more cluster than the number of clusters at the peak) can indicate a good clustering (SAS Institute Inc. 2008a).

As pointed out by Aldenderfer and Blashfield, the difficulty of determining the number of clusters partly has to do with the lack of a null hypothesis. It is difficult to structure such tests when there is no consistent "definition" or statistical properties of a cluster (Aldenderfer and Blashfield 1984). Ketchen and Shook advocate using multiple techniques to determine the number of clusters (1996).

In regards to the use of "stopping rules," Milligan and Cooper's evaluation of thirty such statistics found the Calinski and Harabasz index (pseudo-F in SAS) and the Duda and Hart (basis of the pseudo-T^2in SAS) statistic both recovered the true number of clusters in artificially created datasets extremely well. In fact, they were the top two performers of the thirty statistics evaluated. The CCC statistic also "performed at a competitive rate" (it ranked sixth overall). In the instances that it did not recover the true number of clusters, it displayed a strong tendency towards suggesting too many clusters (Milligan and Cooper 1985).

Validation and related criticisms

After determining the number of groups in the "cluster solution," a researcher should also somehow validate the results. Cluster analysis will offer a solution, even when no true structure exists in the underlying data; therefore, some sort of validation should be important for most research objectives (Punj and Stewart 1983). Unfortunately, validation methods are sometimes subjective and difficult to quantify.

Romesburg suggests primary validity is crucial to any study and should be determined by "how well a cluster analysis achieves its research goal and generates interesting and useful conclusions." Furthermore, Romesburg summarizes measures of secondary validity to include obtaining well-structured clusters, agreement with existing classifications, agreement with expert intuition, agreement with other multivariate methods, agreement between split samples of data, demonstration of stability and robustness, and agreement with the researcher's prior expectations (1984).

Other authors have also suggested that clusters should display stability or consistency, although this should not be used as the sole method for validation (Ketchen and Shook 1996). A common way to evaluate consistency is by using several different clustering methods and comparing the resulting partitions by calculating the "adjusted Rand index," a slightly different version of the classical Rand index (Steinley 2004). First introduced in 1971, the Rand index looks at the cluster membership of two different partitions, each with the same number of clusters, and simply divides the number of "hits" (instances where a pair of objects fall in the same cluster in both partitions or different clusters in both partitions) by the total number of pairs of objects (Rand 1971). Table 5 provides notation for the equations used to calculate the Rand and adjusted Rand indices. Using this notation, a simply represents the quantity of pairs of objects that fall into the same cluster in both partitions; whereas, d represents the quantity of pairs of objects that fall into different clusters in both partitions.

Table 5. Notation for Rand Index and Adjusted Rand Index Equations

	Partition X Pair in same cluster	Partition Y Pair in different clusters
Partition Y Pair in same cluster	a	b
Partition Y Pair in different clusters	c	d

The Rand index calculates the proportion of agreements (*a* and *d*) to the total pairs of objects:

(28) $$RI = \frac{a+d}{a+b+c+d}$$

(Steinley 2004). As introduced by Huburt and Arabie, the adjusted Rand index (ARI) takes things a step further by also accounting for the number of "hits" that occur by mere chance. It is given by

(29) $$ARI = \frac{\binom{N}{2}(a+d)-[(a+b)(a+c)+(c+d)(b+d)]}{\binom{N}{2}^2-[(a+b)(a+c)+(c+d)(b+d)]},$$

where $\binom{N}{2}$ equals the total number of pairs of objects. The ARI is also used in many of the Monte Carlo studies to compare clustering method results to the actual group structure in the artificial data (Steinley 2004).

Aldenderfer and Blashfield also recommend the use of significance tests of *external* variables. Such variables should be relevant (i.e. theoretically related) but not used within the cluster analysis. Unfortunately, relevant external variables are sometimes difficult to determine (1984). Punj and Stewart recommended the use of a holdout sample (1983); however, such a sample is not always available (Ketchen and Shook 1996).Aldenderfer and Blashfield recognized the frequent use of significance tests performed on variables used within the cluster analysis through multivariate analysis of variance (MANOVA). However, the authors show that this will always result positively and therefore they argue this method “is useless at best and misleading at worst” (1984). Although it sounds somewhat elementary, Ketchen and Shook point out that a researcher needs to document his or her methods for determining the number of clusters and validation. In the strategic management applications of cluster analysis which they reviewed, many studies did not relay this information (1996).

CHAPTER III

METHODOLOGY

In order to accomplish the research objectives, cluster analysis methods were applied to primary data, taking into account several of the literature's suggestions for overcoming common challenges of cluster analysis. The following chapter lays out the framework for this study by providing a narrative of the data collection process and a description of the sample collected. Finally, it provides a thorough description of cluster analysis procedures used along with motivation for the selection of procedures used.

Survey administration

An anonymous survey was mailed to 1,400 individuals. A total of 199 responses were received for a 13.8% response rate. According to a case study on survey response rates of farmers, the best months for a farmer to receive a survey are January and February (Pennings, Irwin, and Good 2002). Unfortunately, the time constraints of this study did not allow for the survey to be sent out during that time, and instead surveys were mailed out during the first two weeks of September. This unfortunate timing could be partly to blame for the low response rate since it coincides with the beginning of harvest for the majority of the Midwest and Great Plains.

The study materials received by participants included the following: a cover letter written in accordance with Dillman's "Tailored Design Method" (Dillman and Dillman 2000), a consent information sheet, a "Brief introduction to peer advisory groups in agriculture" information sheet, a survey, and a postage-paid return envelope. The peer advisory group information sheet was written in a fashion as to avoid swaying responses in any certain direction. Since it was uncertain as to whether or not study participants would have previously heard of the peer advisory group concept, this was included as a precautionary measure to ensure that all participants had a basic understanding of what the concept involves. The survey included two parts: questions about the individual/individual's farm and questions about the individual's "ideal" peer advisory group. Five-point Likert-scale responses followed each question.

The lack of literature available on peer advisory groups created a problem when writing questions to include in the survey: what critical variables should be used to cluster the candidates? This study chose to follow a mostly cognitive approach to the writing of survey questions, due to its mostly exploratory nature and limited existing theory. Revisiting Ketchen and Shook's general approaches to variable selection described in Chapter II, a cognitive approach means that the researcher chooses variables largely based on expert opinions (Ketchen and Shook 1996). The survey questions were written mostly based on insights given by involved parties at the "Peer Advisory Groups: Best Practices and Alternative Structures" conference (AAPEX 2011). This included discussions among participants during question-and-answer panels and the results from an opinion survey administered at the conclusion of the conference. Exact verbiage included on the peer advisory group information sheet and survey questions and responses used as variables in this study can be found in Appendix A.

Sample

As described in Chapter I, this study examines cluster analysis methods as they could potentially be applied by a “clearinghouse” organization to a pool of candidates interested in becoming peer advisory group members. In such a case, the pool would most likely not be a representative sample of the population of farm managers. In fact, several individuals at the conference on peer advisory groups suggested that most members of agricultural groups tended to be full-time, larger-scale farmers (AAPEX 2011). Therefore, this study did not select subjects with the intent to construct a representative sample of all farm managers. Subjects were instead selected to target the full-time, larger-scale farm managers. Three different agribusinesses each supplied a small number of names and addresses of full-time farm managers.

For the survey questions regarding the respondent’s farm, the Likert-scale responses were constructed in a way that largely ignores small enterprises. Texas AgriLife Extension specialists assisted in the construction of these scales. Rather than using a scale such as “zero – very small – small – average – large – very large,” the scale followed: “zero – average and below average –above average –large – extremely large.” For further elucidation, table 6 compares the sizes of dairy and hog enterprises of respondents’ farms (for those who reported greater than zero for either) to information from the most recent U.S. Census of Agriculture(United States National Agricultural Statistics Service 2009). Although not a perfect comparison (the cutoff numbers for the ordinal categories differ slightly), the reader can easily discern that the sample most certainly does not represent the entire population of U.S. farms as reported by the USDA.

Table 6. Comparison of U.S. Census of Agriculture Farm Sizes and Survey Sample Farm Sizes

DAIRY					
U.S. CENSUS OF AGRICULTURE			SURVEY SAMPLE		
Head (milk cows)	Number of farms	Percentage of all dairy enterprises	Head (milk cows)	Number of farms	Percentage of all dairy enterprises
1 – 500	66,606	95%	1-600	4	19%
500 – 1,000	1,702	2%	600 – 2,000	10	48%
1,000 – 2,499	1,104	2%	2,000 – 5,000	2	10%
2,499+	478	1%	5,000+	5	24%
Total	69,890		*Total*	21	
HOGS					
U.S. CENSUS OF AGRICULTURE			SURVEY SAMPLE		
Head (total herd)	Number of farms	Percentage of all hog enterprises	Head (total herd)	Number of farms	Percentage of all hog enterprises
1 – 500	59,635	85%	1 – 500	5	24%
500 – 1,000	3,588	5%	500 – 2,000	2	10%
1,000 – 2,000	4,013	6%	2,000 – 5,000	7	33%
2,000+	8,206	12%	5,000+	14	67%
Total	75,442		*Total*	28	

A total of 199 responses were collected. Nine of these were withheld from the dataset used in the remainder of the study. Of these nine, five participants did not provide responses to all of the questions used for variables. The other four were withheld due to unwillingness to share information with fellow peer advisory group members. As described in Chapter II, participation by all members is a key aspect of the peer advisory group concept. On the four survey questions relating to the willingness to share information in certain discussion areas, these four respondents indicated that they were either "somewhat unlikely" or "extremely unlikely" to share information in all of the four areas. Due to this unwillingness to contribute to the peer advisory group, it was decided that these four individuals would make poor group members. Although these respondents represent farm managers uninterested in peer advisory group participation, the purpose of the cluster analysis is to create useful peer advisory groups, not useful descriptive groups. Therefore, these four respondents were withheld from the cluster analysis study.

Cluster analysis and the formation of peer advisory groups

Before presenting the cluster analysis methods used in this study, the underlying problem and research question should be reviewed. Many individuals interested in participating in peer advisory groups find difficulty in identifying other individuals who are interested in the same type of group. A “clearinghouse” organization could potentially act as a match-maker for potential candidates; such an organization would need to identify an effective method for creating peer advisory groups from a pool of candidates. As evidenced in the literature review, cluster analysis methods can be used to identify groups of highly similar objects/individuals as measured across multiple attributes. Cluster analysis is not necessarily the *only* method a clearinghouse could investigate using, but it seems an appropriate place to start. Therefore, this research specifically seeks to answer the following research question: how could a clearinghouse organization apply cluster analysis methods to a pool of candidates to effectively create peer advisory groups congruent to the individuals’ needs and wants?

