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Connecting Resources to Student Achievement: Assessment of the Indeterminacy of District Performance

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Assessment of the Indeterminacy of District Performance[1]

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ABSTRACT

The purpose of this study is to conduct cluster analyses, resulting in groupings of *N*=113 districts based on socioeconomic status (SES), which is the independent variable and primary correlate of performance. It is a quantitative analysis of *N*=113 districts in Massachusetts for the period from 2000 to 2005. The study conducts cluster analyses to evaluate district performance as measured by student achievement. The problem is stated by National Research Council (1999) that: “Indeterminacy characterizes education production”. Indeterminacy is represented by variation in the *N*=113 districts’ performance. The groupings of performance obtained from the cluster analyses provide information about the types and magnitude of indeterminacy. The methodology is based on inductive pattern recognition (Trochim (1985). Hierarchical Cluster Analysis (HCA) is used to group districts along a performance continuum and assess variability between SES and district performance. The hypothesis of the study is that variation in performance relates to change in capacity which derives from positive or negative transformation of resources as they are processed by organizations (Porter, 1985)

I. INTRODUCTION

This study is an exploratory strategy that utilizes cluster analysis to develop groupings of district performance. These groupings provide patterns of performance among *N*=113 districts after controlling and including socioeconomic status.

The need to develop an assessment of indeterminacy of educational performance was identified by the National Research Council (1999). The hypothesis of this research is to assess indeterminate processes that contribute to variations is based on the theoretical concept developed by Porter (1985) in his generic value chain research. The concept is that variation in performance relates to change in capacity, which derives from positive or negative transformation of resources as they are processed by organizations (Porter). In education, this concept was first expressed by Gaudet (2000). He observed that, "[some] school districts add value to the learning readiness of their students as indicated by higher-than-predicted test scores (p.3). The purpose of the cluster analysis is to use the groupings to assess the types and magnitude of performance indeterminacy.

Statement of Problem

The National Research Council (1999) states that the macroeconomics of "educational policymaking is now in a state of indeterminacy. No satisfactory criteria exist by which to make important decisions regarding school finance" (p.161). In the same publication, the National Research Council proposes the need for a qualitative model to address indeterminacy by suggesting that, "indeterminacy will always characterize educational production because of the impossibility of standardizing the characteristics and behavior of key factors of production in the education productivity equation: teachers and students" (p.162).

The problem that this research study investigates is the indeterminate dimension of district performance (Hanushek, 2000, 2003; Rivkin, Hanushek, & Kain, 2005) that cannot be accounted by socioeconomic status (SES) of the community (Coleman et al., 1966; Gaudet, 2000; Walberg, 2006). After 40 years, since the study *Equality of Educational Opportunity*, (1996) known as the *Coleman Report* (Coleman., Campbell, Hobson, McPartland,, Mood, Weinfeld, & York, 1966), the failure of school-based production function research is encapsulated by Hanushek (1986), “The fact that a school spends a lot on each student gives us little information on whether or not it does well in terms of value added to students” (p. 1166).

Significance of Problem

The significance of the problem is that, while there is descriptive literature, including but not limited to Marsano (2003) and Blankstein (2004) about the characteristics of high performance schools, there is little understanding of the processes that result in variance in high or low performance beyond SES.

Fullan (2005) relates the problem to the methodology of this study; the complexity of trying to attribute a change in an activity to a change in performance by stating that, “Assessing the roles of strong intervention for failing schools is quite complicated, even in the narrow sense, because the combination of intended and unintended consequences is difficult to sort out” (p.174).

Research Question

This study conducted cluster analysis to assess groupings of district performance by using the difference between actual and predicted Composite Performance Index (CPI). (See definition in Appendix C).

The research question for this study is:

What does systematic grouping of district performance reveal about the types, nature, and magnitude of indeterminacy in district performance?

II. BACKGROUND OF STUDY

This study is at the intersections and limitations of several knowledge domains. These knowledge domains consist of Porter's (1985) value chain modeling, 40 years of educational production function research, explanatory research based on microeconomic theory, resource utilization, quantity and quality correlates of student achievement, the characteristics of effective schools, complex adaptive systems theory and urban regime theory.

Production functions are macroeconomic economic theory that measure resource inputs against production outputs. Microeconomic research has used various theories including, but not limited to marginal rate of substitution (Brown & Saks, 1981) and cost-benefit analysis by Rice (1997). This research has moved little beyond theoretical analysis. Pan, Rudo, Schneider, and Smith-Hanson (2003) conducted a large-scale resource utilization study that identified effective patterns. The study failed to provide empirical evidence about the relationship between district performance and different utilization strategies. Correlational research has combined all of these economic theories, but has the inherent limitation of generalization to the various education contexts. These studies have reinforced the SES determinate with some stranded empirical research on quality correlates (Hanushek, 2004).

Research on the characteristics of effective schools has focused on generalizing best-practice concepts into patterns that enhance curriculum, instruction and assessment, but has made limited contributions to actual improvement reform.

Finally, complex adaptive systems (CAS) that includes Urban Regime theory is emergent in the social sciences and education (O'Day, 2002). It has wide and deep, and proven applications in biology, economics and artificial intelligence, but has not been used as a framework for analysis in education.

Porter's Value-chain

Porter (1985) combined economic with organizational behavior to establish the concept of the generic value-chain. Since the publication of *Competitive Advantage*, the generic value chain has been a mainstay of business analysis of a company and industry performance. According to Porter's model, value-chain analysis is consists of, "a systematic way of examining all of the activities a firm performs and how they interact is necessary for analyzing the sources of competitive advantage…. the value chain disaggregates a firm into its strategically relevant activities in order the behavior of costs and the existing and potential sources of differentiation" (p.33). Value is added, created or diminished within the discrete activities and at the linkages. The phenomenon occurs through "optimization and coordination" (p.48). An obvious limitation of the application of value-chain concepts to education is that business has the profit motive not found in education. Value transformation occurs in education, but for a variety of motives.

Production Function Economics

Assessing district performance in the contemporary era began with the hallmark study, *Equality of Educational Opportunity*. (Coleman et al., 1966). Part of the value of the *Coleman Report,* is that it established the concept that there are two classes of correlates for student achievement, which are non-school factors characterized by demographics and school-based factors. The primary finding of the *Coleman Report* was that non-school factors were the dominant class of correlates for student achievement. These non-school factors contain several variables, but Sirin (2005) indicates that SES has become the research standard for studies on non-school factors and that income per capita is an acceptable indicator to be used as an independent variable.

The *Coleman Report* (1966) sparked 40 years of extensive research in production function research, which is intended to provide a relationship school-based inputs and student achievement output . Hanushek (2000) provides evidence of magnitude of the shortcomings of production function in a meta –analysis, “377 separate production function studies [of school-based factors] have been published in 90 publications before 1995, but only 27% of studies showed a positive and significant effect. In fact, 7% even suggested that adding resources would harm student achievement” (p. 4203).

This is the epithet for production functions that extend beyond the relationship between SES and student achievement. This is confirmed by a correlation analysis between the independent variable and input of Per Pupil Expenditure (PPX) and the dependent variable that measures district performance (Simpson, Kite, & Gable, 2007). The correlation tables are contained in Appendix B. In Massachusetts, district performance is measured by the index Composite Performance Index (CPI) developed by the Department of Education (DOE). See Appendix C for background and the algorithm for CPI.

Socioeconomics’ Correlation with Performance

Researchers including but not limited to Gaudet (2000), Walberg (2006), and Evers and Clopton (2006) focused on the relationship between SES as the independent variable and student achievement. In the study of the second-year of the Massachusetts School and District Accountability System, Gaudet suggested that, “84 percent of the variation in the average MCAS score is explained by demographics” (p.15). Walberg had similar findings that indicated that 93 percent of the variance in twelfth-grade mathematics scores in a large national sample was attributed to “poverty and the related socioeconomic and demographic factors” (p.80).

Tables 1 and 2 confirm a significant relationship between SES and district performance for the *N*=113 districts used in this study. Table 1 is a summary of the relationship between the independent variable of income per capita and mathematics CPI for the years 2001-2005. This correlation, when converted to a coefficient of determination (R_2) confirms a greater amount of the variability related to performance than any other potential quantity correlate.

Table 1

Correlation Coefficients for Districts in Mathematics 2001-2005

Coefficients	MATH01	MATH02	MATH03	MATH04	MATH05
Pearson's Correlation	0.786	0.780	0.776	0.795	0.783
Kendall's tau Correlation	0.633	0.617	0.614	0.626	0.626
Spearman's rho	0.801	0.791	0.793	0.803	0.802

Note. Simpson, Kite & Gable, 2008

Table 2 provides both parametric and non-parametric correlation indicators, because the sample data, could be interpreted as parametric, but may not meet all of the criteria indefensibly. All of the correlations are significant at the 0.01 level as two-tailed tests.

Table 2 is a summary of the relationship between the independent variable of income per capita and English Language Arts CPI for the years 2001-2005.

Table 2

Correlation Coefficients for District CPI in ELA 2001-2005

Coefficients	ELA01	ELA02	ELA03	ELA04	ELA05
Pearson's Correlation	0.703	0.680	0.725	0.734	0.725
Kendall's tau Correlation	0.606	0.585	0.625	0.628	0.624
Spearman's rho	0.778	0.757	0.800	0.803	0.796

Note. Simpson, Kite & Gable, 2007

These correlations are consistent with the findings of Gaudet (2000) and Walberg (2006). Table 2 indicates similar relationships as mathematics between SES and student achievement. A difference between both of these analyses and previous research cited in this inquiry is that it depicts longitudinal consistency in the relative strength of the correlations (Simpson, Kite, & Gable, 2007).

Also, each researcher investigated the outliers in the relationship to identify high performing, low SES districts (Walberg, 2006) or low performing, high SES districts (Evers & Clopton, 2006). These outliers represent a type of indeterminacy within the determinate relationship. Gaudet (2000) conducted a narrower analysis of MCAS scores and found that “there was a 39 scaled score point range of variation between the district’s actual and demographically-predicted score. This range extends from 25 points above the expected score to 14 points under the expected score” (p.16). In this analysis, Gaudet, used demographically similar districts labeled as “Middle Massachusetts” (p. 15).

The results from single regression analyses using a similar parameter to limit the sample to districts that have similar demographics and a limited range of size *N*=113 Massachusetts districts revealed a range difference between actual and predicted CPI of 21.87 in ELA and

25.04 in mathematics on a 100 point scale that has a y-intercept greater than 51. (Simpson, Kite, & Gable, 2007).

Resource Allocation

Researchers including, but not limited to Brown and Saks (1981), Ferguson and Ladd (1995), Hanushek (2004), Monk and Hussian (2000), Pan, Rudo, Schneider and Smith-Hanson (2003), and Rice (1997), using a wide variety of methodologies provide limited evidence that some resource allocation strategies can contribute to variation in student achievement. It is important to note the difference between resource allocation and utilization. Coleman (1972) encapsulates this difference, “The problem arises from the fact that inputs can be viewed in two entirely different ways: inputs as disbursed by the school system and inputs received by the child” (p. 151). Even though each study presented a valid concept, none provided empirical evidence that can be generalized beyond the context of the study.

Using data from 2005 from the N=113 districts in this study, In 2005, adding the percent of regular education expenses as an independent variable along to SES in a multiple regression analysis produced empirical evidence about resource allocation. For mathematics, it increases the explanation of variation by 2.6%, which is significant at the p=.007 level. For ELA, it increases the explanation of variation by 1.8%, but is only significant at the p=.034. The output of the analyses is contained in Appendix D (Simpson, Kite, & Gable, 2008). Even though the analysis produced empirical evidence, neither of the results reduces the magnitude of indeterminacy.

Complex Adaptive Systems

Corcoran and Goetz (1995) suggest that reform based on capacity building has made education more complex with the uncertainty of internal and external contexts. Elmore (2005) provides support for the need for a systematic and theoretical framework for understanding the complexity of education when describing an approach often taken in reform efforts, "pushing hard on a few strategic places in the system of relations surrounding the problem and then carefully observing the results" (p. 29)

The framework for this study is Complex Adaptive Systems (CAS) theory. Levin (2002) provides an overview of CAS when he states, "that observations of nature is the theoretical basis, but the notion CAS has found expression in everything from cells to societies, in general with reference to the self-organization of complex entities across scales of space, time and organizational complexity" (p. 3). According to Levin, the idea of organisms adapting if they are to survive natural selection process has a parallel in economics known as "Pareto optimal utilization of resources" (p.4).

Anderson (1999) provides the rationale for using CAS as a framework stating that, "Modern complexity theory suggests that some systems with many interactions among highly differentiated parts can produce surprisingly simple, predictable behavior, while others generate behavior that is impossible to forecast, though they feature simple laws" (p. 217). Whelan & Williams (2003) suggest that the emergent patterns in CAS are straightforward, because despite the many interactions between agents [people and groups of people] there are relatively few variables.