As illustrated by the examples given in tables 1 and 2 in the literature review, peer advisory groups can be structured in a variety of ways. During the conference on agricultural peer advisory groups, conference participants broke into small focus groups and discussed amongst themselves some pertinent issues. Each group then summarized to the entire group some of the opinions of the small groups, and these opinions were taken into great consideration when determining how to cluster individuals in this study. A few examples include the following:

- "We had a discussion about whether it was appropriate to do a business-oriented peer advisory group or a production-oriented peer advisory group… determine the common ground for the group. What may be best for one group of five or six people is not going to be best for the other, and that would be an important initial point…if you wanted one and it felt like the group was going to do the other, it might be appropriate for you to excuse yourself and look for another group" (AAPEX 2011).
- "Overall, we feel that there's no one way to build a peer group. There's no one right focus for a peer group. But the key is to find a group of interested individuals who have decided on a common goal for that group" (AAPEX 2011).
- "The long-term planning and strategic planning is something that maybe some peer groups want to focus on rather than the daily operation performance-type peer group. And perhaps there is a need for more than one peer group that you need to belong to. It was brought up that perhaps a performance, locally-based peer group for production challenges and another group would be…the distanced group would focus on things that you don't really want your neighbors to know. So that would be like the finance and banking. And then another thing that was

brought up was the same-size operations or like-kind operations might be something that you'd want to be involved in because you might feel a little more at ease or comfortable and you could compare notes" (AAPEX 2011).

- "Define exactly what kind of group you want and what exactly you need. You have to know that before you move forward" (AAPEX 2011).
- "Is it a group that's going to talk about strategic ideas or tactical ideas? Are we going to start at production? And then are we going to be able to get to that high level of the business or are we going to stay at a level that's pretty comfortable, but a little more tactical and day-to-day? " (AAPEX 2011)

Based on comments such as these and the structures of the existing peer advisory groups given as examples in tables 1 and 2 of the literature review, the following set of assumptions were developed.

(1) Individuals seek different types of information from agricultural peer advisory groups. It is preferred for an individual to be grouped with other people who are likely to share that type of information with the peer advisory group.

(2) Some individuals expressed the desire to receive information and advice from people who manage farms with *similar* attributes. It is then assumed that these individuals are more likely to be satisfied being placed into a group with individuals who manage farms similar to their own.

(3) Other individuals expressed the desire to receive information and advice from people who manage farms with *different* attributes. It is then assumed that these

individuals are more likely to be satisfied being placed into a group with individuals who manage farms different from their own.

These assumptions were used as a cognitive basis for developing the approach of this study. Punj and Stewart stated that "the ultimate test of a set of clusters is its usefulness" (1983). For many other applications of cluster analysis, its usefulness is its descriptive ability. However, the results of this cluster analysis will only be useful if the candidates (the objects being clustered) are personally satisfied with the peer advisory groups into which they are placed. Although actual satisfaction cannot be measured within this study, it can be reasonably assumed that a candidate would be more satisfied with a peer advisory group which matches or nearly matches what he or she expressed (through the survey responses) was desirable for an "ideal peer advisory group."

The typical objective of a clustering method is to minimize the within-group variance of clusters while maximizing between-group variance. However, this objective does not apply perfectly to the creation of peer advisory groups. First of all, since the groups are not for descriptive purposes, separation between the groups (maximization of between-group variance) is not of much importance. It is perfectly acceptable for two peer advisory groups to be similar to one another as long as members of each group are satisfied with the group into which they have been placed. Secondly, Assumption 3 does not fit well with the goal of minimizing within-group variance across all attributes: some (but not all) individuals want *diversity* among members of their group for certain attributes. In such cases, minimizing the within group variance of that specific attribute could potentially create a peer advisory group that would not satisfy those individuals.

Therefore, an alternative approach will be proposed which will attempt to mitigate this problem. More traditional methods will also be utilized as controls for comparison.

Data, manipulations, and proximity measures

A cognitive approach was taken for variable selection and all variables/attributes are described in table 7. An important consideration should be noted: geographical distance between farms has been ignored as a potential variable in this study. Although this could have provided a very interesting dimension, the survey could not have remained completely anonymous with the collection of geographic information, such as zip codes. Nevertheless, a clearinghouse organization could potentially use the methodology developed here as a "first step" and further break down large groups of individuals by geographical distances between farms. The data can be separated into two categories: "desire for group" variables and actual "farm characteristics." The "desire for group" variables include what topics he or she is likely to discuss with fellow peer advisory group members and the degree of homogeneity/diversity among members desired. After repeatedly seeing several common themes in the actual topics discussed among agricultural peer advisory groups, the potential discussion topics were aggregated into four categories for the survey questions: production, financial, organizational management, and education/skills development (iprod, ifinc, iorgmg, ieduc). The supplement materials which were included with the surveys briefly described these four categories and gave a few examples of specific topics which might be discussed for each. The supplemental materials can be found in Appendix A. The homogeneity/diversity attributes most commonly seen in peer advisory groups were sectors of agriculture the farm is involved in and the size of the farming operation. The survey also collected responses for the desire for homogeneity of age and education level, but very few respondents indicated the desire for homogeneity of these attributes; therefore, these variables were discarded. Thus, the two attributes regarding degree of homogeneity/diversity within group are sector of agriculture (dsect) and size of operations (dsize).

Table 7. Variable Summary[1]

Variable Name	Variable Type	Question	Response Coding
iprod (V01)	Desire for group Ordinal	*How likely are you to share information regarding production issues?*	1 Extremely unlikely 2 Somewhat unlikely 3 Neutral 4 Somewhat likely 5 Extremely likely
ifinc (V02)	Desire for group Ordinal	*How likely are you to share information regarding financial issues?*	1 Extremely unlikely 2 Somewhat unlikely 3 Neutral 4 Somewhat likely 5 Extremely likely
iorgmg (V03)	Desire for group Ordinal	*How likely are you to share information regarding organizational management issues?*	1 Extremely unlikely 2 Somewhat unlikely 3 Neutral 4 Somewhat likely 5 Extremely likely
ieduc (V04)	Desire for group Ordinal	*How likely are you to share information regarding education and skills development?*	1 Extremely unlikely 2 Somewhat unlikely 3 Neutral 4 Somewhat likely 5 Extremely likely
dsect (V05)	Desire for group Ordinal	*Indicate the degree of similarity/diversity which you prefer for the sectors of agriculture that group members' respective farms are involved in.*	1 Extremely diverse 2 Somewhat diverse 3 Neutral 4 Somewhat similar 5 Extremely similar

[1] Questions here are not word-for-word as they appeared in the actual survey. For exact verbiage, the reader is referred to Appendix.

Table 7. Continued

Variable Name	Variable Type	Question	Response Coding
dsize (V06)	Desire for group Ordinal	*Indicate the degree of similarity/diversity which you prefer for the physical sizes of group members' respective farms.*	1 Extremely diverse 2 Somewhat diverse 3 Neutral 4 Somewhat similar 5 Extremely similar
fconv (V07)	Farm characteristics Ordinal	*Conventional crops (acres)*	1 Zero 2 Less than 2,500 3 2,500 – 5,000 4 5,000 – 10,000 5 Greater than 10,000
forgan (V08)	Farm characteristics Ordinal	*Organic crops (acres)*	1 Zero 2 Less than 1,000 3 1,000 – 2,500 4 2,500 – 5,000 5 Greater than 5,000
fprodu (V09)	Farm characteristics Ordinal	*Produce & specialty crops (acres)*	1 Zero 2 Less than 100 3 100 – 300 4 300 – 1,000 5 Greater than 1,000
fdairy (V10)	Farm characteristics Ordinal	*Dairy (average total cows)*	1 Zero 2 Less than 600 3 600 – 2,000 4 2,000 – 5,000 5 Greater than 5,000
ffeed (V11)	Farm characteristics Ordinal	*Beef – feedlot (average total head, one-time capacity)*	1 Zero 2 Less than 1,000 3 1,000 – 10,000 4 10,000 – 25,000 5 Greater than 25,000
fgraze (V12)	Farm characteristics Ordinal	*Beef – non-feedlot (average total head)*	1 Zero 2 Less than 250 3 250 – 500 4 500 – 1,000 5 Greater than 1,000
fhogs (V13)	Farm characteristics Ordinal	*Hogs (average total head, one-time capacity)*	1 Zero 2 Less than 500 3 500 – 2,000 4 2,000 – 5,000 5 Greater than 5,000

As described in the literature review, some researchers choose to manipulate data by standardization or removal of outliers before proceeding with the analysis. Outliers will be left in the sample, as the goal is to place *all* candidates into peer advisory groups, not just those who fit neatly. Standardization of the data is not necessary since all variables are measured on the same 5-point scale.

Since Punj and Stewart argued that the selection of proximity measure is typically of little importance, this study will not spend much time comparing results of different proximity measures and attempting to determine the "ideal" measure. As suggested by the literature, the researcher should take into consideration which data translations (i.e. elevation or shape) are important before choosing a proximity measure. The additive translation property (elevation) is very important in this situation, so "shape" proximity measures such as the correlation or cosine coefficients should not be considered. The CLUSTER procedure within SAS uses the Euclid distance by default; therefore, the Euclidean distance will be used since the variables are quantitative in nature.

Clustering methods and determination of the number of clusters

This study will employ several different clustering methods as controls. These controls will be compared to the proposed approach which will be fully described later. The controls will include the average linkage method (using Euclid distance), Ward's method, K-means, and the two-stage clustering method.

For the K-means method, the number of clusters suggested by Ward's method will be used for initialization, as suggested by the literature. No seeds will be designated; the SAS defaults will be used. For the two-stage clustering method, the number of clusters and cluster centroids suggested by Ward's method will be used as "seeds" in the implementation of the k-means method. The cluster membership identified by the k-means method is then the final result of the two-stage method. For all applications (the controls and the proposed approach), the CCC, pseudo-F, and pseudo-T^2 statistics will be consulted for the determination of the number of clusters, as suggested by the literature. Since the literature found CCC to have slightly lesser performance of the three, it will be used only for reinforcement.

Proposed alternative: the "dual-phase" approach

The discrepancy between assumptions (2) and (3) given earlier in this chapter creates a unique problem. For example, some individuals may want to form a peer advisory group consisting of *only* corn farmers; whereas, others may prefer to be a part of a group that includes individuals who are *not* corn farmers. Since a normal cluster analysis seeks to minimize within-group variance, clustering *all* objects by all variable including farm characteristics (V07 – V13) could potentially lead to a group consisting of members who all produce corn but some members who *want* fellow members who do *not* produce corn. In other words, some individuals do *not* want minimum variance within their peer advisory group for certain attributes.

An alternative approach will now be proposed for this unique situation. This approach will be benchmarked against the controls in the final evaluation in order to justify (or negate) the need for this unique approach. The proposed approach uses two phases for the analysis, as illustrated in figure 4. In order to prevent being confused with the two-stage clustering method, this proposed method will be referred to as a "dual-phase" approach.