The patterns that develop from actions by agents with other agents are schema (Dooley, 1996). These schema have strength and nature in the patterns produced by the actions of agents, which are predictable, because these agents follow rules based on a series of options (Anderson, 1999; Dooley, 1996; Staber, & Sydow, 2002). Holland, 1975) explains the process of agents selecting options by suggesting, "discovery of the optimum a long, perhaps never-to-be-completed task, so the best among *tested* options must be exploited at every step. At the same time uncertainties must be reduced rapidly, so that knowledge of *available* options increases rapidly” (p.1). Morel & Ramanujam (1999) provide the argument for using a CAS framework as part of an empirically-sound methodology when they state, “Appearance of patterns which are due to the collective behavior of the components of the system…. The emerging properties are independent, observable and empirically verifiable patterns” (p.279).

Conclusion

Each of these domains is based on established research, but cannot be used exclusively to explain the relationship between resources and performance. The intersections and limits contribute to understanding, characteristics of, or framework for assessing the types, nature and magnitude of indeterminacy of district performance as measured by composite student achievement.

III. METHODOLOGY

Sample

The study is ex post facto for the years 2001-2005. The sampling frame for this study consists of *N*=328 operating school districts in Massachusetts. The *N*=113 sample is non-probability and purposive (Huck, 2008) that employs a screening process that results in what Gaudet (2000) described as “Middle Massachusetts, [which he defined] as 140 districts concentrated in the demographic middle of the state” (p. 15). Table 3 contains the descriptive statistics for the *N*=113 districts. It contains the range of income per capita that is considered middle Massachusetts for this study. The table also contains the range of actual CPI scores.

Table 3

Descriptive Statistics for N=113 Middle Massachusetts Districts

Category	Range	Min	Max	Mean	Standard Deviation
1999 Per Capita Income	$17,734	$18,624	$36,358	$25,804	$4,103
2004 Per Capita Income	$26,393	$16,954	$43,347	$28,305	$6,149
2005 Per Capita Income	$23,826	$16,213	$40,039	$26,786	$5,647
2001 CPI ELA	24.05	69.08	93.12	84.76	5.21
2002 CPI ELA	22.13	72.15	94.27	86.06	5.23
2003 CPI ELA	19.83	74.91	94.74	86.90	4.45
2004 CPI ELA	18.89	75.93	94.83	87.59	4.14
2005 CPI ELA	18.00	76.00	94.00	87.06	4.06
2001 CPI MATH	32.88	51.74	84.61	69.44	7.60
2002 CPI MATH	36.20	49.78	85.98	70.12	7.76
2003 CPI MATH	35.16	53.26	88.42	73.25	7.00
2004 CPI MATH	25.62	61.50	87.13	74.80	6.36
2005 CPI MATH	27.20	61.00	88.20	75.62	6.35

Note. Simpson, Kite, & Gable, 2007

The process for identifying the *N*=113 middle Massachusetts districts consists a series of steps. The sample also excludes districts with less than *N*=1,000, and more than *N*=7,000 students. The final sample of *N*=113 also eliminates affluent and disadvantaged communities. The methodology used for obtaining the *N*=133 consists of a series of simple regressions that culled-out communities with high or low *z*-values for income per capita using the 1.96 threshold.

Data Collection

The data sources for the quantitative sequences are from the Massachusetts Departments of Education and Department of Revenue. The SES data are from the Massachusetts Department of Revenue (2003). Data for district performance analysis came from results published by the Department of Education (DOE) (2005, 2006).

Instrumentation

This study develops groupings of performance along the various continua of performance for the *N*=113 districts, which is accomplished with cluster analysis. According to Cheung & Chan (2005), “Cluster analysis is a generic term for a collection of methodologies or heuristic rules for classifying subjects into groups” (p.957).

This study is limited to cluster analysis of English Language Arts for the period of years 2001 to2005. The completed study includes cluster analysis for mathematics and a combination of ELA with mathematics.

Hierarchical Cluster Analysis (HCA) is the clustering technique used for this study. It groups subjects based on user-determined features. The user-defined input [feature] of this study is the difference between actual and predicted CPI for 2001 to 2005. These four data points for each district are entered in as a single cluster. The purpose is to capture the patterns of temporal variation in performance.

Data Analyses

HCA is an iterative process that can use several algorithms for analysis. Based on the data and research question, this study conducts: (a) complete linkage; (b) single linkage; (c) Wards algorithm; and (d) average linkage (Guest & McLellan, 2003). Complete linkage is also known as the furthest neighbor clustering method, because it a dissimilarity model. Simple linkage is known as the nearest neighbor method, because it clusters data based on similarities. It is important to note that these methods have the same proximities, but produce different shaped dendograms.

Dendograms are two dimensional diagrams that represent the union at each successive stage of clusters analysis. The vertical listing of cases, which are the districts merely represent and ordering within clusters. Interpretation of hierarchical dendograms is based on the relationships between the rescaled distances of the cluster analysis, i.e. the longer the horizontal distance the greater the dissimilarity with the adjacent case or cluster. The term furthest neighbor in complete-linkage clustering is somewhat misleading, because the relationship between cases and clusters for all techniques is based on the least difference between the cases. Furthest neighbor merely refers to the algorithm, which fuses the cases based on furthest proximity. It is a mirror-algorithm to nearest-neighbor of single linkage, but as seen in the agglomeration schedules these algorithms can produce the same ordering of cases. The difference is that single-linkage clustering of this data produced greater vertical rescaled differences and fewer horizontal linkages, which represent the relationship of proximity within the dendogram.

Average-linkage clusters data according to the average distances between every pair of data. Wards method is based on the least error in the sum-of-squares. For all clustering in this study the Euclidean distance method is used and the output are standardized values. HCA of the performance of the *N*=113 districts along the various dimensions of performance and variability provides “an understanding of the underlying relationships” (Cheung & Chan, 2005, p. 955).

Given the latitude allowed for cluster analysis in SPSS, understanding the theoretical foundations lead to valid analysis. Building on previous research in construct validity by Cronbach & Meehl (1955), Campbell & Stanley (1963), Campbell & Fiske (1959) and Cook &

Campbell (1979) (cited in Trochim, 1985, p. 576), Trochim (1985) began to operationalize the concept of cluster analysis in performance measurement with investigations using inductive pattern matching. He identified “program pattern matches, measurement pattern matches and outcome pattern matches” (p.581). These concepts align with the theoretical template for conducting cluster analysis. The primary concepts include that: (a) there is no ‘perfect’ conceptualization, only useful ones are explainable relative to the research question; (b) degrees of relevance exist that may or may not be found in the representation; alternatives can exist; (c) the process is highly contextual; (d) equally valid patterns can emerge at the limits of a context.

IV. FINDINGS

The results of the data analysis using SPSS for complete-linkage, simple-linkage and average-linkage are contained in Appendix E. The key to interpreting dendograms is that the distances are not necessarily an actual metric, but rather a proximity in an ancestor relationship to the next case or cluster.

This concept is apparent in the columns of the accompanying schedules. The basic concept for the formation of the dendogram is found in the columns labeled Stage ‘Cluster First Appears’. ‘Cluster 1’ and ‘Cluster 2’, which represent when cases and groups of cases are first combined, but the ‘Next Stage’ column indicates that clustering is not a serial process; it is iterative as the algorithm searches and re-searches cases until all ancestor fusions are exhausted. The coefficients indicate the proximity within and between clusters. The larger the increase in the change between stages the more distinction between the adjacent clusters. The agglomeration schedule has been modified to include a difference and percent change between the stages. This is done to assist in the interpretation by locating the significant changes for the stages.

The dendograms and agglomeration schedules in Appendix E are source data for inductive interpretation of relationships in performance, and should not be viewed deductively, because the only metric that they reveal is relative relationships based on the rescaled distances. The rescaled distances are ‘standardized’ proximities based on the range of the data set, but not standardized in the typical z-score statistic. Interpretation of these dendograms and agglomeration schedules relate to the theoretical basis of Trochim’s (1985) primary concept of pattern matching. The data in Appendix E are only conceptualizations that are in the context of the research question, which seeks types and magnitudes of the indeterminacy of district performance.

The key to interpreting dendograms is that the distances are not necessarily an actual metric, but rather a proximity in an ancestor relationship. As expected with this data set, complete and single-linkage analysis produced the same agglomeration schedule, but diametrically different dendograms. Average-linkage produced a dendogram more similar to complete-linkage, but the ordering found in the agglomeration schedules have some similarities and differences. Complete-linkage clustering appears to provide a good representation of the relationships between the data, but the other output is not discarded, because it also provides a basis for comparison and can be a source of alternative clusters that are viable.

Figure 1 is first 13 districts, beginning with Melrose, in the complete-linkage method. It provides a representation of two groupings of districts. The first group includes Melrose, Wakefield, Scituate, Reading and Easton, which are characterized as consistently moderate and positive performing districts. The Fairhaven, Rockport, Amesbury, Tyngsborough and Millbury are characterized as higher performing districts, but less consistent with a significant negative year. Winthrop, Burlington and Falmouth transition between the two distinct groups, which is a good representation of the concept of a performance continuum. The groupings that are identified are three levels of clustering, seen in Figure E1 in Appendix E. To reiterate the data for these data is the difference between actual CPI and a statistically-predicted CPI. The 3 levels of clustering depicted in Figure 1 indicate distinct and gradual [ancestoral] relationships. This is reinforced by agglomeration schedule, which provides a significant percent change for the transition districts of 5.9%, 5.8% and 4.2%. By combining these increases, the 15.9% increase validates the representation found in Figure 1. In terms of indeterminacy in the difference between actual CPI and the predicted value for all of the districts represented in Figure 1 is minor, *because of* the clustering. These districts have established similar “readiness for learning of students” (Gaudet, 2000, p.3), even though they may have achieved this readiness with very different strategies.