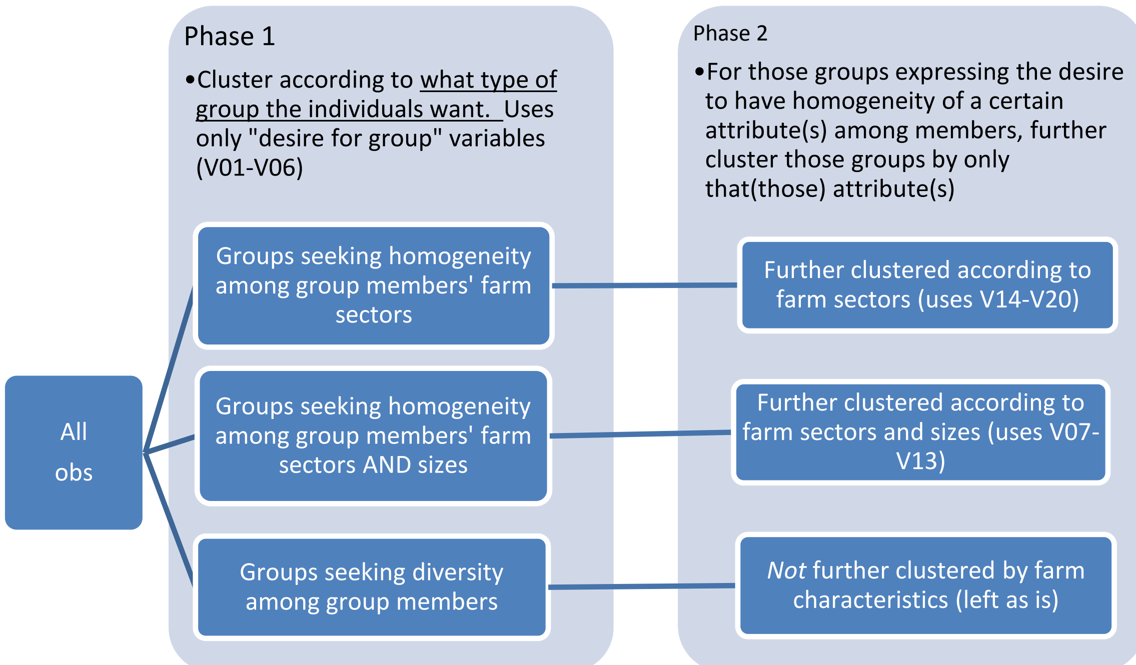

Figure 4. Process flow for the dual-phase approach

First, all individuals are clustered according to the "desire for group" variables (V01-V06). Each cluster is then looked at individually to see if group members generally want to have diversity or homogeneity among members' farm characteristics. The treatment of each cluster will be as follows:

- The cluster has a mean value of less than 4.0 for both V05 and V06
    - Determination: the cluster seeks diversity among members' farms (sector and size)
    - Treatment: the cluster will be left as is

- The cluster has a mean value of greater than or equal to 4.0 for both V05 and V06
    - Determination: the cluster seeks homogeneity among members' farms (sector and size)
    - Treatment: the cluster will be further clustered according to the farm characteristics variables (V07-V13 in table 7)
- The cluster has a mean value of greater than or equal to 4.0 for V05 and less than 4.0 for V06
    - Determination: the cluster seeks homogeneity among members' farm sectors and seeks diversity among members' farm sizes
    - Treatment: the cluster will be further clustered according to the farm sector variables (V14-V20 in table 8)

The farm sector variables, V14-V20 described in table 8, are simply binary variables created directly from the farm characteristics variables. If the enterprise type is present on the farm (i.e. the number of acres or head is greater than zero) then the binary variable is equal to one.

Table 8. Farm sector variable summary

Variable Name	Variable Type	Sector	Response Coding	
scconv (V14)	Farm sector Binary	Conventional crops	0 1	Not present Present
scorgc (V15)	Farm sector Binary	Organic crops	0 1	Not present Present
scspcl (V16)	Farm sector Binary	Produce & specialty crops	0 1	Not present Present
scdair (V17)	Farm sector Binary	Dairy	0 1	Not present Present
scbfl (V18)	Farm sector Binary	Beef – feedlot	0 1	Not present Present
scbcc (V19)	Farm sector Binary	Beef – non-feedlot	0 1	Not present Present
schog (V20)	Farm sector Binary	Hogs	0 1	Not present Present

This dual-phase approach could be carried out with any clustering method (e.g. Ward's method, average linkage, K-means, Two-stage method). Since multiple authors promoted its use in the literature, the two-stage clustering method will be used here. The process will be the same as the one described for the two-stage clustering method control: Ward's method will be used to determine a set of cluster "seeds" before carrying out the K-means. Since both Ward's method and the K-means method bypass the proximity matrix, the selection of a proximity measure is not necessary.

Although using two-stage clustering method for two different phases of the analysis seems rather inelegant, it is hypothesized that using two separate phases will do a superior job of placing candidates into peer advisory groups which satisfy their wants. Even though a simpler cluster analysis method (such as average linkage or Ward's method) could be implemented to simplify the methodology, several authors promoted the use of a two-stage approach in order to mitigate some of the short comings of both hierarchical and partitioning methods. The following step-by-step outline view of the cluster analysis methods to be used is provided for additional clarification of the preceding description of methods for the proposed dual-phase approach.

- PHASE ONE: Analyze all individuals using the variables involving discussion topics (V01-V04) and diversity/homogeneity desired (V05-V06)
    - Phase one, stage one—use Ward's method to identify number of clusters and cluster centroids
    - Phase one, stage two—use the Ward's method centroids as initial seeds for k-means analysis
- PHASE TWO: Analyze each cluster identified in phase one as an individual dataset
    - If a cluster has a mean value less than 4.0 for variables V05 and V06, leave as is and do not subject to phase two analysis
    - If a cluster has a mean value less than 4.0 for variable V06 and a mean value greater than or equal to 4.0 for variable V05, subject the cluster to the phase two analysis using the binary sector variables (V14-V20)
        - Phase two, stage one—use Ward's method to identify number of sub-clusters and centroids
        - Phase two, stage two—use the Ward's method centroids as initial seeds for k-means analysis

- If a cluster has a mean value greater than 4.0 for variables V05 and V06, subject the cluster to the phase two analysis using the farm characteristics variables (V07-V13)
  - Phase two, stage one—use Ward's method to identify number of sub-clusters and centroids
  - Phase two, stage two—use the Ward's method centroids as initial seeds for k-means analysis

Evaluation criteria

The cluster solutions resulting from both the controls and the proposed dual-phase approach will be evaluated to assist in answering the research question. Many applications of cluster analysis necessitate the researcher to validate clustering results in order to draw conclusions about an entire population. However, using the actual cluster solutions to draw conclusions about a population of farm managers is not of any particular interest in this research.

Instead, this research is looking at the process, specifically looking at how well each approach (the proposed dual-phase approach and the controls) performs in the creation of peer advisory groups which satisfy the wants of the members. This evaluation is key in answering the research question: how could a clearinghouse organization apply cluster analysis methods to a pool of candidates to effectively create peer advisory groups congruent to the individuals' needs and wants? The evaluation will rely on the assumptions provided earlier in the methodology to assess how well each cluster could be reasonably assumed to satisfy the desires of its members.

After drawing a conclusion regarding the research question, additional commentary will also be provided regarding the unique nature of peer advisory groups and how it relates to certain observations made during the study. This will include the functional usefulness of the peer advisory groups created, general observations contrary to researcher's prior expectations, and miscellaneous concerns regarding the use of cluster analysis methods for the creation of peer advisory groups.

CHAPTER IV

RESULTS AND DISCUSSION

This chapter presents and discusses the results of the study. First, the results of the control methods will be briefly described. Next, results of the proposed alternative approach will be laid out. In order to answer the research question, a thorough evaluation of its performance relative to the controls will be provided. Finally, additional discussion regarding the clustering results as they specifically pertain to the unique setting of peer advisory groups.

Clustering results of control methods

The method implemented as Control 1 was the average linkage method (UPGMA) applied to all observations using all primary variables (V01-V13) using the Euclid distance measure. As shown in figure 5 below, the pseudo t-squared very strongly suggested twenty-two clusters and the CCC somewhat supported this number. The pseudo F was somewhat inconclusive[2]. Therefore, the twenty-two cluster membership will be used in the final evaluation.

[2] For information on interpreting the cluster number criteria, the reader is referred to the literature review.

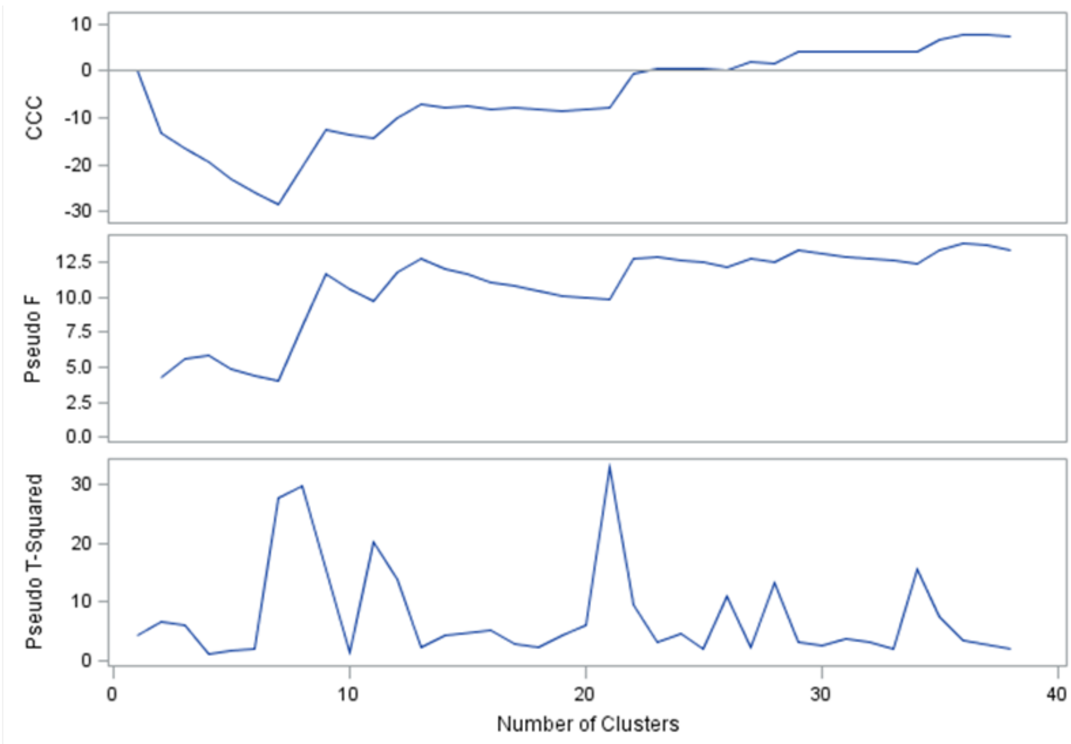

Figure 5. Control 1 cluster number criteria

The method implemented as Control 2 was Ward's method applied to all observations using all primary variables (V01-V13). As shown in figure 6, all three of the criterion strongly suggested five clusters. Therefore, the five cluster membership will be used in the final evaluation.

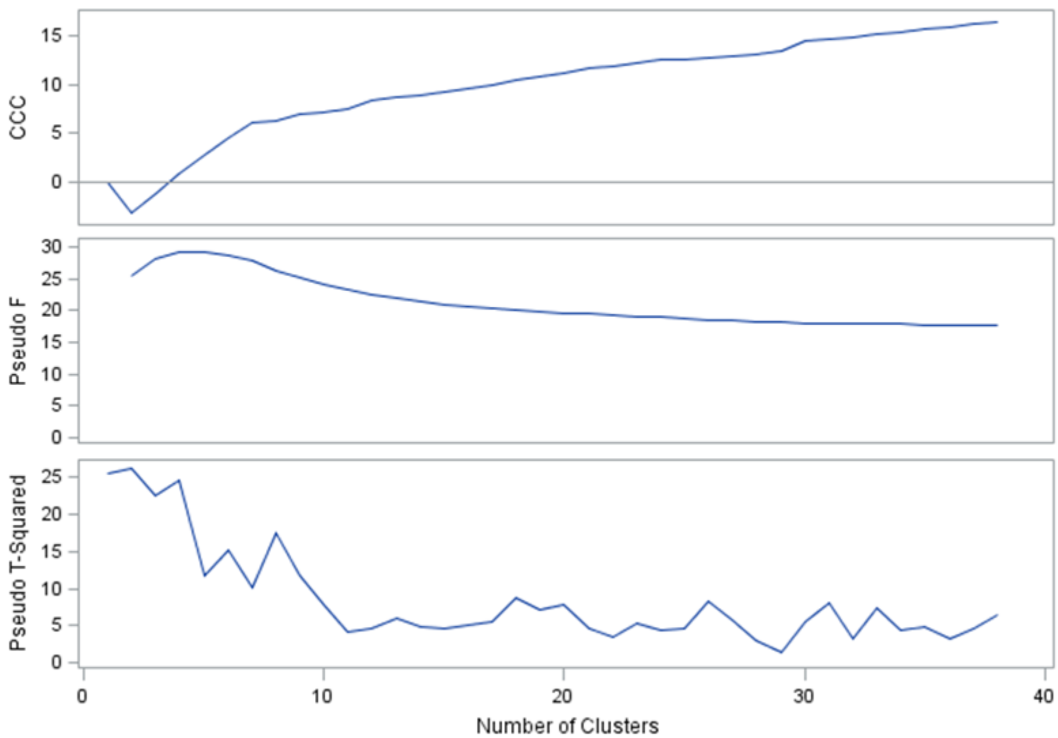

Figure 6. Control 2 cluster number criteria

The method implemented as Control 3 was the k-means method applied to all observations using all primary variables (V01-V13). As suggested in the literature review, the number of clusters suggested by Ward's method (five) was used to initiate the k-means. No "seeds" were designated to initialize the k-means in Control 3.

The method implemented as Control 4 was the two-stage method applied to all observations using all primary variables (V01-V13). It used the number of clusters (five) and cluster "seeds" suggested by Ward's method for initialization. A membership summary for each of these four control methods will be provided later in this chapter.

Clustering results of proposed alternative approach

The first phase of the proposed alternative approach seeks to separate candidates into clusters based on what they are looking for in a group. As the reader may recall from the methodology, the proposed alternative approach does immediately use all of the variables (as the controls do). Instead, only the "desire for group" variables (V01-V06) were used in the first phase of the analysis. In order to implement the two-stage clustering approach, Ward's method was first used to identify the number of clusters and centroids to be used in the K-means analysis. As shown in figure 7 below, the pseudo t-squared statistic very strongly suggested seven or eighteen clusters. The pseudo F and CCC mostly agreed with seven clusters.

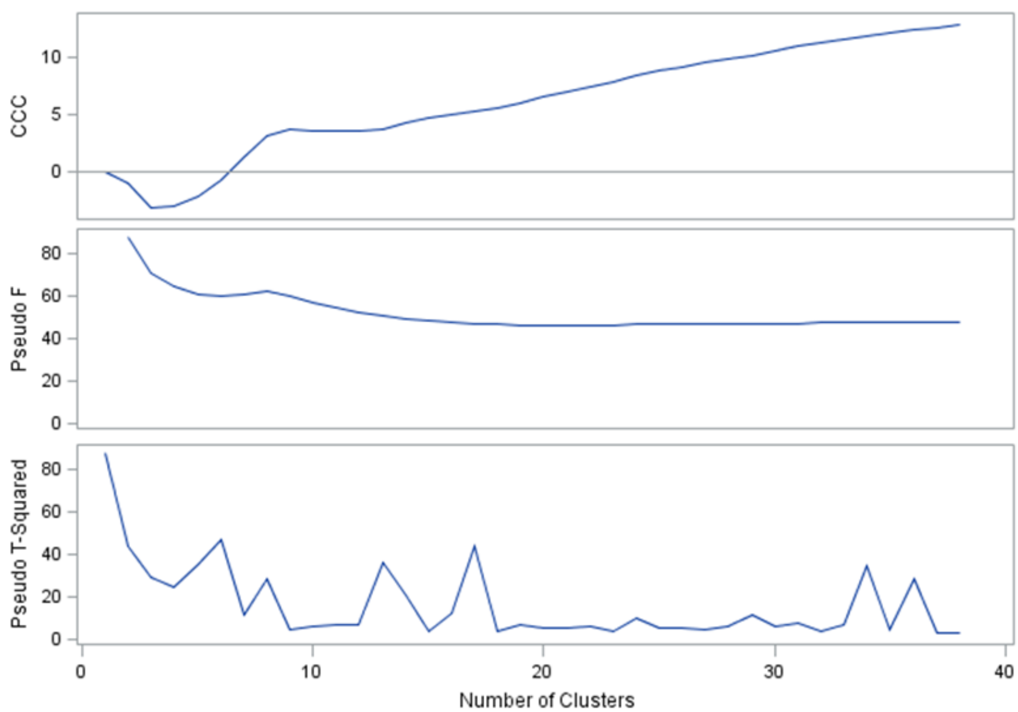

Figure 7. Phase one, stage one cluster number criteria

The seven centroids of the Ward's method cluster solution were therefore used as the "seeds" for the second stage of phase one. The resulting two-stage method membership summary for phase one is provided in table 9.

Table 9. Seven Cluster Solution Membership Summary for Phase One

	Qty of members	iprod	ifinc	iorgmg	ieduc	dsect	dsize
Cluster 1	35	**4.94**	**4.63**	**4.94**	**4.94**	**1.86**	**1.77**
		(.33)	(.48)	(.23)	(.23)	(.35)	(.42)
Cluster 2	51	**4.88**	**4.49**	**4.90**	**4.96**	**4.25**	**3.84**
		(.33)	(.54)	(.30)	(.19)	(.44)	(.41)
Cluster 3	29	**4.90**	**4.79**	**4.93**	**4.93**	**2.14**	**3.59**
		(.30)	(.41)	(.5)	(.25)	(.57)	(.56)
Cluster 4	23	**4.52**	**4.17**	**4.13**	**3.65**	**4.30**	**4.09**
		(.58)	(.48)	(.54)	(.56)	(.46)	(.41)
Cluster 5	19	**3.59**	**3.53**	**4.00**	**4.11**	**2.16**	**2.37**
		(.76)	(.50)	(.46)	(.64)	(.49)	(.74)
Cluster 6	15	**4.80**	**4.40**	**4.73**	**4.67**	**3.87**	**1.73**
		(.40)	(.71)	(.44)	(.47)	(.34)	(.44)
Cluster 7	18	**4.00**	**2.28**	**3.72**	**3.83**	**4.06**	**3.50**
		(1.05)	(.65)	(.93)	(1.07)	(.62)	(.69)

Note: Variable cells include mean (bold) and standard deviation (in parentheses)

Each phase one cluster was individually examined to determine which ones should be subjected to the second phase of the analysis. As can be seen in table 9 above, clusters 1, 3, 5, and 6 all have mean values of less than 4.0 for the variables *dsect* and *dsize* and will therefore be left as is. Clusters 2 and 7 both have a mean of greater than 4.0 for *dsect* and less than 4.0 for *dsize*—these clusters were therefore be subjected to the phase two analysis using the binary sector variables (V14-V20). Cluster 4 has a mean of greater than 4.0 for both variables *dsect* and *dsize*—this cluster was therefore subjected to the phase two analysis using the ordinal variables relating to both size and sector of each individual enterprise (V07-V13).

The determination of the number of clusters was slightly more difficult in the second phase than it was in phase one. Some of the cluster number criteria were inconclusive. Unfortunately, this meant somewhat subjective decisions were made as to how many sub-clusters to use. Table 10 summarizes the choices made for the number of clusters of each. The actual cluster number criteria graphs which were consulted are provided in Appendix B.

Table 10. Summary of Sub-Cluster Centroids to be Used in Phase Two, Stage Two

Cluster	Number of sub-clusters	Comments
2	6	The pseudo t-squared suggested either four or six sub-clusters. The pseudo F and CCC both tended more towards six clusters; therefore, the seeds suggested for six clusters will be used for stage two.
4	9	The pseudo t-squared very strongly suggested nine sub-clusters. The pseudo F and CCC were mostly inconclusive. Therefore, the seeds suggested for nine clusters will be used for stage two.
7	3	The pseudo t-squared very strongly suggested three sub-clusters. The pseudo F and CCC were mostly inconclusive. Therefore, the seeds suggested for three clusters will be used for stage two.

The k-means method was then implemented using the designated "seeds" suggested by Ward's method for Clusters 2, 4, and 7. For cluster 4, no memberships were changed as a result of the k-means. Slight changes occurred in Clusters 2 and 7.

Evaluation

The results of the controls and the proposed alternative ("dual-phase") approach must be evaluated in order to answer the research question. Before providing an evaluation, it is illustrative to provide an adjusted rand index (ARI) comparison of the different approaches used in the methodology here. The ARI here is not meant to suggest that one method is better than another. Instead, shows percent agreement between two methods (adjusting for the agreement which occurred merely due to chance). In order to compare methods using ARI, each method must use the same number of clusters. Therefore, the calculations in table 11 use the memberships for twenty-two clusters in order to stay consistent with the proposed dual-phase approach. The numbers here suggest that a lot of the agreement between cluster method solutions were due to chance, with the exception of the agreement between Ward's method and the two-stage method. This makes sense since the Ward's method centroids were used as "seeds" within the two-stage method. The numbers here are simply intended to underscore the importance of the selection of the proper clustering method, because cluster membership of different methods can potentially be drastically different from one another.