Figure 1. First 13 districts in agglomeration schedule for complete-linkage

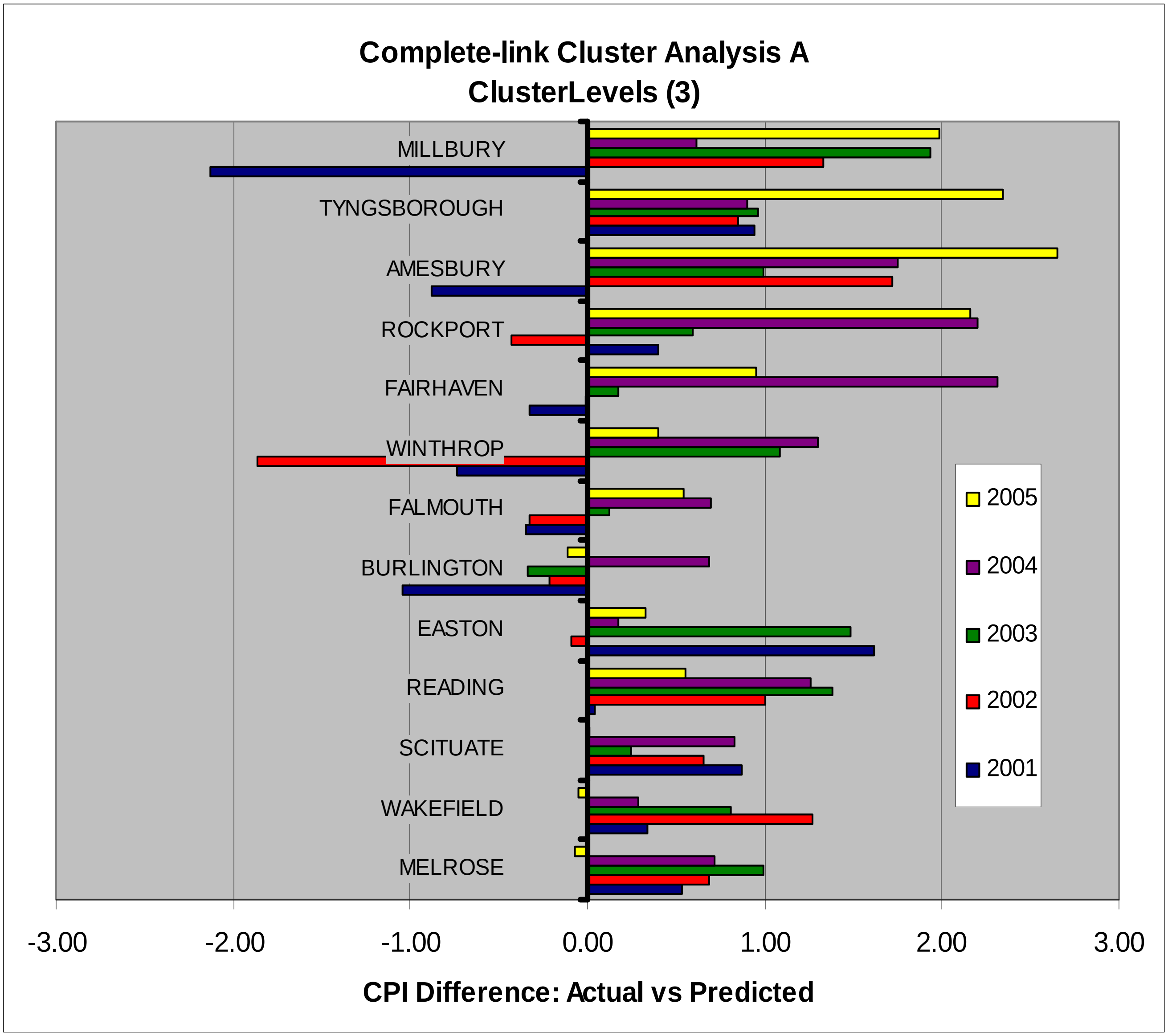
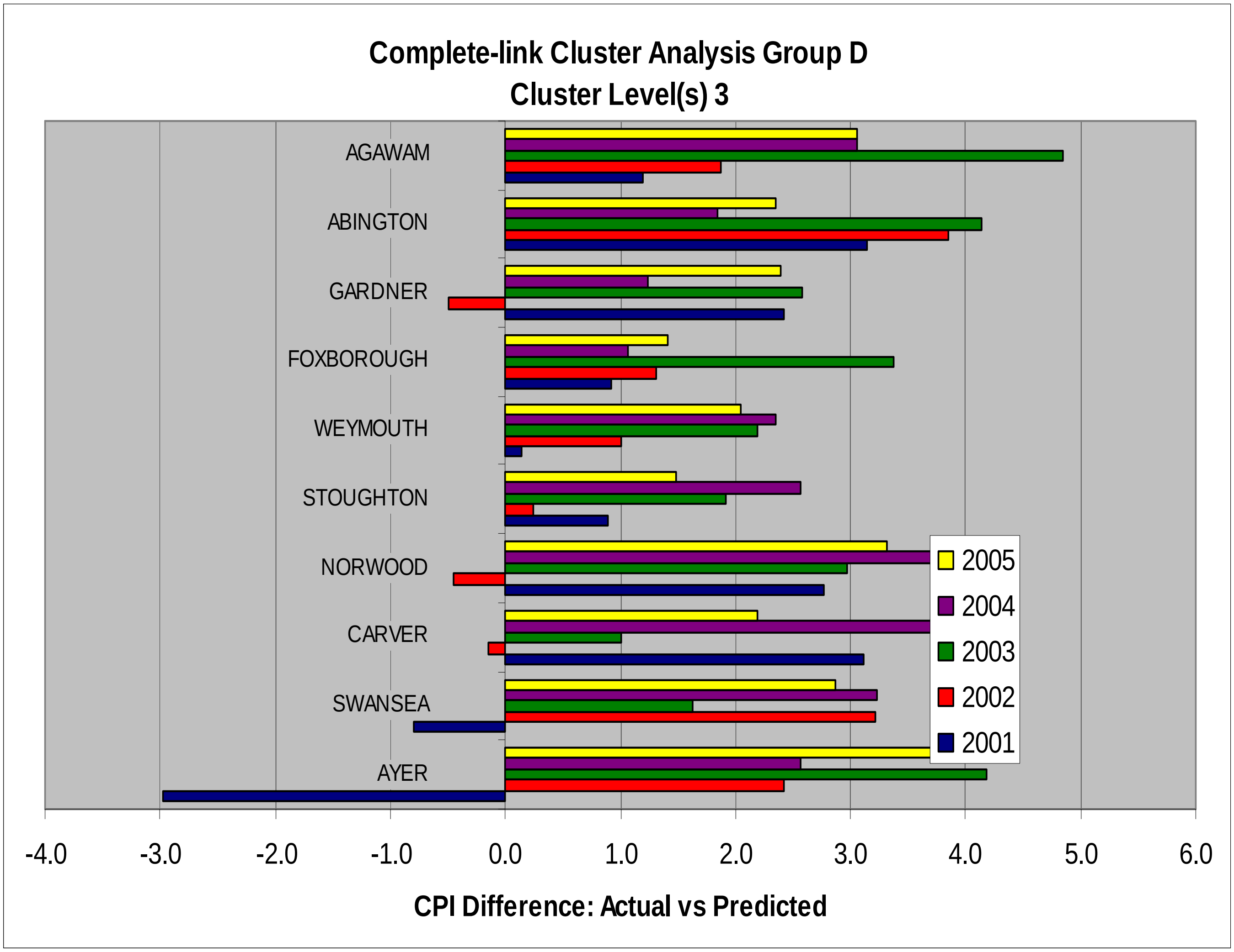


Figure 2 is a representation of 3 cluster groups that are four levels 'down' the dendogram from the districts in Figure 1. Starting with Agawam, the grouping can be characterized as consistently moderate-high performance districts until Norwood when some inconsistency appears, even though Gardner has a single negative year. The association of Gardner with Abington, Foxborough and Agawam provides support that assessing indeterminacy requires interpretation of data rather than accepting a single criteria cluster analysis as the final indicator of performance. Gardner has the lowest per capita income of all *N*=113 districts, while Abington ranks 78, Foxborough ranks 10 and Agawam ranks 88 in the socioeconomic indicator. Even though the predicted-score CPI is based on the independent variable per capita income, interpretation of all of the data places Gardner as perhaps the highest performing district in the *N*=113 sample. This represents a distinct type of indeterminacy that is outside of the context of these cluster analyses. This concept is fundamental in conducting pattern matching (Trochm, 1985) with cluster analysis, which is that degrees of relevance exist that may or may not be found in the representation; alternatives can exist; (c) the process is highly contextual; (d) equally valid patterns can emerge at the limits of a context.

Figure 2. Complete-linkage relationship of high performing districts with various SES



V. CONCLUSIONS and FUTURE RESEARCH

The primary indeterminacy that this study investigates is variation in student achievement as represented by CPI that cannot be explained by SES. For the data from the *N*=113 districts studied in this research, approximately 35% to 55% of the variability in performance cannot be explained by SES. (Simpson, Kite, & Gable, 2007). The difference in variability represents a form of indeterminacy within the determinate portion of district performance. This indeterminacy is expressed in the difference in SES rank and Actual CPI rank. For instance, it is significant that

West Boylston ranks 84 to 71 in per capita income, but ranks 23 for ELA in 2001, 17 for 2002, 19 for 2003, 42 in 2004 and 20 in 2005.

A second type of indeterminacy identified in previous papers is the variability in actual CPI and predicted CPI as indicated by the range of differences (Simpson, Kite, & Gable, 2007, 2008). Analysis of this type of indeterminacy is both related and unrelated to the first type of indeterminacy. For example, Abington and Gardner have similar patterns of performance in ELA from 2001 to 2005, but Abington ranks 78th in 1999 income per capita and Gardner ranks 113; last in income per capita for the *N*=113 districts.

Another form of indeterminacy is seen in the difference between ELA and Mathematics actual vs. predicted performance. For example, Easthampton performed poorly in ELA, but excelled in Mathematics. This represents a programmatic indeterminacy. Even though Gaudet (2003) suggested the some districts “add value to student readiness for learning” (p.3), it does not appear to be homogenous across the curriculum content.

The final significant form of indeterminacy that is unique to this study is a temporal change in performance. This indeterminacy could be attributed to several factors. . For example Middleboro excelled in ELA for the years 2001 through 2003, but began a significant decline in 2004 and 2005.

Future Research

This study is part of an ongoing research project. In future research, the data from this study are used in multidimensional scaling (MDS) to model an empirical process for assessing the strength and nature of thematic patterns of resource utilization for a subset of *N*=23 districts (Foster, 2000; Lewin, 2002; Holland, 1975). The cluster analyses from this study will be used to establish matrices of performance. These matrices that represent a continuum of performance and socioeconomics that provides a starting-point for MDS. The MDS study will be a mixedmethod strategy that evaluates the *N*=23 on a likert-scale and thematic narratives from the categories that were established for the Educational Quality and Accountability (EQA) audits conducted on the *N*=23 districts. The categories that EQA audited, which are analogous to Porter's (1985) strategically relevant activities are: (a) Leadership, Governance and Communication; (b) Curriculum and Instruction; (c) Assessment and Program Evaluation; (d) Human Resource Management and Professional Development; (e) Access, Participation and Student Academic Support; and (f) Financial and Asset Management Effectiveness and Efficiency.

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APPENDIX A

Definition of Terms

Capacity Building

Elmore (2005) states that,” Capacity is defined by the degree of successful interaction of students and teachers around content” (p.118). Cohen, Raudenbusch and Ball (2002) developed a model for capacity that suggests that the education delivery system must be designed around the three portals of capacity, which are the student, teacher and content (as cited in Elmore, 2005, p. 119).

Complex Adaptive Systems

(CAS) “Self-organization of complex entities across scales of space, time and organizational complexity (Levin, 2002, p. 3) CAS theory is important to education delivery systems, because intervention will result in a range of patterns of outcomes, which can be used to evaluate the effect of an intervention on the organization.

Education Delivery System

The organizational structure that contains the distinct activities that provides instruction and learning. For this study, it is visually represented by Porter’s (2000) generic value chain framework.

Marginal Rate of Substitution

It differs from production function analysis, because it examines the marginal changes within the education delivery system rather than aggregated or isolated inputs and outputs. The equation for marginal rate of substitution depicted by Salvatore (2003) is:

$$(\Delta X)(MuU_X) = -(\Delta Y)(MU_Y) \text{ which converts to}$$

$$MU_X/MU_Y = -\Delta Y/\Delta X = MRS_{XY} \quad (4)$$

“Marginal rate of substitution (MRS_{XY}) refers the amount of Y that the individual is willing to exchange per unit of X and maintain the same level of satisfaction” (p. 65). Since there can be a single or multiple X, the equation is analogous to the slope of the line for a regression equation. This equation is adapted to this inquiry; for the independent variable or variables X, which include SES, and the series of resource allocation inputs how does the dependent variable Y of student achievement change incrementally.

Pareto Optimal	Resource allocation, in nature or economics, that results in the maximum utilization for the cell, organism or a defined societal group.
Production Function	[A process] characterized by the deterministic relationship between inputs and outputs (that is, a given set of inputs always produces exactly the same amount of outputs) Furthermore, it is assumed that all inputs can be substituted freely. (Hanushek, 1986, p.1149)
Resource Allocation	The ways in which fiscal and non-fiscal resources are divided between competing needs and expended for educational purposes (Pan, et. al., 2003, p.5)
Socioeconomic Status	A measure of a student's position along a continuum of wealth. In the Coleman Report (1966) It is was a position that was influenced by whether the student was a minority positioned at the lower end of the continuum. In contemporary terms, it is analogous to demographic. Its significance is that lower SES student " systematically achieve less than more advantaged students" (Rivkin, S., Hanushek, E. and Kain, J., 2005, p. 450)

APPENDIX B

Background and Algorithm for Composite Performance Index (CPI)

Data used to determine the CPI of a school district or subgroups of students are based on Adequate Yearly Progress (AYP); which is represented by the following equation:

$$A + (B \text{ or } C) + D = AYP \qquad (1)$$

A represents the participation rate of students in MCAS for regular education or alternative assessment for special education students. *B* is the average school, district, or subgroup CPI. *C* may be used as an alternative when the Cycle IV, 2005-2006 school year, improvement target is met. *D* is either a combination of 8th grade attendance rate above, a 1% improvement over the previous cycle or Competency Determination, graduation as measured by passing MCAS, greater than 70% (Massachusetts Department of Education, 2006).

CPI rates the school and district's gain toward achieving the NCLB goal for each district, school and subgroup of students. This rating system is depicted in Table 1.

Table 1

Composite Performance Index rating system for Adequate Yearly Progress for schools and districts in Massachusetts

Performance Rating	CPI Range
Very High	90 - 100
High	80 - 89.9
Moderate	70 - 79.9
Low	60 - 69.9
Very Low	40 -59.9
Critically Low	0 - 39.9

Note. From "School Leaders Guide to the 2006 Cycle IV Accountability and Adequate Yearly Progress (AYP) Reports," By Massachusetts Department of Education. p. 3. (2006)

APPENDIX C

Correlation Analyses of Production Function for *N*=113 Districts

The independent variable for Table1C and Table 2C is Per Pupil Expenditure (PPX). The dependent variable is the District's Composite Performance Index CPI. The data supports the lack of any discernible relationship between total spending and student achievement, except for a negative value.