Table 11. ARI Comparison for 22 Cluster Memberships

	Average	Ward's	K-Means	Two-Stage	Dual-phase (using two-stage method)
Average		37%	45%	38%	17%
Ward's	37%		47%	95%	23%
K-Means	45%	47%		49%	24%
Two-Stage	38%	95%	49%		23%
Dual-phase	17%	23%	24%	23%	

As previously described, the typical objective of cluster analysis methods is to minimize within-group variance while maximizing between-group variance. The maximization of between-group variance, however, is not a necessary requirement for the unique setting of peer advisory groups. Of all methods used (controls and the proposed alternative), the average linkage method resulted in the lowest within-group variance. Of the other three controls, the two-stage method had the lowest within-group variance, as should be expected since it uses the intelligent "seeds" suggested by Ward's method to further reassign memberships to further optimize the k-means procedure.

It was also argued, however, that the minimization of within-group variance across all attributes does not fit well with the assumption that some participants are seeking diversity among members for certain attributes. The ultimate test here is then to determine which method resulted in clusters which best met the desires of members, not simply the least variance. Table 12 below provides some description of each of the final clusters for all methods used. The column labeled "Avg St Dev for discussion topics" is a simple average of the standard deviations for variables V01, V02, V03, and V04. For the columns labeled as "Desire for diversity of sector?" and "Desire for diversity of size?" the mean value for variables V05 and V06 were used to make the determination. If the mean value fell between 1.0 and 2.99, it was categorized as "Yes." If the mean value fell between 3.0 and 3.99, it was categorized as "Somewhat." If the mean value was 4.0 or greater, it was categorized as "Yes." For the columns labeled as "Actual diversity of sector" and "Actual diversity of size," descriptions of very low, low, moderate, high, and very high were assigned. These were based on researcher judgment of the standard deviations and ranges of values for variables V07 through V13 for size and V14 through V20 for sector. The number of members in the cluster was also considered in some instances. For example, a cluster with 30 members and 50% of them operating hog enterprises might be considered moderate diversity; whereas, a cluster with only 2 members and 50% of them operating hog enterprises might be considered high diversity. When making assignments, the intent was to err on the side of moderation.

Table 12. Cluster Solution Summaries

Cluster	Members	Avg St Dev for discussion topics	Desire for diversity of sector?	Desire for diversity of size?	Actual diversity of sector	Actual diversity of size
	CONTROL 1 –AVERAGE LINKAGE WITH EUCLID DISTANCE					
1	45	0.619	Yes	Yes	Moderate	Moderate
2	62	0.577	No	Somewhat	High	High
3	19	0.443	Somewhat	Somewhat	Low	Moderate
4	19	0.368	Yes	Yes	Low	Moderate
5	5	0.300	Yes	Somewhat	Very low	Moderate
6	5	0.322	No	Somewhat	Very low	Low
7	10	0.811	No	Somewhat	Very high	Moderate
8	2	0.000	Yes	Yes	Moderate	Very low
9	7	0.468	Yes	Yes	Low	Moderate
10	3	0.471	No	Somewhat	Very low	Very low
11	2	0.500	No	No	Moderate	Low
12-22	*One member*					
	CONTROL 2 –WARD'S METHOD					
1	39	0.495	Yes	Yes	High	Low
2	72	0.670	No	Somewhat	Very high	High
3	21	0.515	Somewhat	Somewhat	Low	High
4	23	0.492	Yes	Yes	Moderate	Moderate
5	35	0.955	Somewhat	Somewhat	Very high	Very high
	CONTROL 3 –K-MEANS (NO SEEDS)					
1	37	0.659	Somewhat	Somewhat	Very high	Very high
2	64	0.561	Yes	Yes	High	High
3	*One member*					
4	13	0.477	Somewhat	Somewhat	Moderate	Moderate
5	75	0.807				

Table 12. Continued

Cluster	Members	Avg St Dev for discussion topics	Desire for diversity of sector?	Desire for diversity of size?	Actual diversity of sector	Actual diversity of size
	CONTROL 4 –TWO-STAGE METHOD					
1	50	0.551	Yes	Yes	Moderate	Moderate
2	71	0.735	No	Somewhat	Moderate	High
3	20	0.496	Somewhat	Somewhat	Very low	Moderate
4	23	0.507	Yes	Yes	Moderate	Low
5	26	0.975	Somewhat	Somewhat	Moderate	Moderate
	PROPOSED ALTERNATIVE: DUAL-PHASE APPROACH (USING TWO-STAGE METHOD)					
1	35	0.320	Yes	Yes	High	Very high
2A	17	0.296	No	Somewhat	Very low	High
2B	9	0.354	No	Somewhat	Low	Very high
2C	5	0.100	No	No	Very low	Moderate
2D	5	0.222	No	No	Low	Moderate
2E	9	0.203	No	Somewhat	Low	Low
2F	6	0.304	No	No	Low	Moderate
3	29	0.304	Yes	Somewhat	Very high	Very high
4A	10	0.506	No	No	Low	Low
4B	2	0.000	No	No	Low	Low
4C	2	0.375	No	No	Very low	Low
4D	3	0.236	No	No	Very low	Low
4E	2	0.375	No	No	Low	Low
4F	*One member*					
4G	*One member*					
4H	*One member*					
4I	*One member*					
5	19	0.589	Yes	Yes	High	Very high
6	15	0.506	Somewhat	Yes	Moderate	Moderate
7A	9	0.813	No	Somewhat	Low	High
7B	7	1.011	No	Somewhat	High	Moderate
7C	2	0.375	Somewhat	Somewhat	Very low	Moderate

First, the standard deviations of the discussion topic variables (V01-V04) were considered. According to Assumption (1) stated in the methodology, it is preferred for an individual to be grouped with other people who are likely to share similar types of information with the peer group. A very low standard deviation is preferred as it suggests that members of the cluster are mostly willing to discuss the same topics. Clusters observed with relatively large standard deviations were considered to be issues and are described in table 13. Next, the satisfaction of desired level of diversity was evaluated. This was first considered by simply comparing each cluster's mean value for desired level of diversity (Columns "Desire diversity of sector?" and "Desire diversity of size?" in table 13) to the actual levels of diversity in the cluster. Issues that were noted are described in table 13. To err on the side of moderation, differences between desired levels and actual levels were not considered "issues" if the desired level was noted as "somewhat" or if the actual level was noted as "moderate."

Table 13. Issues Encountered in Results

Method	Cluster	# Members	Issue
Control 1	2	62	On average, members did not want diversity of sector but there was actually high diversity of sectors.
Control 1	4	19	On average, members wanted diversity of sector but there was actually low diversity of sectors.
Control 1	5	5	On average, members wanted diversity of sector but there was actually very low diversity of sectors.
Control 1	7	10	Quite large standard deviations for discussion topics. On average, members did not want diversity of sector but there was actually very high diversity of sectors.
Control 1	8	2	On average, members wanted diversity of size but there was actually very low diversity of size.
Control 1	9	7	On average, members wanted diversity of sector but there was actually low diversity of size.
Control 2	1	39	On average, members wanted diversity of size but there was actually low diversity of size.
Control 2	2	72	On average, members did not want diversity of sector but there was actually very high diversity of sector.
Control 2	5	35	Quite large standard deviations for discussion topics.
Control 3	5	75	Quite large standard deviations for discussion topics.
Control 4	4	23	On average, members wanted diversity of size but there was actually low diversity of size.
Control 4	5	26	Quite large standard deviations for discussion topics.
Dual-Phase	7A	9	Quite large standard deviations for discussion topics.
Dual-Phase	7B	7	Quite large standard deviations for discussion topics. On average, members did not want diversity of sector but there was actually high diversity of sector.

It was quite surprising to see no issues with agreement between desired diversity and actual diversity for Control 3. This was mostly due to the fact that the majority of the categories for Control 3 were marked as "somewhat" desiring diversity or actually having "moderate" diversity which, as previously stated, were not considered major issues. Simply looking at what the average desire of the group is does not necessarily suffice, however. Therefore, the desired diversity of each individual member was also compared to the actual diversity of the individual's respective cluster. For this, the following instances were considered "extreme" cases:

- an individual who indicated the desire for a peer advisory group with *extremely diverse* sectors of agriculture and was assigned to a group with either low or very low diversity of sectors
- an individual who indicated the desire for a peer advisory group with *extremely diverse* enterprise sizes and was assigned to a group with either low or very low diversity of enterprise sizes
- an individual who indicated the desire for a peer advisory group with *extremely similar* sectors of agriculture and was assigned to a group with either high or very high diversity of sectors
- an individual who indicated the desire for a peer advisory group with *extremely similar* enterprise sizes and was assigned to a group with either high or very high diversity of sizes.

These extreme cases would be considered to be individuals with a very high likelihood of being unsatisfied with the group into which they were placed based on the assumptions of this study. The number of extreme cases noted in the cluster solutions of each method is summarized in table 14 below.

Table 14. Extreme cases noted

Method	Extreme cases
Control 1	19
Control 2	30
Control 3	23
Control 4	12
Dual-Phase	3

After considering the information provided in tables 13 and 14, it can reasonably be concluded that the proposed dual-phase approach most effectively created peer advisory groups which satisfied the desires of members. The issues that were encountered in the results of the dual-phase approach affected a very small number of individuals. The dual-phase approach also resulted in the fewest number of extreme cases in which an individual would very likely be dissatisfied with the group into which he or she was assigned. It should be noted that the dual-phase approach here used the two-stage clustering method. The approach could be implemented using other methods such as average linkage or Ward's method. Outcomes of the dual-phase approach using these were not evaluated here, but it could be hypothesized that they would perform better than using average linkage or Ward's method *without* the dual-phase approach.

Now that a solution to the research question has been identified, additional commentary will be provided regarding the unique nature of peer advisory groups and how it relates to certain observations made during the study. Peer advisory groups are most effective with five to fifteen members. The results, however, have a wide range of cluster sizes. Under the dual-phase approach, nine of the clusters have fewer than five members and four of the clusters have more than fifteen members. The groups which are too large could perhaps be further divided into smaller groups; however, there is no solution for groups which are too small.

During the data collection phase, it was observed that a very large number of respondents indicated a high degree of willingness to discuss *all* discussion topics. As described in the literature review, there is a tendency for agricultural peer advisory groups to focus on one or two general areas of discussion topics; therefore, the actual observations here were contrary to prior researcher expectations. The time a manager has to dedicate to a peer advisory group meeting is limited—participants can either discuss many topics in little detail or a few topics in great depth. It was expected that more respondents would have interest in looking at things much more in-depth and clusters would show a preference for one or two of the discussion topics. This, however, was not the case. There is a possibility that the original expectation was flawed. However, there are other potential reasons for this. Perhaps the survey questions lacked clarity and respondents did not understand that indicating a strong willingness to discuss all topics means spending less time discussing each in-depth. Some respondents may have simply indicated "extremely likely" to discuss all topics because they did not put much time or thought into the answers. Also, by indicating "extremely likely" for all four discussion topics, an individual might simply have a strong desire to be a part of *any* type of peer advisory group discussion, regardless of which topics the group discusses in-depth.