The sample frame is *N*=365 districts in Massachusetts. The *N*=113 districts represent "middle Massachusetts" Gaudet (2000) of the districts that have a limited range of demographics, i.e. large, small, affluent, poverty and regional districts are excluded for the sample. The effect is that the results of the correlation analyses are minimally influenced by outlier data-points.

Table 1C

Correlation Between Per Pupil Expenditure (PPX) and District CPI in English Language Arts (ELA) for the Years 2001 - 2005

		ELA01	ELA02	ELA03	ELA04	ELA05	ELA06
PPX_01	Pearson Correlation	-0.24					
	Sig. (2-tailed)	0.01					
PPX_02	Pearson Correlation		-0.27				
	Sig. (2-tailed)		0.00				
PPX_03	Pearson Correlation			-0.13			
	Sig. (2-tailed)			0.16			
PPX_04	Pearson Correlation				-0.12		
	Sig. (2-tailed)				0.20		
PPX_05	Pearson Correlation					-0.27	
	Sig. (2-tailed)					0.00	
PPX_06	Pearson Correlation						-0.22
	Sig. (2-tailed)						0.02

Table 2C

Correlation Between Per Pupil Expenditure (PPX) and CPI in Mathematics (MATH) for the Years 2001 - 2005

		MATH01	MATH02	MATH03	MATH04	MATH05	MATH06
PPX_01	Pearson Correlation	-0.17					
	Sig. (2-tailed)	0.07					
PPX_02	Pearson Correlation		-0.17				
	Sig. (2-tailed)		0.07				
PPX_03	Pearson Correlation			-0.09			
	Sig. (2-tailed)			0.36			
PPX_04	Pearson Correlation				-0.09		
	Sig. (2-tailed)				0.32		
PPX_05	Pearson Correlation					-0.21	
	Sig. (2-tailed)					0.03	
PPX_06	Pearson Correlation						-0.20
	Sig. (2-tailed)						0.03

APPENDIX D

Marginal Resource Allocation Analysis

Appendix D presents data regarding the relationship between marginal resource allocation within the education delivery system and district performance as measured by student achievement. Multiple regression analysis is used with the independent variable of SES and district CPI as the dependent variable. Percent of spending on regular education was added as the second independent variable.

As expected, the output presented in Tables D1 and D2 indicate the demographic indicator is dominant, but the spending in the functional category of regular instruction can have a consistent relationship to student achievement, which provides insight beyond aggregate production function analyses.

Tables D1 and D2 depict the results of multiple regression analyses for the two independent variables of demographics quantified by 2005 per capita income representing socioeconomic status (SES), the ratio of spending within the districts for regular education and the dependent variables of English Language Arts (ELA05 CPI) and Mathematics (MATH05 CPI). Prior to conducting each of the multiple regressions the assumptions of normality, linearity, homoscedasticity and independence of residuals were examined by developing plots of the standardized predicted values (i.e. the standardized residuals). Examination of the plots for English Language Arts and Mathematics data indicate that the assumptions are reasonable (Tabachnick & Fidell, 2001).

The coefficient of determination (R^2) listed in Table D1 indicates that income per capita (05Inc_capita) , used as an indicator of SES explains 58% of the variation in achievement in Mathematics. Adding the variable for regular education spending (05% Reg_Instr) to the equation increases the explanation of variation by 2.6%, which is significant at the p=.007 level. Again, we note that the sample size contributes to the significant findings, support is present for the ability of the instructional variable to contribute to enhancing the explanation of variation in Mathematics achievement . This R^2 for Mathematics combined with the similar R^2 for English Language Arts provide support for the consistency of relationship of the percent of resources allocation to regular education instruction to student achievement. (Simpson, Kite & Gable, 2008)

TABLE D1

Summary Statistics for Multiple Regression Analysis for Independent Variables SES (Income Per Capita) and Percent Spent on Regular Education Instruction and Student Achievement in 2005 English Language Arts (ELA05)

REGRESSION MODEL SUMMARY

Descriptive Statistics

	Mean	Std. Deviation	N = 117
05ELA_CPI	86.67	4.49	
05%_Reg_Instr	.48	.037	
05Inc_capita	$28,092	$6,428	

Regression Statistics

	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.74(a)	.55	.55	3.02582	.550	140.33	1	115	.000
2	.75(b)	.57	.56	2.97918	.018	4.63	1	114	.034

a Predictors: (Constant), 05Inc_capita
b Predictors: (Constant), 05Inc_capita, 05%_Reg_Instr
c Dependent Variable: 05ELA_CPI

Coefficients

	Standardized Coefficients		
	Beta	t	Sig.
1 (Constant)		57.28	.000
05Inc_capita	.74	11.85	.000
2 (Constant)		17.47	.000
05Inc_capita	.72	11.55	.000
05%_Reg_Instr	.13	2.15	.034

a Dependent Variable: 05ELA_CPI

Note. Simpson, Kite & Gable (2008)

TABLE D2

Summary Statistics for Multiple Regression Analysis for Independent Variables SES (Income per capita) and Percent Spent on Regular Education Instruction and Student Achievement in Mathematics 2005 (MATH05)

REGRESSION MODEL SUMMARY

Descriptive Statistics

	Mean	Std. Deviation	N =115
05MATH_CPI	75.41	6.49	
05%_Reg_Instr	.48	.04	
05Inc_capita	$28,303	$6,277	

Regression Statistics

	R	R Square	Adjusted R Square	Standard Error of Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig F Change
1	.76(a)	.58	.58	4.21	.583	157.83	1	113	.000
2	.78(b)	.61	.60	4.09	.026	7.49	1	112	.007

a Predictors: (Constant), 05Inc_capita
b Predictors: (Constant), 05Inc_capita, 05%_Reg_Instr
c Dependent Variable: 05MATH_CPI

Coefficients

	Standardized Coefficients Beta	t	Sig.
1 (Constant)		29.12	.000
05Inc_capita	.76	12.56	.000
2 (Constant)		7.73	.000
05Inc_capita	.73	12.00	.000
05%_Reg_Instr	.17	2.74	.007

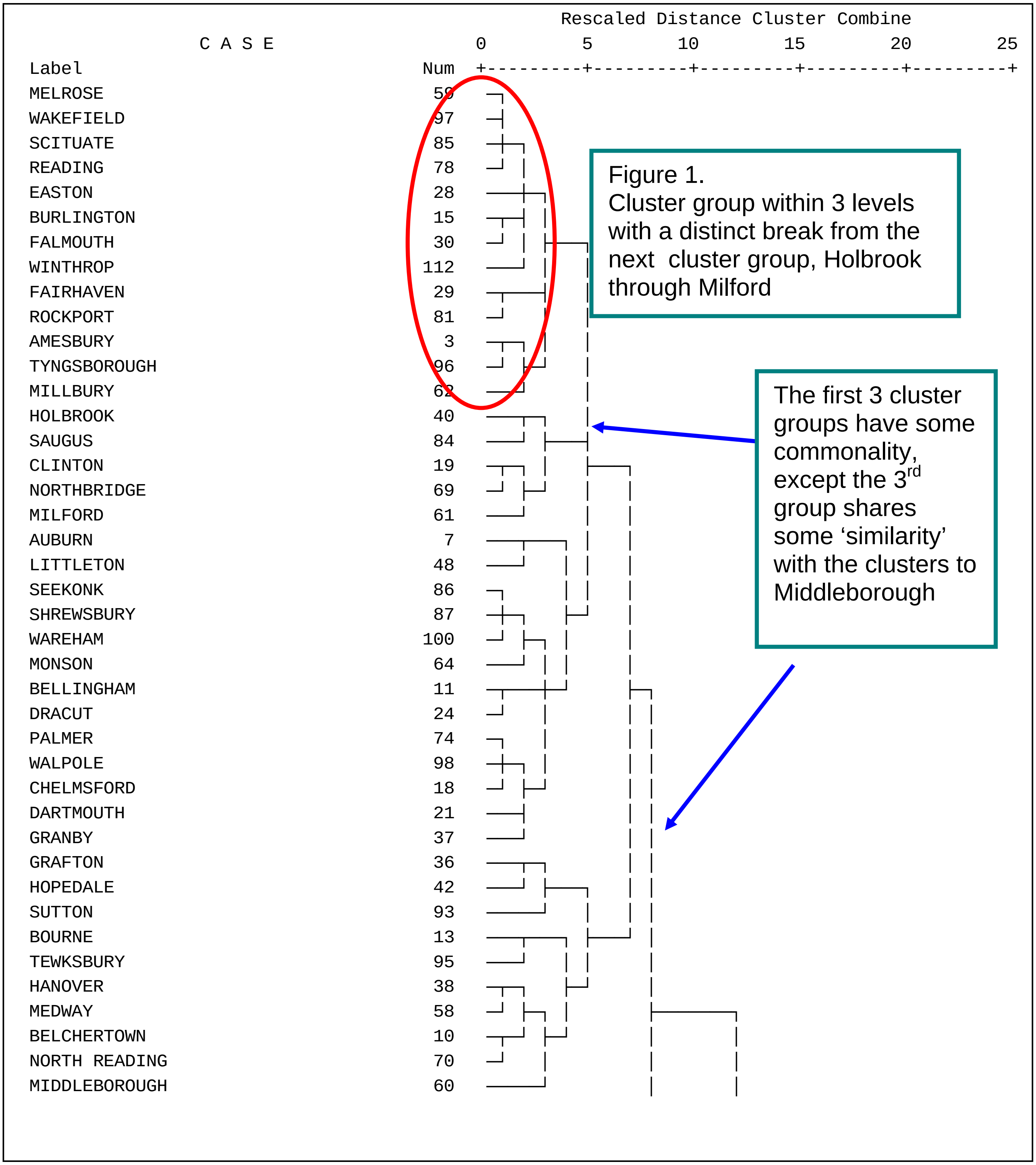
a Dependent Variable: 05MATH_CPI

Note. Simpson, Kite & Gable (2008)

APPENDIX E

Cluster Analysis Dendograms and Agglomeration Schedules

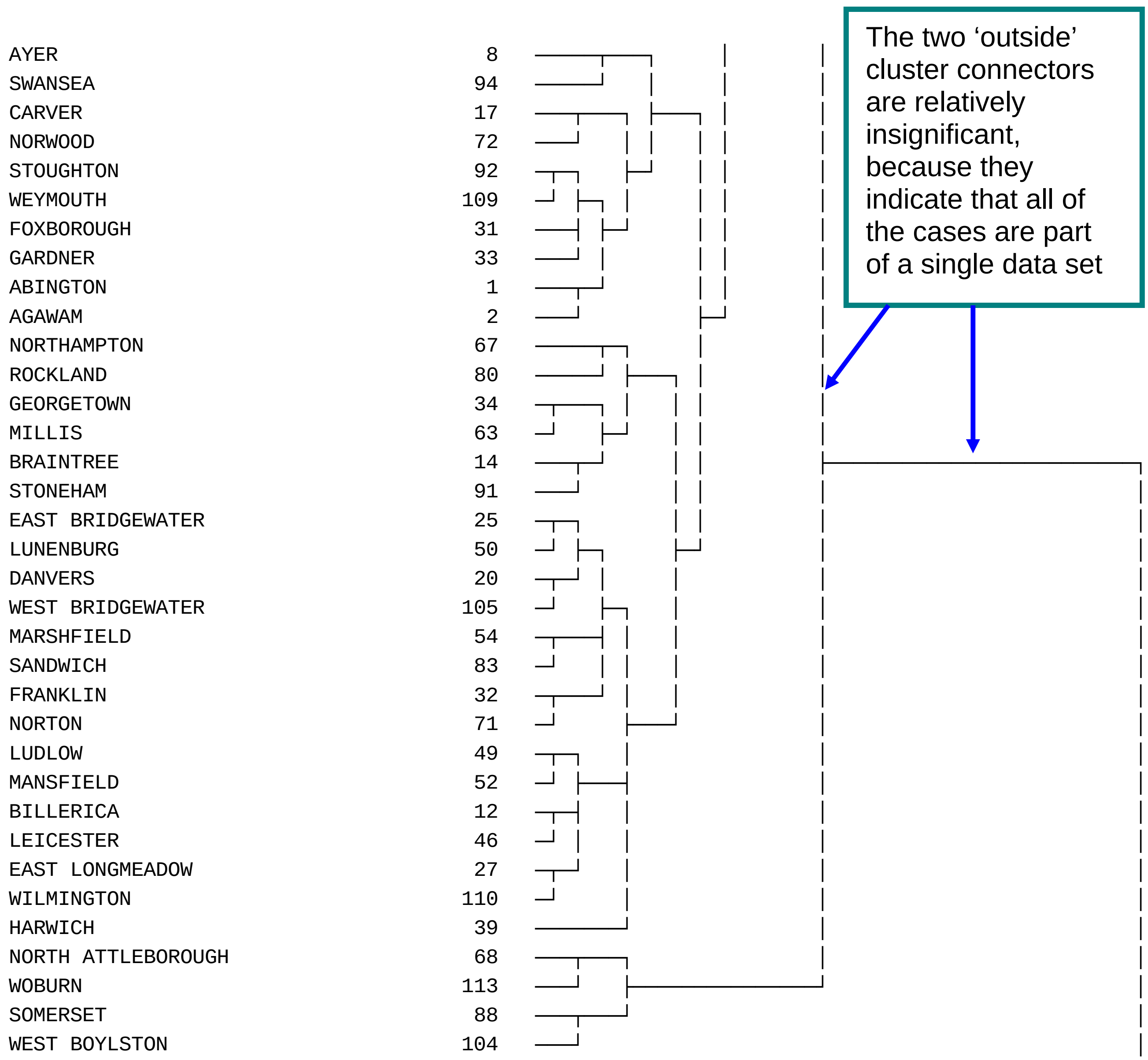
Figure E1. Complete Linkage Dendogram *N*=1to 41