Finally, general concerns with using cluster analysis methodology for creating peer advisory groups should be noted. Although the flexibility of cluster analysis allows the user to customize the analysis to best fit the data, the numerous choices the user must make can create problems. First, the user must fully understand the intricacies of all the available options and how to implement the procedure in statistical software. Unfortunately, a "clearinghouse" organization for creating peer advisory groups may not have such an individual or available software and would need to hire a consultant to assist with the cluster analysis procedures. Also, a couple particular traits of peer advisory groups are somewhat difficult to address through cluster analysis. It is difficult to "force" the cluster analysis to create groups of five to fifteen members (the optimum peer advisory group size) while still creating satisfactory groups. Also, geographical distance between members could be a challenge to address. Similarly to the homogeneity/diversity among members' sectors and sizes of operations, examples of peer advisory groups show varying degrees of closeness/distance between members. Groups might consist of members in a rather small geographical area, members within a certain region (maybe three or four different states), or members from very diverse areas across the country. Unfortunately, the anonymity of the survey prevented the collection of geographical location information so addressing this aspect was not possible. However, even if this were to be collected, it still might be somewhat difficult to incorporate into a cluster analysis. Simply assigning an individual to a "region" category does not account for the closeness of individuals near the border of two regions. Calculating the actual distance between every individual pair of candidates' zip codes would be time consuming. Finally, the goal of this cluster analysis application was to place *all* candidates from the pool into a suitable peer advisory group. Therefore, no outliers were removed during the analysis. Cluster analysis results can be greatly impacted by outliers in many cases, however, which is another slight cause for concern.

CHAPTER V

SUMMARY AND CONCLUSIONS

This concluding chapter provides a brief summary and conclusion of this thesis research. Limitations of this study will also be acknowledged. Finally, recommendations for further research are suggested.

Summary and conclusions

Many individuals struggle with identifying other people to participate in a peer advisory group with. Some have suggested that a "clearinghouse" organization be created to assist in the formation of peer advisory groups. There are multiple approaches that a clearinghouse organization could take to creating the groups. This thesis focused on the use of cluster analysis by the clearinghouse and sought to determine an effective means of using cluster analysis methods to create peer advisory groups which met the desires of members from a pool of candidates.

A peer advisory group blends aspects of peer groups with qualities of business advisory boards. *Homophily*, or member sameness, characterizes peer groups and can result from selection or socialization. Peer groups are often naturally occurring, such as high school cliques but are also sometimes created artificially for a specific purpose, such as a book club. Some peer groups like Delphi forecasting groups or Alcoholics Anonymous purposefully assemble to learn from one another, similar to peer advisory groups. These, however, lack the business advisory aspect of a peer advisory group. A business advisory board is a panel of experts, usually with different backgrounds and expertise, which provides feedback, advice, and support to a CEO. Rather than the one-way interaction of a business advisory board, the peer advisory group members all act as advisory board members for one another. The "peer advisory group" concept aggregates the common themes of many individual examples of similar groups which may have different designations. Three major themes of all peer advisory groups are active participation, equality, and confidentiality. Specific examples of peer advisory groups illustrate how groups can be structured quite differently from one another. A few potential benefits of peer advisory groups include: open and objective observations, exposure to diversity, a support structure, assistance in identifying blind spots and prioritizing issues, and a sounding board.

In reviewing many examples of peer advisory groups and opinions of individuals who have been a part of a peer advisory group, it was concluded that potential candidates should be placed with other individuals who have similar goals and desires for the group. Therefore, cluster analysis seemed an appropriate method with which to attempt to create peer advisory groups.

Cluster analysis procedures attempt to group entities into nearly homogeneous "clusters" based on their similarity of given attributes and it is commonly used for creating descriptive configurations or classification systems. It can easily work with multiple variables and many of the methods are fairly straightforward algebraic algorithms. The most common methods fall into two popular categories: hierarchical methods and partitioning methods. Hierarchical methods combine objects and clusters one-by-one. The researcher must then determine the appropriate number of clusters. Conversely, partitioning methods use a pre-defined number of clusters and "sweep" through the data, rearranging the cluster memberships until a certain criterion is optimized.

When applying cluster analysis, a researcher must answer many questions. What variables should be used? Should the data be standardized? How should the similarity between observations and clusters be measured? What number of clusters is appropriate? Are the results useful and valid? In addition to these, a very wide array of specific methods can be used. The literature provides many criticism of cluster analysis, most importantly its reliance on sometimes subjective researcher decisions. To assist researchers in overcoming some of the challenges, multiple authors have offered suggestions of ways to help alleviate some of these subjective decisions.

In order to address the research question, this study collected primary data via mail survey to create a hypothetical "candidate pool" from which to attempt to create a set of peer advisory groups. The ultimate test of the cluster results in this case are whether or not members could be reasonably expected to be satisfied with the group into which they were placed and three key assumptions were made regarding this satisfaction based on the literature review. One of these assumptions created a bit of a challenge. Typically, the objective of cluster analysis involves minimizing within-group variance. However, one of the assumptions suggested that some individuals would be more satisfied with a group containing diversity among certain attributes, meaning that certain individuals do not want to be placed into a group with minimum variance for certain variables. Therefore, this study proposed an approach to mitigate this problem. Four control methods were also implemented with which to compare the effectiveness.

The proposed alternative approach (the "dual-phase" approach) was designed to be completed in two phases. The first phase clustered individuals based on what each individual desires for his or her group to involve, a notion suggested by the careful review of examples of agricultural peer advisory groups. Variables for this phase related to what discussion areas the individual was likely to share with the group and the individual's preferred level of homogeneity or diversity among fellow members' farming operations. The clusters identified in the first phase were then examined individually. If the cluster, on average, showed the desire to consist of diverse farming operations, it was left as-is. If the group, on average, showed the desire to consist of homogeneous farming operation, the group was subjected to the second phase of the analysis. Variables for this phase related to the actual farming operations of the producers. Using separate phases for the analysis helped lessen the potential for grouping of individuals by farm characteristic who preferred to participate in a peer advisory group with managers of different types of farms.

Several of the literature's suggestions for improving analyses were incorporated throughout the study: cognitive variable selection, the use of "stopping rule" indices for selecting a number of clusters, and the two-stage method which uses hierarchical and partitioning methods in tandem.

Finally, results of the controls and the proposed alternative were evaluated in order to determine the method which most effectively created peer advisory groups which could be reasonably assumed to satisfy the members. Based on one of the study's assumptions, clusters with relatively large standard deviations for the discussion topic variables were considered to be potential issues. Also, groups which resulted in actual diversity levels opposite that of the average desired level of diversity (e.g. the group on average desired a high level of diversity but the group actually consisted of a low level of diversity) were considered potential issues. Of the methods implemented in the study, the potential issues affected the fewest number of people under the proposed dual-phase approach. To further examine desired versus actual levels of diversity on an individual basis (rather than the average desire of the group), "extreme" cases were identified. For example, an individual who expressed the desire for a "very high" level of diversity for a peer advisory group and was assigned to a group with either a low or very low level of diversity would be considered an "extreme" case—one in which the individual (according to the study's assumptions) has a very high likelihood of being unsatisfied with his or her assigned group. Of the methods implemented in the study, the fewest number of extreme cases were identified under the proposed dual-phase approach. Therefore, it was concluded that the proposed dual-phase approach most effectively created peer advisory groups which satisfied the desires of members.

Limitations

It is recognized that this study certainly did not examine every possible cluster analysis methodology which cluster analysis could be used to create peer advisory groups. Different combinations of attributes, proximity measures, clustering methods, and/or cluster number identification techniques might be appropriate for further comparisons. As was noted in the evaluation, the dual-phase approach was implemented in this study using the two-stage clustering method, but could have also been implemented using other clustering methods such as average linkage or Ward's method. As is the case for many cluster analysis applications (as well as many other statistical analyses), this study included some degree of unavoidable researcher subjectiveness. For example, the descriptions provided in table 12 might have been coded in a slightly different manner by a different researcher. Every attempt was made, however, to code these as consistently as possible so that any bias would at least be consistently biased across the evaluations and not biased in favor of one specific approach.

After conducting the analysis, a few problems were uncovered which could not be adequately addressed in thesis. Several of these have to do with the construction of the survey with which the primary data were collected. First of all, the scales for the diversity/homogeneity were somewhat confusing. By indicating "somewhat diverse," are respondents also implying "somewhat similar" at the same time? Also, it was somewhat difficult to distinguish the diversity/homogeneity of a farm's sector of agriculture since many farms are involved in several different enterprises. This could potentially cause issues when clustering based on sector. For example, Cluster 2F of the proposed dual-phase approach consisted entirely of produce/specialty crop producers who indicated a preference for homogeneity of sector of agriculture. One member, however, also has a dairy operation. What if when this individual indicated a preference for fellow members of a similar sector of agriculture, he or she was referring to other *dairy* farmers? In this situation, that individual would not have received a group that fits his desires since he is the only dairy farmer in the group. Therefore, it could potentially be useful to ask participants which specific sector(s) of agriculture, if any, they preferred to be grouped with. In addition, the conventional crops category aggregated a very large number of crops. Although many of these can be grown somewhat interchangeably, some producers may want a group of mostly corn farmers or mostly cotton farmers. This difference was not addressed here.

In addition, there also seems to be room for improvement regarding the discussion focus questions. As described in the final evaluation, it was surprising result for so many respondents to indicate they were "extremely likely" to participate in *all* four types of discussions, as this was not at all what current peer advisory group members conveyed at the peer advisory group conference. Perhaps an additional question could be asked to indicate an *order* of preference, from most preferred to least preferred. Furthermore, the data used here came from freewill survey participants who may have never previously heard of the peer advisory group concept. It would be interesting to see if responses from this study's participants would be markedly different from that of actual candidates—individuals who are taking active steps to become a part of a group and most likely already have *some* prior knowledge of the peer advisory group concept.

The inability to collect geographic information about the producers also limits this study. Since some groups tend to consist of members who are quite geographically dispersed and others consist of members who live in smaller vicinity, the actual geographic distance between potential members could have been used as a second phase variable. As previously noted in the methodology, however, determining a best way to put geographical location into an attribute form usable in cluster analysis could be a challenge.

The final and perhaps most limiting aspect here involves the lack of an appropriate measurement for the "goodness of fit" of each cluster solution. Again, this application is quite different from the typical goals of cluster analysis. Here, the goal is not to create a robust descriptive configuration. Are the candidates (objects) satisfied with the groups into which they were placed? Although assumptions about what would lead to member satisfaction were used to try to answer this, the ultimate test would be to actually form the groups and later measure the satisfaction of members of the groups. Unfortunately, this was not plausible within the realm of this study.