APPENDIX E

Cluster Analysis Dendograms and Agglomeration Schedules

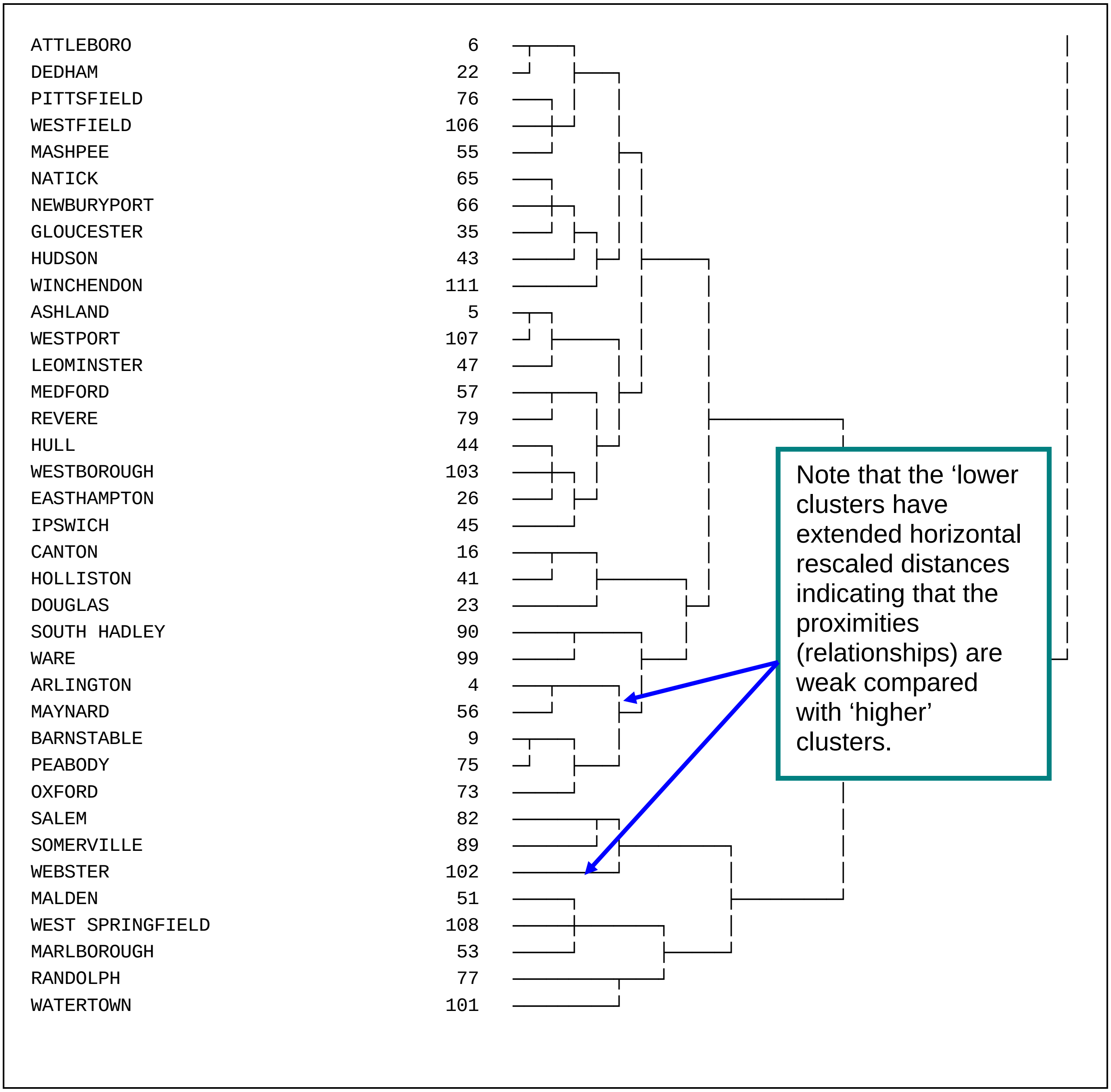
Figure E2. Complete Linkage Dendogram *N*=41 to 76



APPENDIX E

Cluster Analysis Dendograms and Agglomeration Schedules

Figure E3. Complete Linkage Dendogram Stage 76 to 113



APPENDIX E

Cluster Analysis Dendograms and Agglomeration Schedules

Table E1.

Complete Linkage Agglomeration Schedule Stage 1 to 52

	Cluster Combined					Stage Cluster First Appears		
Stage	Cluster 1	Cluster 2	Coefficients	Difference	%Change	Cluster 1	Cluster 2	Next Stage
1	59	97	.243			0	0	3
2	15	30	.357	.114	46.9%	0	0	34
3	59	85	.370	.013	3.6%	1	0	19
4	92	109	.374	.004	1.1%	[illegible]	[illegible]	[illegible]
5	74	98	.385	.011	3.1%	[illegible]	[illegible]	[illegible]
6	12	46	.408	.023	**5.9%**	[illegible]	[illegible]	[illegible]
7	18	74	.431	.023	**5.8%**	[illegible]	[illegible]	[illegible]
8	38	58	.450	.018	**4.2%**	[illegible]	[illegible]	[illegible]
9	86	87	.454	.004	0.9%	[illegible]	[illegible]	[illegible]
10	10	70	.463	.009	2.1%	[illegible]	[illegible]	[illegible]
11	54	83	.469	.006	1.2%	[illegible]	[illegible]	[illegible]
12	27	110	.472	.003	0.7%	[illegible]	[illegible]	[illegible]
13	9	75	.492	.020	**4.3%**	[illegible]	[illegible]	[illegible]
14	5	107	.505	.013	2.6%	[illegible]	[illegible]	[illegible]
15	25	50	.534	.029	**5.7%**	[illegible]	[illegible]	[illegible]
16	19	69	.539	.006	**1.1%**	0	0	41
17	29	81	.541	.001	0.3%	0	0	65
18	34	63	.546	.006	**1.1%**	0	0	66
19	59	78	.555	.008	1.5%	3	0	27
20	49	52	.570	.015	2.7%	0	[illegible]	[illegible]
21	11	24	.624	.055	**9.6%**	0	[illegible]	[illegible]
22	6	22	.628	.004	0.7%	0	[illegible]	[illegible]
23	20	105	.629	.001	0.2%	0	[illegible]	[illegible]
24	86	100	.632	.003	0.5%	9	[illegible]	[illegible]
25	3	96	.634	.001	0.2%	0	[illegible]	[illegible]
26	32	71	.645	.011	1.8%	0	[illegible]	[illegible]
27	28	59	.665	.020	3.1%	0	[illegible]	[illegible]
28	44	103	.665	.000	0.0%	0	[illegible]	[illegible]
29	14	91	.677	.012	1.8%	0	[illegible]	[illegible]
30	65	66	.696	.018	2.7%	0	[illegible]	[illegible]
31	76	106	.699	.003	0.5%	0	[illegible]	[illegible]
32	64	86	.728	.029	4.2%	0	24	71
33	40	84	.746	.018	2.5%	0	0	76
34	15	112	.750	.004	0.6%	2	0	56
35	13	95	.754	.004	0.6%	0	0	89
36	26	44	.764	.010	1.3%	0	28	63
37	31	33	.769	.005	0.7%	0	0	50
38	16	41	.770	.002	0.2%	0	0	87
39	12	27	.778	.007	1.0%	6	12	52
40	10	38	.785	.008	1.0%	10	8	73
41	19	61	.789	.003	0.4%	16	0	76
42	36	42	.800	.012	1.5%	0	0	72
43	4	56	.814	.014	1.8%	0	0	92
44	68	113	.820	.006	0.7%	0	0	90
45	55	76	.822	.002	0.2%	0	31	64
46	21	37	.831	.009	1.1%	0	0	47
47	18	21	.842	.011	1.3%	7	46	61
48	57	79	.864	.022	2.6%	0	0	86
49	17	72	.868	.004	0.4%	0	0	88
50	31	92	.869	.001	0.1%	37	4	77
51	3	62	.893	.024	2.7%	25	0	65
52	12	49	.930	.037	**4.1%**	39	20	83

Significant cumulative change indicating that Winthrop, Falmouth and Burlington are collectively transition clusters.

Note that 'jumps' in percent change, which indicates a break between cluster groups is a relative metric.

APPENDIX E

Cluster Analysis Dendograms and Agglomeration Schedules

Table E2.

Complete Linkage Agglomeration Schedule Stage 53 to 82

	Cluster Combined					Stage Cluster First Appears		
Stage	Cluster 1	Cluster 2	Coefficients	Difference	%Change	Cluster 1	Cluster 2	Next Stage
53	5	47	.938	.008	0.9%	14	0	97
54	1	2	.938	.001	0.1%	0	0	77
55	20	25	.953	.015	1.6%	23	15	78
56	15	28	1.003	.049	**5.2%**	34	27	75
57	88	104	1.012	.010	1.0%	0	0	90
58	35	65	1.023	.010	1.0%	0	30	74
59	7	48	1.051	.029	2.8%	0	0	82
60	67	80	1.080	.029	2.8%	0	0	80
61	11	18	1.085	.005	0.5%	21	47	71
62	32	54	1.125	.039	3.6%	26	11	78
63	26	45	1.147	.023	2.0%	36	0	86
64	6	55	1.184	.036	3.2%	22	45	91
65	3	29	1.188	.004	0.3%	51	17	75
66	14	34	1.203	.015	1.3%	29	18	80
67	51	108	1.208	.005	0.4%	0	0	70
68	8	94	1.212	.004	0.4%	0	0	98
69	90	99	1.222	.010	0.8%	0	0	102
70	51	53	1.266	.043	3.5%	67	0	105
71	11	64	1.274	.008	0.6%	61	32	82
72	36	93	1.290	.016	1.3%	42	0	96
73	10	60	1.310	.020	1.6%	40	0	89
74	35	43	1.337	.027	2.1%	58	0	81
75	3	15	1.372	.035	2.6%	65	56	93
76	19	40	1.386	.013	1.0%	41	33	93
77	1	31	1.425	.040	2.9%	54	50	88
78	20	32	1.454	.029	2.0%	55	62	85
79	9	73	1.465	.011	0.7%	13	0	92
80	14	67	1.499	.034	2.3%	66	60	101
81	35	111	1.510	.010	0.7%	74	0	91
82	7	11	1.598	.088	**5.8%**	59	71	99

APPENDIX E

Cluster Analysis Dendograms and Agglomeration Schedules

Table E2.

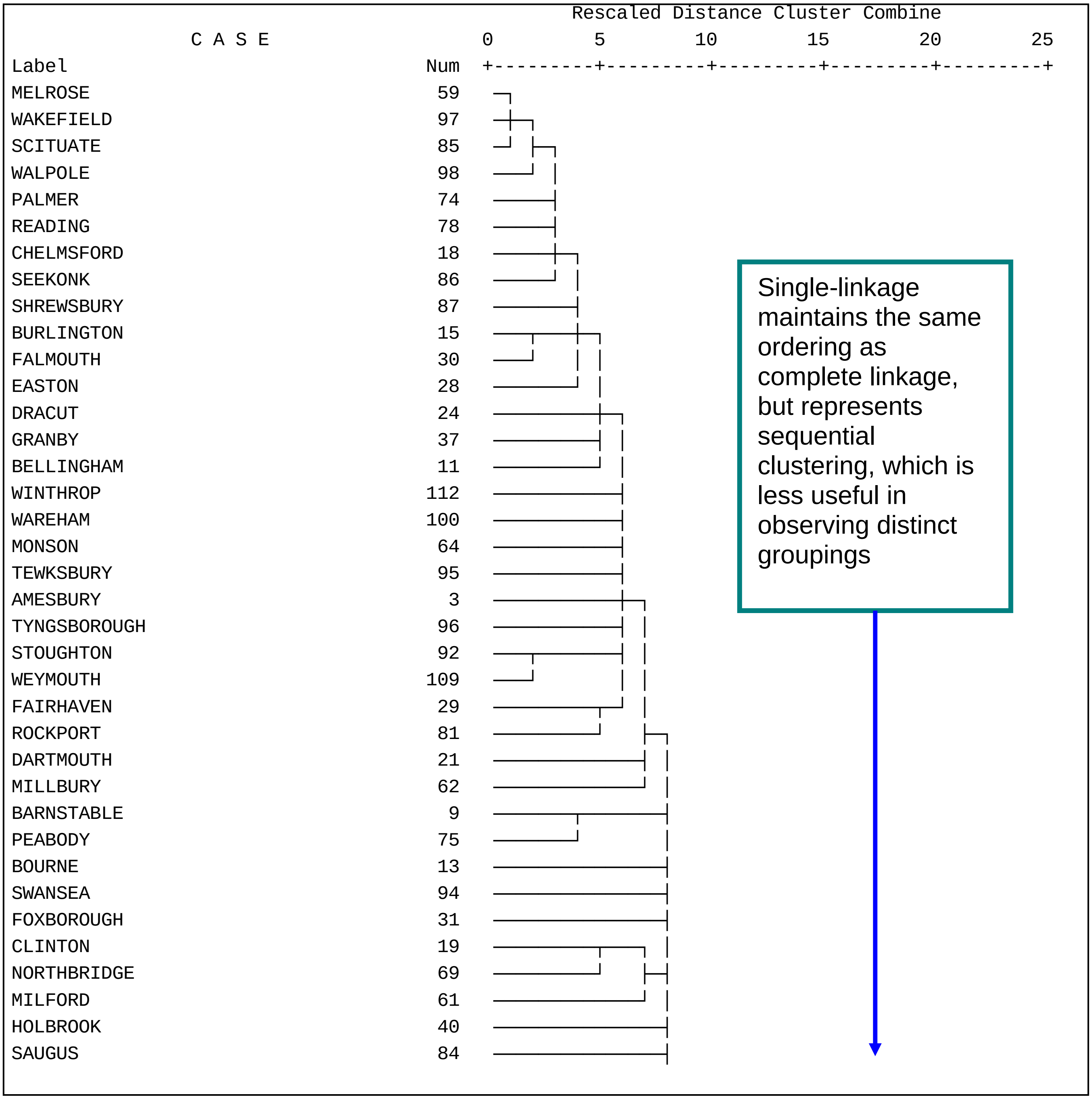
Complete Linkage Agglomeration Schedule Stage 83 to 113

	Cluster Combined					Stage Cluster First Appears		
Stage	Cluster 1	Cluster 2	Coefficients	Difference	%Change	Cluster 1	Cluster 2	Next Stage
83	12	39	1.606	.008	0.5%	52	0	85
84	82	89	1.634	.028	1.7%	0	0	95
85	12	20	1.718	.084	**5.1%**	83	78	101
86	26	57	1.720	.003	0.1%	63	48	97
87	16	23	1.721	.001	0.1%	38	0	106
88	1	17	1.748	.026	1.5%	77	49	98
89	10	13	1.836	.088	**5.0%**	73	35	96
90	68	88	1.863	.027	1.5%	44	57	110
91	6	35	1.983	.120	**6.4%**	64	81	100
92	4	9	2.011	.028	1.4%	43	79	102
93	3	19	2.037	.026	1.3%	75	76	99
94	77	101	2.076	.038	1.9%	0	0	105
95	82	102	2.120	.044	2.1%	84	0	109
96	10	36	2.141	.021	1.0%	89	72	104
97	5	26	2.185	.044	2.1%	53	86	100
98	1	8	2.222	.037	1.7%	88	68	103
99	3	7	2.259	.037	1.7%	93	82	104
100	5	6	2.472	.212	9.4%	97	91	108
101	12	14	2.476	.005	0.2%	85	80	103
102	4	90	2.645	.169	6.8%	92	69	106
103	1	12	2.780	.135	5.1%	98	101	107
104	3	10	2.887	.107	3.8%	99	96	107
105	51	77	2.966	.079	2.8%	70	94	109
106	4	16	3.268	.301	10.2%	102	87	108
107	1	3	3.536	.268	8.2%	103	104	110
108	4	5	3.670	.134	3.8%	106	100	111
109	51	82	4.021	.351	9.6%	105	95	111
110	1	68	4.882	.860	21.4%	107	90	112
111	4	51	6.443	1.561	32.0%	108	109	112
112	1	4	10.635	4.192	65.1%	110	111	0

APPENDIX E

Cluster Analysis Dendograms and Agglomeration Schedules

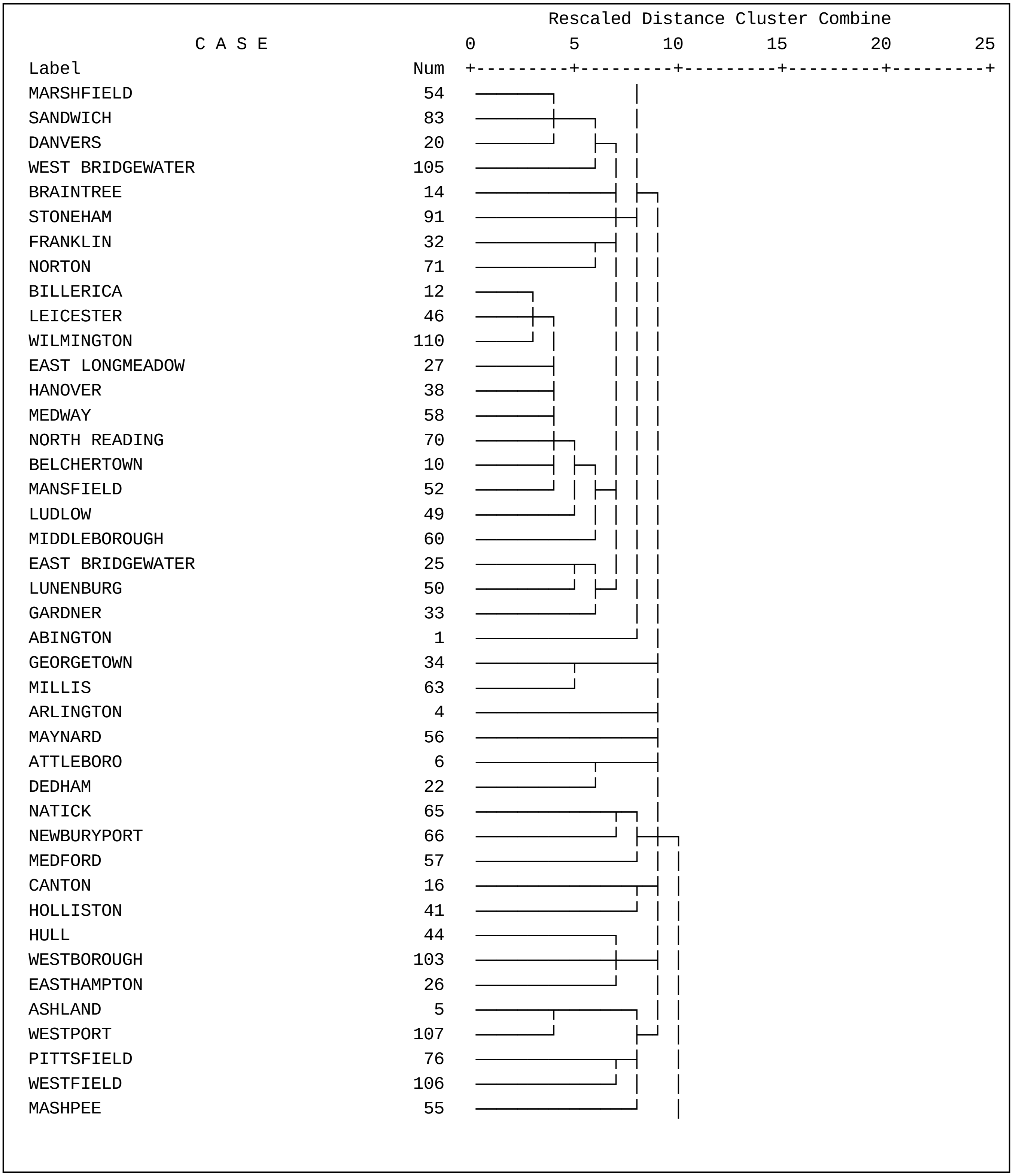
Figure E4. Single Linkage Dendogram Stage 1 to 38



APPENDIX E

Cluster Analysis Dendograms and Agglomeration Schedules

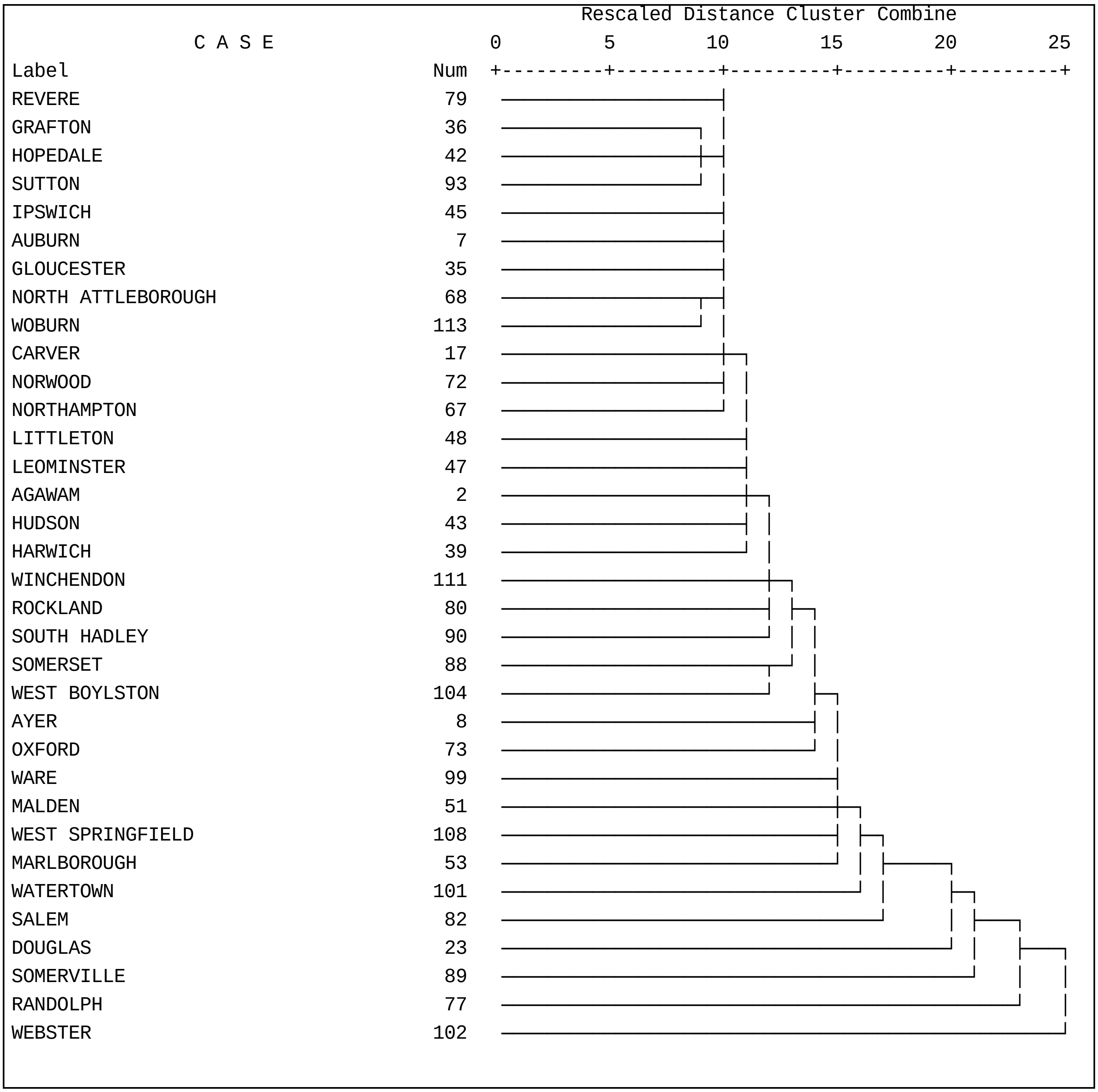
Figure E5. Single Linkage Dendogram Stage 38 to 79



APPENDIX E

Cluster Analysis Dendograms and Agglomeration Schedules

Figure E5. Single Linkage Dendogram Stage 80 to 113



APPENDIX E

Cluster Analysis Dendograms and Agglomeration Schedules

Table E4.