Recommendations for further research

As can easily be discerned from the lack of academic literature regarding peer advisory groups, plenty of opportunities for new research in that area are available. A few of these could have been particularly useful to this study as a more concrete foundation for some of the conclusions which heavily relied on specific real-world examples. Academic research on common traits among peer advisory groups, as well as aspects which specific groups differentiate from one another could be beneficial. It might also be interesting to examine member satisfaction of peer advisory groups and the personal and group characteristics which may or may not be related to that satisfaction. Also, do the most effective members (as perceived by fellow members) share any certain traits? Common reasons as to why so few peer advisory groups exist among agricultural producers could also provide interesting results: perhaps there are underlying perceptions from farmers which could be addressed. Further investigations could also be completed evaluating the potential uses of methods other than cluster analysis for the formation of peer advisory groups.

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APPENDIX A

SURVEY

The mail survey administered for this study included a cover letter, consent information sheet, a “Brief introduction to peer advisory groups in agriculture” information sheet, and the survey. The survey was divided into Sections A and B. Section A included questions about the individual and the individual’s farming operation. Section B included questions about the individual’s hypothetical “ideal” peer advisory group. This Appendix first includes the exact verbiage from the “Brief introduction to peer advisory groups in agriculture” information sheet and then provides tables of the exact survey questions and Likert-scale responses used as variables in the study.

Information sheet verbiage

Many farmers feel as though they are “on an island.” Even though there may be many other farmers within his or her social circle, a farmer may have problems discussing certain topics or issues with these individuals. This might be because they manage very different operations and therefore face completely different problems. It may also be that they do not feel comfortable sharing intimate details with someone in the same community as their own.

Peer advisory groups can be formed as a way for members to exchange ideas and learn from the experiences and opinions of others. There is not one specific template for how a peer advisory group should function, because each group is tailor-made to be exactly what the members want it to be.

- A “peer” group is made up of people who think of each other as equals: members respect one another’s ideas, opinions, and suggestions.
- Everyone actively participates in peer advisory groups—meetings of these groups are not the type where you sit in an audience and listen to somebody else speak the entire time.
- Groups sometimes share and discuss very personal or guarded information.
- Groups are built on a foundation of confidentiality and trust among members.
- Most (not all) groups are relatively small, in order to maintain an intimate and confidential relationship among group members.
- Groups can evolve over time. For example, the group might change what type of information is shared, how often the group meets, or even add/eliminate members from the group.
- Similarity/Diversity among members varies from group to group. Some might feel that similarity is beneficial because individuals with farms very similar to your own are more likely to face similar problems to your own. On the other hand, some might feel that diversity is beneficial since there will be more opportunity for different opinions and new perspectives.

Group members determine what topics are discussed at meetings. The following list includes broad categories and very simple examples of topics that existing agricultural peer advisory groups have stated that they sometimes discuss. Keep in mind that one single group does not necessarily share information within ALL of these categories.

Production Issues

Examples:

Benchmarking herd metrics or crop yields

Identifying areas needing improvement and how to achieve targets/goals

Financial Issues

Examples:

Key ratios and cost per head/acre comparisons

Enterprise budgeting

Organizational Management Issues

Examples:

Management succession/transitions

Employee performance

Education and Skills development

Examples:

Hiring consultants to come and work with the group on specific issues (for example, improving marketing strategies)

Discussing current issues such as new technologies, conservation practices, or livestock disease concerns

Survey questions and Likert-scale responses

This first set of questions was included in Part A (Individual Profile) of the survey. These questions were proceeded with the following instructions:

> "Please answer the following farm size questions according to total quantity *managed*. For example, include all livestock that your farm might contract feed, even if your farm does not technically own the animals."

Table 15. Survey Questions and Likert-Scale Responses (Individual Profile)

Question	Responses
Conventional crops (acres)	Zero
Examples: corn, soybeans, wheat,	Less than 2,500
cotton, sorghum, potatoes, rice,	2,500 – 5,000
barley, alfalfa, etc.	5,000 – 10,000
	Greater than 10,000
Organic crops (acres)	Zero
	Less than 1,000
	1,000 – 2,500
	2,500 – 5,000
	Greater than 5,000
Produce & specialty crops (acres)	Zero
Examples: lettuce, tomatoes,	Less than 100
onions, sweet corn, berries,	100-300
melons, orchards, vineyards,	300-1,000
tobacco, etc.	Greater than 1,000
Dairy	Zero
	Less than 600
	600-2,000
	2,000-5,000
	Greater than 5,000
Beef – feedlot (average total head,	Zero
one-time capacity)	Less than 1,000
	1,000 – 10,000
	10,000-25,000
	Greater than 25,000
Beef—non-feedlot (average total	Zero
head)	Less than 250
	250-500
	500-1,000
	Greater than 1,000
Hogs (average total head, one-	Zero
time capacity)	Less than 500
	500-2,000
	2,000-5,000
	Greater than 5,000

The next two sets of questions were included in Section B of the survey. The introduction to this section included the following text:

> "For Section B, consider if you were to create your own "ideal" peer advisory group and respond to the questions with what you would want the value of each attribute to be. **There are no right or wrong answers—these values are specific to you and what benefits you seek to obtain from your group**."

The following four questions within Section B were preceded with the text:

> "The following set of topics may or may not be discussed within peer advisory groups. Answer according to <u>*how likely you are to share information*</u> about each topic within your own "ideal" group. For examples, of each topic, please refer to the enclosed 'Brief introduction to peer advisory groups in agriculture' sheet."

Table 16. Survey Questions and Likert-Scale Responses (Discussion Topics)

Questions	Responses (same five responses were available for all four questions)
Production issues	Extremely unlikely
Financial issues	Somewhat unlikely
Organizational management issues	Neutral
Education and skills development	Somewhat likely
	Extremely likely

This final set of questions within Section B was preceded with the text:

> "As stated on the 'Brief introduction to peer advisory groups in agriculture' sheet:

'Some might feel that similarity is beneficial because individuals with farms very similar to your own are more likely to face similar problems to your own. On the other hand, some might feel that diversity is beneficial since there will be more opportunity for different opinions and new perspectives.'

Keeping this in mind, please indicate the degree of similarity/diversity which you prefer among members of your "ideal" group for the following attributes:"

Table 17. Survey Questions and Likert-Scale Responses (Within-Group Similarity/Diversity

Questions	Responses (same five responses were available for all four questions)
Ages of group members	Extremely diverse
Level of formal education of group members	Somewhat diverse
Sectors of agriculture that the group members' respective farms are involved in (i.e. row crop, beef, hogs, dairy, fruit/vegetable, etc.)	Neutral Somewhat similar Extremely similar
Physical sizes of the group members' respective farms (head of livestock or acres of cropland)	

The reader should note that age and education level were included as potential variables in this section. A very small percentage of respondents indicated the desire for homogeneity of these attributes. Therefore, these variables were omitted from the study.

APPENDIX B

PHASE TWO, STAGE ONE DOCUMENTATION

The following figures provide documentation for the choice of sub-cluster centroids (as provided in table 10) to be used in phase two, stage two of the proposed alternative method. For information on interpreting the cluster number criterion, the reader is referred to the literature review.