Single Linkage Agglomeration Schedule Stage 1 to 34

	Cluster Combined					Stage Cluster First Appears		
Stage	Cluster 1	Cluster 2	Coefficients	Difference	%Change	Cluster 1	Cluster 2	Next Stage
1	59	97	.243			0	0	2
2	59	85	.299	.056	**23.2%**	1	0	3
3	59	98	.318	.019	6.2%	2	0	6
4	15	30	.357	.039	**12.2%**	0	0	14
5	92	109	.374	.017	**4.8%**	0	0	34
6	59	74	.385	.011	3.1%	3	0	7
7	59	78	.390	.005	1.2%	6	0	8
8	18	59	.399	.009	2.4%	0	7	9
9	18	86	.405	.005	1.3%	8	0	13
10	12	46	.408	.003	0.8%	0	0	11
11	12	110	.434	.026	**6.3%**	10	0	15
12	38	58	.450	.016	3.7%	0	0	16
13	18	87	.454	.004	0.9%	9	0	14
14	15	18	.455	.001	0.3%	4	13	20
15	12	27	.455	.000	0.1%	11	0	18
16	38	70	.457	.002	0.4%	12	0	17
17	10	38	.463	.006	1.3%	0	16	18
18	10	12	.467	.004	0.8%	17	15	24
19	54	83	.469	.002	0.4%	0	0	21
20	15	28	.470	.001	0.3%	14	0	25
21	20	54	.483	.013	2.7%	0	19	38
22	9	75	.492	.010	2.0%	0	0	59
23	5	107	.505	.013	2.6%	0	0	70
24	10	52	.510	.005	1.0%	18	0	30
25	15	24	.521	.011	2.1%	20	0	31
26	25	50	.534	.013	2.5%	0	0	41
27	19	69	.539	.006	1.1%	0	0	51
28	29	81	.541	.001	0.3%	0	0	34
29	34	63	.546	.006	1.1%	0	0	73
30	10	49	.570	.023	**4.2%**	24	0	36
31	15	37	.576	.006	1.1%	25	0	32
32	11	15	.586	.011	1.9%	0	31	33
33	11	112	.593	.006	1.1%	32	0	35
34	29	92	.616	.024	**4.0%**	28	5	45

APPENDIX E

Cluster Analysis Dendograms and Agglomeration Schedules

Table E5.

Single Linkage Agglomeration Schedule Stage 35 to 71

	Cluster Combined					Stage Cluster First Appears		
Stage	Cluster 1	Cluster 2	Coefficients	Difference	%Change	Cluster 1	Cluster 2	Next Stage
35	11	100	.618	.002	0.3%	33	0	40
36	10	60	.626	.008	1.2%	30	0	49
37	6	22	.628	.002	0.4%	0	0	78
38	20	105	.629	.001	0.2%	21	0	56
39	3	96	.634	.005	0.7%	0	0	44
40	11	64	.635	.001	0.2%	35	0	43
41	25	33	.637	.002	0.4%	26	0	49
42	32	71	.645	.008	1.2%	0	0	54
43	11	95	.645	.000	0.0%	40	0	44
44	3	11	.649	.004	0.5%	39	43	45
45	3	29	.649	.000	0.1%	44	34	47
46	44	103	.665	.016	2.5%	0	0	52
47	3	21	.676	.011	1.7%	45	0	57
48	14	91	.677	.001	0.1%	0	0	55
49	10	25	.691	.014	2.0%	36	41	54
50	65	66	.696	.005	0.7%	0	0	67
51	19	61	.696	.001	0.1%	27	0	60
52	26	44	.698	.001	0.2%	0	46	71
53	76	106	.699	.001	0.2%	0	0	58
54	10	32	.708	.009	1.4%	49	42	55
55	10	14	.715	.006	0.9%	54	48	56
56	10	20	.715	.001	0.1%	55	38	62
57	3	62	.721	.006	0.9%	47	0	59
58	55	76	.739	.017	2.4%	0	53	70
59	3	9	.742	.003	0.5%	57	22	63
60	19	40	.743	.001	0.1%	51	0	61
61	19	84	.746	.003	0.3%	60	0	66
62	1	10	.749	.003	0.4%	0	56	68
63	3	13	.754	.005	0.7%	59	0	64
64	3	94	.756	.001	0.2%	63	0	65
65	3	31	.764	.008	1.1%	64	0	66
66	3	19	.766	.002	0.3%	65	61	68
67	57	65	.767	.001	0.1%	0	50	80
68	1	3	.769	.001	0.2%	62	66	73
69	16	41	.770	.002	0.2%	0	0	74
70	5	55	.785	.014	1.9%	23	58	71
71	5	26	.797	.012	1.5%	70	52	74

APPENDIX E

Cluster Analysis Dendograms and Agglomeration Schedules

Table E6.

Single Linkage Agglomeration Schedule Stage 72 to 113

Stage	Cluster Combined: Cluster 1	Cluster Combined: Cluster 2	Coefficients	Difference	%Change	Stage Cluster First Appears: Cluster 1	Stage Cluster First Appears: Cluster 2	Next Stage
72	36	42	.800	.004	0.5%	0	0	79
73	1	34	.800	.000	0.0%	68	29	75
74	5	16	.807	.007	0.8%	71	69	81
75	1	4	.813	.006	0.7%	73	0	76
76	1	56	.814	.002	0.2%	75	0	78
77	68	113	.820	.006	0.7%	0	0	88
78	1	6	.825	.005	0.6%	76	37	80
79	36	93	.833	.008	1.0%	72	0	84
80	1	57	.845	.012	1.4%	78	67	81
81	1	5	.854	.010	1.1%	[illegible]	[illegible]	[illegible]
82	1	79	.864	.010	1.2%	[illegible]	[illegible]	[illegible]
83	17	72	.868	.004	0.4%	[illegible]	[illegible]	[illegible]
84	1	36	.869	.001	0.1%	[illegible]	[illegible]	[illegible]
85	1	45	.873	.003	0.4%	[illegible]	[illegible]	[illegible]
86	1	7	.880	.007	0.8%	[illegible]	[illegible]	[illegible]
87	1	35	.886	.007	0.8%	[illegible]	[illegible]	[illegible]
88	1	68	.888	.002	0.2%	[illegible]	[illegible]	[illegible]
89	1	17	.898	.010	1.1%	[illegible]	[illegible]	[illegible]
90	1	67	.906	.008	0.9%	89	0	91
91	1	48	.931	.024	2.7%	90	0	92
92	1	47	.932	.002	0.2%	91	0	93
93	1	2	.938	.006	0.6%	92	0	94
94	1	43	.941	.003	0.3%	93	0	95
95	1	39	.956	.015	1.6%	[illegible]	[illegible]	[illegible]
96	1	111	1.012	.056	**5.9%**	[illegible]	[illegible]	[illegible]
97	88	104	1.012	.000	0.0%	[illegible]	[illegible]	[illegible]
98	1	80	1.019	.007	0.7%	[illegible]	[illegible]	[illegible]
99	1	90	1.057	.038	3.7%	[illegible]	[illegible]	[illegible]
100	1	88	1.100	.043	**4.1%**	[illegible]	[illegible]	[illegible]
101	1	8	1.159	.059	**5.3%**	[illegible]	[illegible]	[illegible]
102	1	73	1.184	.026	2.2%	[illegible]	[illegible]	[illegible]
103	51	108	1.208	.023	2.0%	[illegible]	[illegible]	[illegible]
104	1	99	1.222	.015	1.2%	[illegible]	[illegible]	[illegible]
105	1	51	1.229	.007	0.5%	[illegible]	[illegible]	[illegible]
106	1	53	1.249	.020	1.6%	[illegible]	[illegible]	[illegible]
107	1	101	1.332	.082	**6.5%**	[illegible]	[illegible]	[illegible]
108	1	82	1.407	.076	**5.7%**	107	0	109
109	1	23	1.593	.186	**13.2%**	108	0	110
110	1	89	1.634	.041	2.5%	109	0	111
111	1	77	1.805	.172	**10.5%**	110	0	112
112	1	102	1.962	.156	**8.6%**	111	0	0

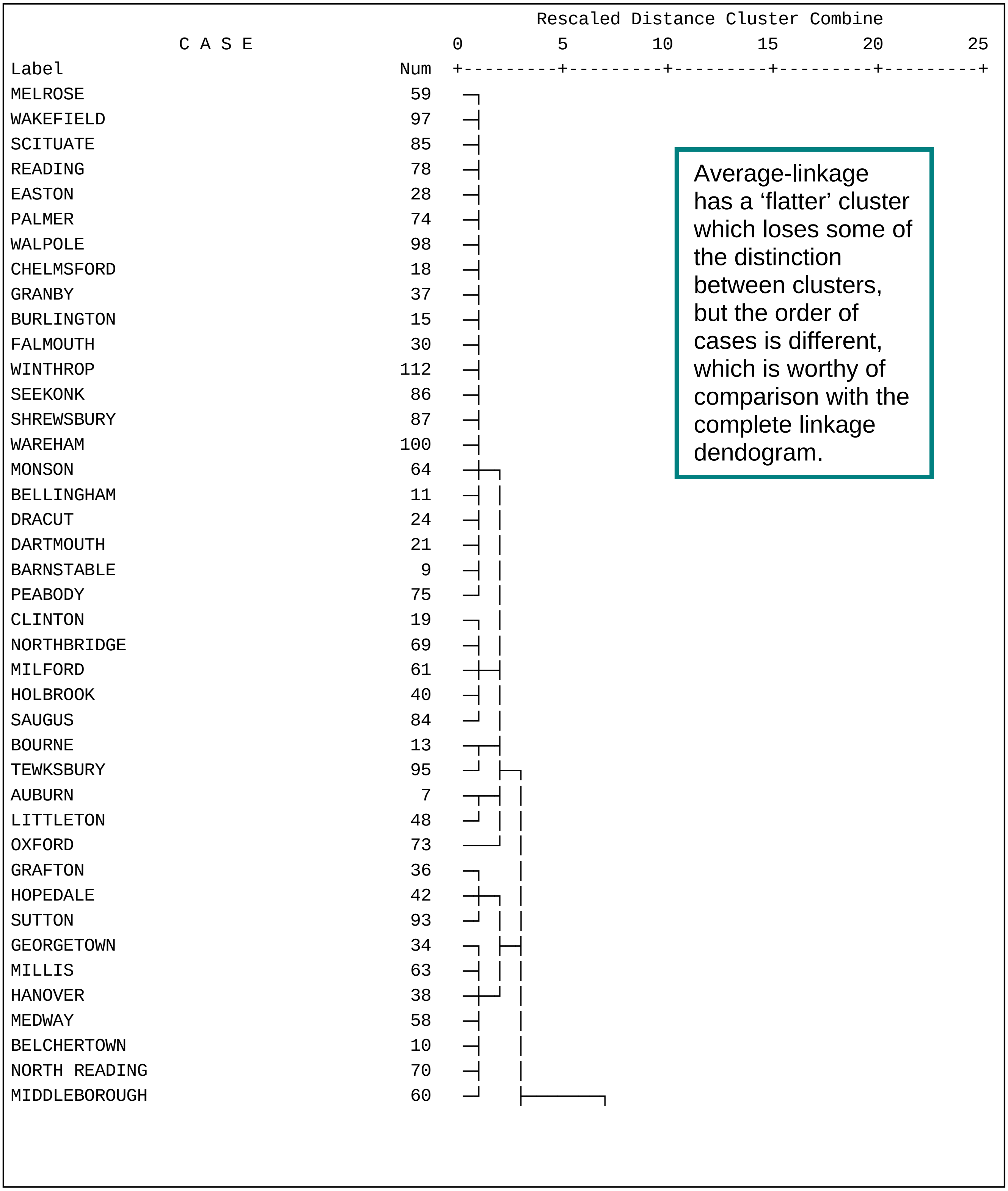
The lack of significant change between any set of clusters reduces the value of single-linkage clustering for this data set.

The significant change at the 'bottom' of the schedule for all 3 methods indicates a type of outlier in cluster analysis. These same districts do not connect well with the overall data-set.