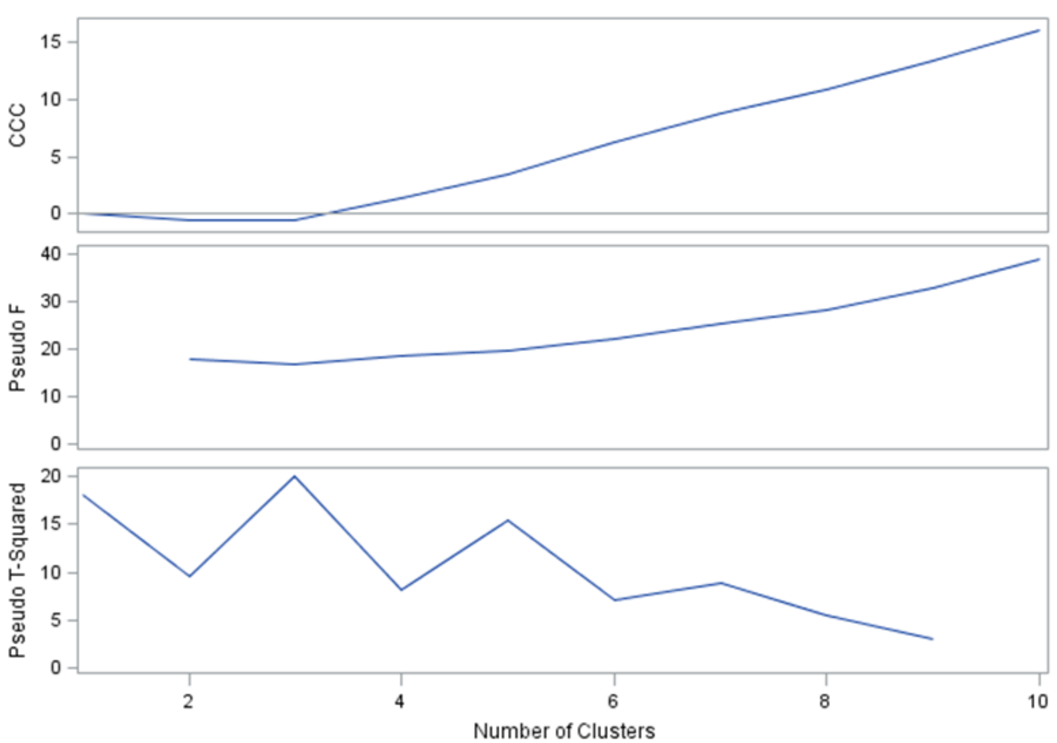

Figure 8. Phase two, stage one cluster number criteria for Cluster 2

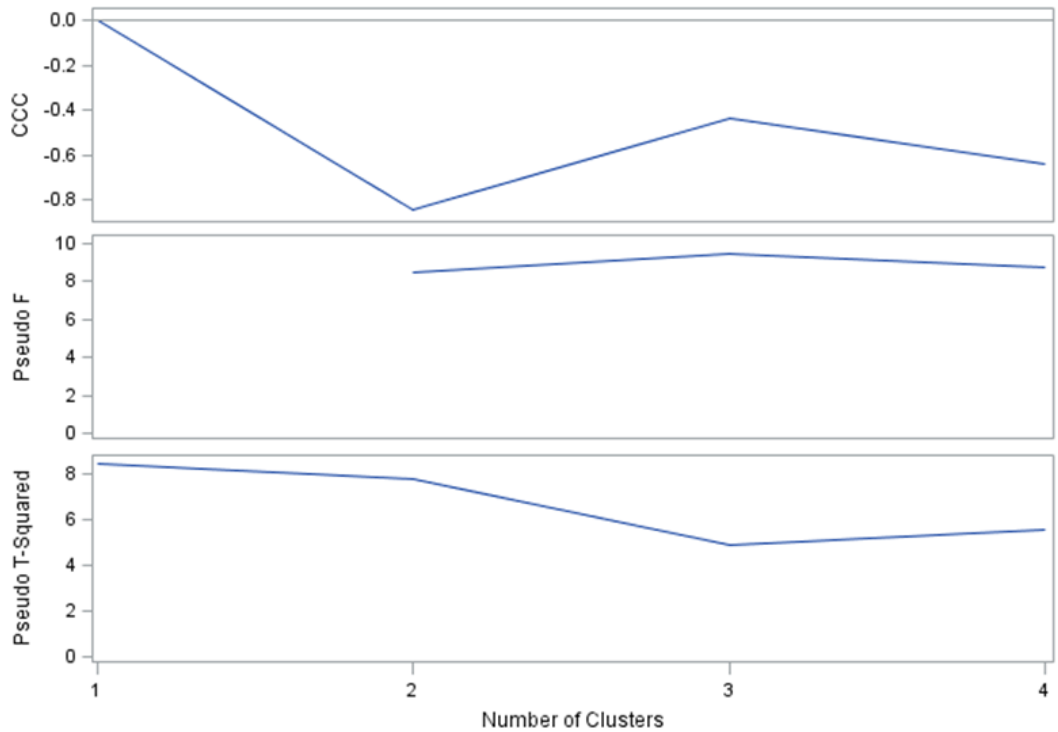

Figure 9. Phase two, stage one cluster number criteria for Cluster 4

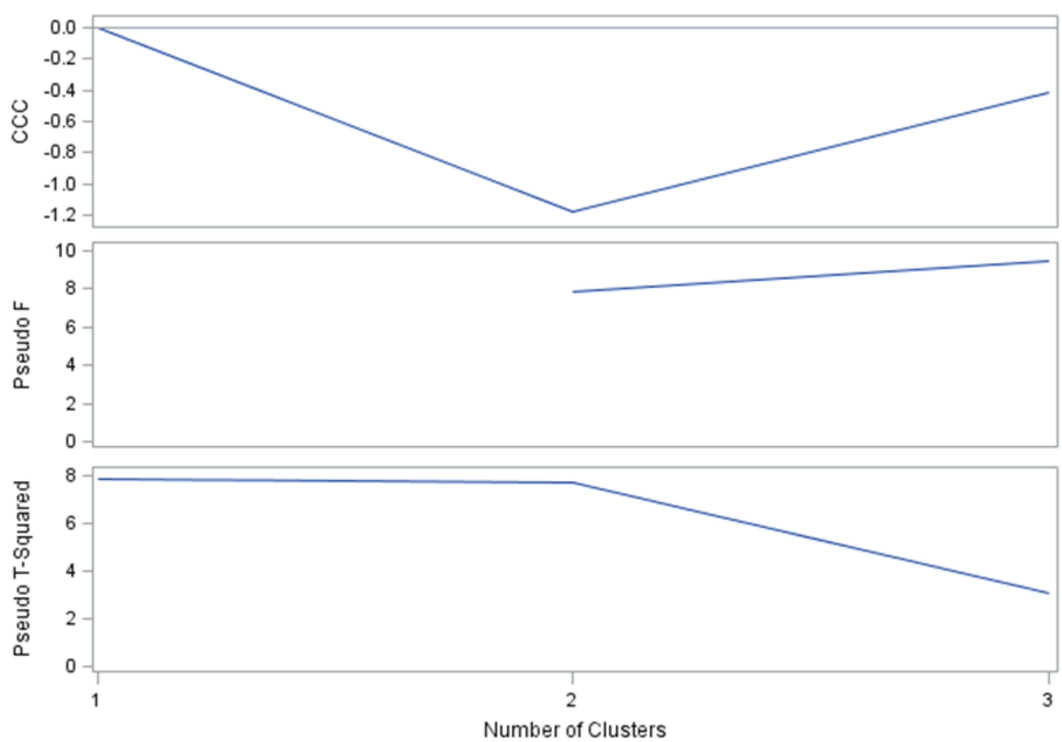

Figure 10. Phase two, stage one cluster number criteria for Cluster 7

APPENDIX C

SAS CODE

```
ods graphics on;
ods html;

******* CONTROL METHODS******;
title1 'CONTROL1: Average linkage with Euclid';
proc cluster data=thesis.data2 method=average ccc pseudo plots=all
outtree=Thesis.CTRL1tree;
var iprod ifinc iorgmg ieduc dsect dsize fconv forgan fprodu fdairy ffeed fgraze fhogs;
run;

goptions hby=.5in htext=.25pct htitle=1pct;
axis1 order=(0 to 1.75 by .25);
axis2 order=(0 to 0.15 by .05);
axis3 order=(0 to 2.25 by .25);

title1 'CONTROL1: 22 cluster solution';
proc tree data=thesis.CTRL1tree out=thesis.CTRL1solution nclusters=22 haxis=axis1
horizontal;
copy iprod ifinc iorgmg ieduc dsect dsize fconv forgan fprodu fdairy ffeed fgraze fhogs;
run;

title1 'CONTROL2: Wards method';
proc cluster data=thesis.data2 method=ward ccc pseudo plots=all
outtree=thesis.CTRL2tree;
var iprod ifinc iorgmg ieduc dsect dsize fconv forgan fprodu fdairy ffeed fgraze fhogs;
run;

title1 'CONTROL2: 5 cluster solution';
proc tree data=thesis.CTRL2tree out=thesis.CTRL2solution nclusters=5 haxis=axis2
horizontal;
copy iprod ifinc iorgmg ieduc dsect dsize fconv forgan fprodu fdairy ffeed fgraze fhogs;
run;

title1 'CONTROL3: Kmeans with no seeds and 5 clusters';
proc fastclus data=thesis.data2 out=thesis.CTRL3 maxclusters=5 maxiter=100;
id obs;
var iprod ifinc iorgmg ieduc dsect dsize fconv forgan fprodu fdairy ffeed fgraze fhogs;
```

```
run;

title1 'CONTROL4: Kmeans with seeds suggested by Wards';
proc fastclus data=thesis.Data2 seed=thesis.Ctrl4seeds out=thesis.Ctrl4solution
maxclusters=5 maxiter=100;
id obs;
var iprod ifinc iorgmg ieduc dsect dsize fconv forgan fprodu fdairy ffeed fgraze fhogs;
run;

******* PROPOSED ALTERNATIVE DUAL-PHASE APPROACH******;

goptions hby=.75in htext=.5pct htitle=3pct;
axis1 order=(0 to 0.4 by .10);

title1 'PROPOSED: PHASE ONE, STAGE ONE';
proc cluster data=thesis.data2 method=ward ccc pseudo plots=all
outtree=Thesis.PH1ST1tree;
var iprod ifinc iorgmg ieduc dsect dsize;
run;

title1 'PROPOSED: PHASE ONE, STAGE ONE, 7 cluster solution';
proc tree data=thesis.PH1ST1tree out=thesis.PH1ST1 nclusters=7 haxis=axis1
horizontal;
copy iprod ifinc iorgmg ieduc dsect dsize;
run;

title1 'PROPOSED: PHASE ONE, STAGE TWO: K-means with seeds for 7 clusters';
proc fastclus data=thesis.data2 seed=thesis.propseeds out=thesis.PH1ST2 maxclusters=7
maxiter=100;
id obs;
var iprod ifinc iorgmg ieduc dsect dsize;
run;

******* PHASE TWO******;
title1 'PROPOSED: PHASE TWO STAGE ONE, CLUSTER 2';
proc cluster data=thesis.ph2cl2dat method=ward pseudo plots=all
outtree=Thesis.ph2cl2st1tree;
id obs;
var scconv scorgan scprodu scdairy scfeed scgraze schogs;
run;

goptions hby=1.3in htext=1.5pct htitle=3pct;
axis1 order=(0 to 1.25 by .15);
axis2 order=(0 to 0.40 by .10);
```

```
title1 'PROPOSED: PHASE TWO STAGE ONE, CLUSTER 2';
proc tree data=thesis.ph2cl2st1tree out=thesis.ph2cl2st1 nclusters=6 haxis=haxis2
horizontal;
copy scconv scorgan scprodu scdairy scfeed scgraze schogs;
run;

title1 'PROPOSED: PHASE TWO STAGE ONE, CLUSTER 7';
proc cluster data=thesis.ph2cl7dat method=ward pseudo plots=all
outtree=Thesis.ph2cl7st1tree;
id obs;
var scconv scorgan scprodu scdairy scfeed scgraze schogs;
run;

title1 'PROPOSED: PHASE TWO STAGE ONE, CLUSTER 7';
proc tree data=thesis.ph2cl7st1tree out=thesis.ph2cl7st1 nclusters=3 haxis=haxis2
horizontal;
copy scconv scorgan scprodu scdairy scfeed scgraze schogs;
run;

title1 'PROPOSED: PHASE TWO STAGE ONE, CLUSTER 4';
proc cluster data=thesis.ph2cl4dat method=ward pseudo plots=all
outtree=Thesis.ph2cl4st1tree;
id obs;
var fconv forgan fprodu fdairy ffeed fgraze fhogs;
run;

title1 'PROPOSED: PHASE TWO STAGE ONE, CLUSTER 4';
proc tree data=thesis.ph2cl4st1tree out=thesis.ph2cl4st1 nclusters=9 haxis=haxis2
horizontal;
copy fconv forgan fprodu fdairy ffeed fgraze fhogs;
run;

******* PHASE TWO STAGE TWO******;
title1 'PROPOSED: PHASE TWO, STAGE TWO: Cluster 2 with seeds for 6 sub-
clusters';
proc fastclus data=thesis.ph2cl2dat seed=thesis.ph2cl2seeds out=thesis.ph2cl2st2
maxclusters=6 maxiter=100;
id obs;
var scconv scorgan scprodu scdairy scfeed scgraze schogs;
run;

title1 'PROPOSED: PHASE TWO, STAGE TWO: Cluster 7 with seeds for 3 sub-
clusters';
```

```
proc fastclus data=thesis.ph2cl7dat seed=thesis.ph2cl7seeds out=thesis.ph2cl7st2
maxclusters=3 maxiter=100;
id obs;
var scconv scorgan scprodu scdairy scfeed scgraze schogs;
run;

title1 'PROPOSED: PHASE TWO, STAGE TWO: Cluster 4 with seeds for 9 sub-
clusters';
proc fastclus data=thesis.ph2cl4dat seed=thesis.ph2cl4seeds out=thesis.ph2cl4st2
maxclusters=3 maxiter=100;
id obs;
var fconv forgan fprodu fdairy ffeed fgraze fhogs;
run;

ods html close;
ods graphics off;
```

VITA

Kayla Marie Doerr was raised on her family's farm in Creighton, Nebraska. She graduated from Plainview Public High School in May 2005. In May of 2009, she received a Bachelor of Technology in agriculture-agribusiness from Northwest Missouri State University. Upon returning to Nebraska after graduation, Kayla worked full-time for a year before moving to College Station, Texas in May of 2010 to pursue her Master's degree in agricultural economics. After her completion of coursework at Texas A&M in December of 2011, Kayla began working for Informa Economics as a commodity analyst.

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