APPENDIX E

Cluster Analysis Dendograms and Agglomeration Schedules

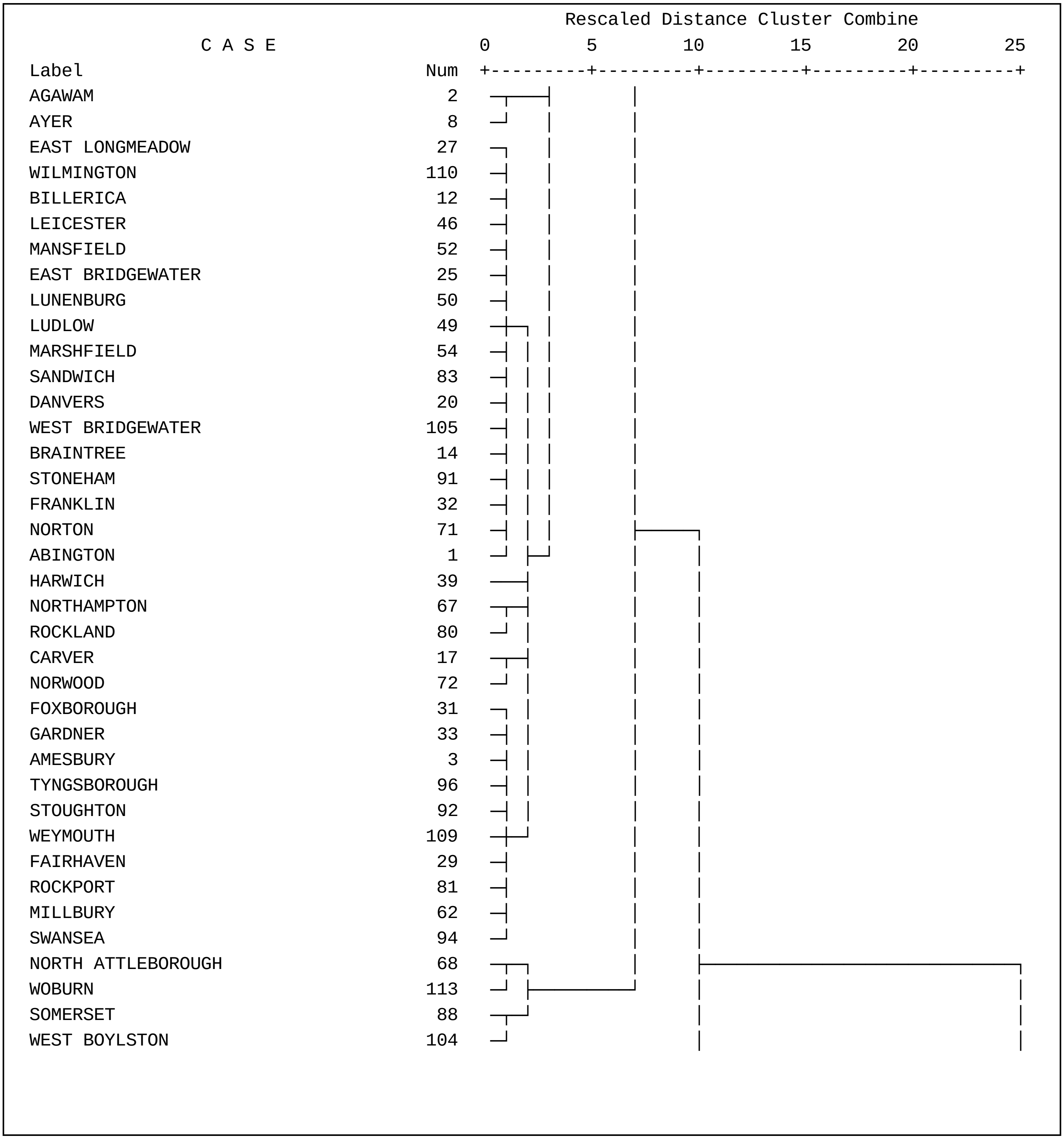
Figure E7. Average Linkage Dendogram Stage 1 to 38



APPENDIX E

Cluster Analysis Dendograms and Agglomeration Schedules

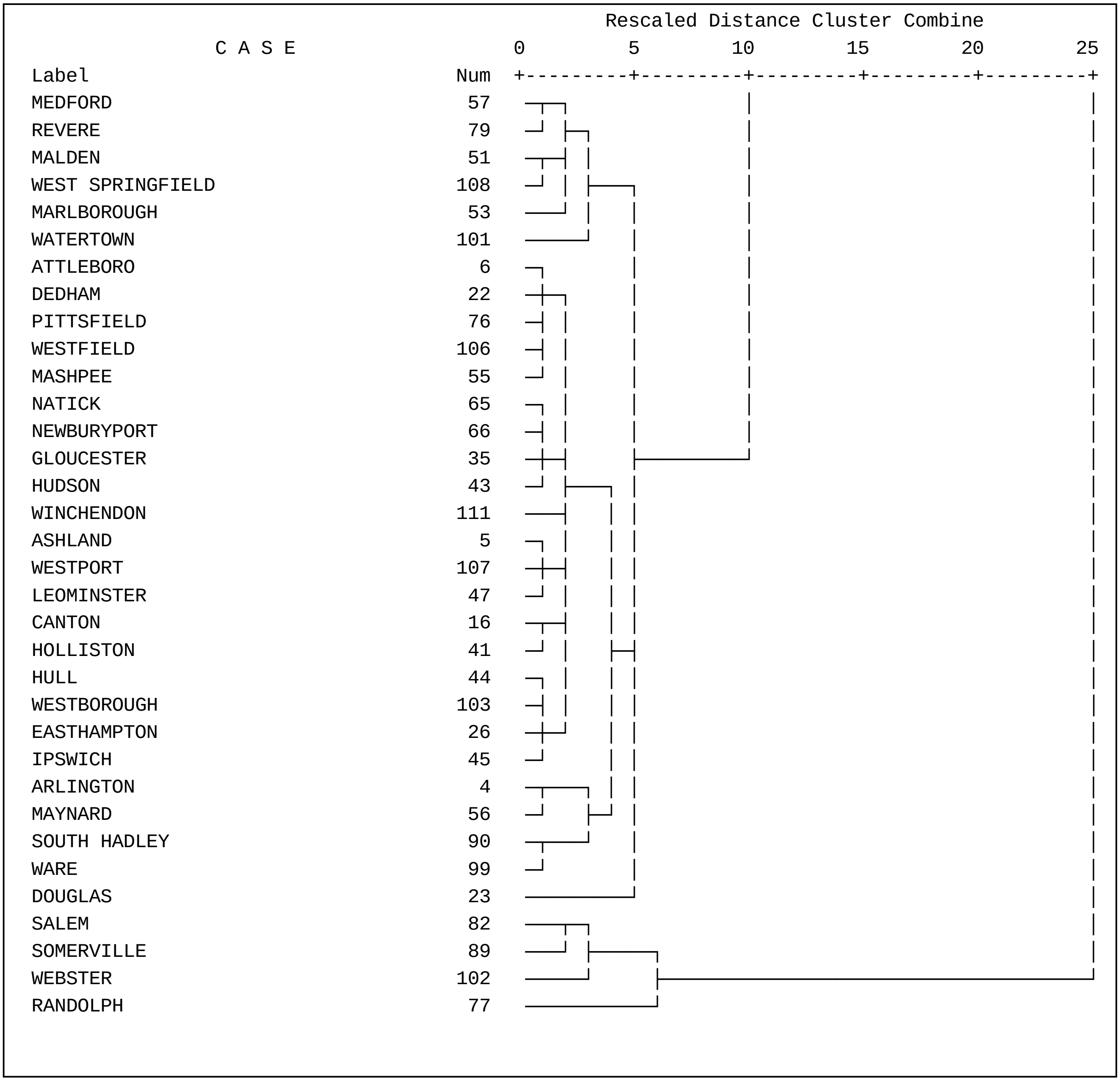
Figure E8. Average Linkage Dendogram Stage 39 to 76



APPENDIX E

Cluster Analysis Dendograms and Agglomeration Schedules

Figure E9. Average Linkage Dendogram Stage 77 to 113



APPENDIX E

Cluster Analysis Dendograms and Agglomeration Schedules

Table E7.

Average Linkage Agglomeration Schedule Stage 1 to 41

	Cluster Combined					Stage Cluster First		
Stage	Cluster 1	Cluster 2	Coefficients	Difference	%Change	Cluster 1	Cluster 2	Next Stage
1	59	97	.059			0	0	2
2	59	85	.113	.054	47.82%	1	0	14
3	15	30	.127	.014	11.14%	0	0	30
4	92	109	.140	.012	8.88%	0	0	42
5	74	98	.148	.009	5.84%	0	0	7
6	12	46	.166	.018	**10.79%**	0	0	20
7	18	74	.173	.006	3.71%	0	5	34
8	38	58	.202	.029	14.54%	0	0	22
9	86	87	.206	.004	1.70%	0	0	24
10	10	70	.214	.009	4.01%	0	0	22
11	54	83	.220	.005	2.38%	0	0	52
12	27	110	.223	.003	1.41%	0	0	36
13	9	75	.242	.019	8.03%	0	0	75
14	59	78	.243	.001	0.38%	2	0	21
15	5	107	.255	.012	4.63%	0	0	57
16	25	50	.285	.030	**10.51%**	0	0	40
17	19	69	.291	.006	2.08%	0	0	38
18	29	81	.292	.001	0.51%	0	0	42
19	34	63	.299	.006	2.09%	0	0	77
20	12	52	.306	.008	2.46%	6	0	36
21	28	59	.337	.031	**9.08%**	0	14	34
22	10	38	.367	.030	**8.22%**	10	8	62
23	11	24	.390	.023	**5.83%**	0	0	43
24	86	100	.391	.002	0.39%	9	0	32
25	6	22	.395	.004	0.92%	0	0	66
26	20	105	.396	.001	0.32%	0	0	52
27	3	96	.402	.006	1.42%	0	0	49
28	32	71	.416	.014	3.48%	0	0	56
29	44	103	.442	.026	**5.93%**	0	0	37
30	15	112	.457	.014	3.17%	3	0	53
31	14	91	.459	.002	0.40%	0	0	64
32	64	86	.465	.006	1.33%	0	24	58
33	65	66	.484	.019	3.89%	0	0	59
34	18	28	.488	.004	0.79%	7	21	46
35	76	106	.488	.001	0.12%	0	0	47
36	12	27	.523	.035	**6.69%**	20	12	61
37	26	44	.535	.012	2.21%	0	29	69
38	19	61	.553	.018	3.31%	17	0	67
39	40	84	.556	.003	0.47%	0	0	67
40	25	49	.556	.000	0.08%	16	0	61
41	13	95	.569	.012	2.16%	0	0	87

APPENDIX E

Cluster Analysis Dendograms and Agglomeration Schedules

Table E8.

Average Linkage Agglomeration Schedule Stage 41 to 82

	Cluster Combined					Stage Cluster First		
Stage	Cluster 1	Cluster 2	Coefficients	Difference	%Change	Cluster 1	Cluster 2	Next Stage
42	29	92	.570	.002	0.27%	18	4	49
43	11	21	.590	.020	3.37%	23	0	58
44	31	33	.591	.001	0.19%	0	0	70
45	16	41	.594	.002	0.40%	0	0	92
46	18	37	.601	.008	1.31%	34	0	53
47	55	76	.611	.009	1.54%	0	35	66
48	36	42	.640	.030	4.61%	0	0	72
49	3	29	.645	.004	0.64%	27	42	65
50	4	56	.663	.019	2.82%	0	0	105
51	68	113	.673	.010	1.44%	0	0	93
52	20	54	.701	.028	4.04%	26	11	76
53	15	18	.712	.011	1.54%	30	46	60
54	57	79	.747	.035	4.67%	0	0	90
55	17	72	.753	.006	0.84%	0	0	85
56	1	32	.844	.091	**10.77%**	0	28	64
57	5	47	.874	.030	3.41%	15	0	96
58	11	64	.881	.007	0.82%	43	32	60
59	35	65	.916	.034	3.74%	0	33	74
60	11	15	.918	.002	0.23%	58	53	75
61	12	25	.922	.004	0.44%	36	40	80
62	10	60	1.021	.099	9.73%	22	0	77
63	88	104	1.025	.004	0.37%	0	0	93
64	1	14	1.026	.001	0.11%	56	31	76
65	3	62	1.042	.016	1.49%	49	0	70
66	6	55	1.071	.029	2.73%	25	47	89
67	19	40	1.077	.006	0.59%	38	39	84
68	7	48	1.105	.028	2.53%	0	0	97
69	26	45	1.125	.019	1.72%	37	0	92
70	3	31	1.155	.031	2.65%	65	44	78
71	67	80	1.167	.012	1.00%	0	0	91
72	36	93	1.179	.012	1.06%	48	0	86
73	2	8	1.343	.163	**12.17%**	0	0	101
74	35	43	1.350	.007	0.51%	59	0	83
75	9	11	1.355	.006	0.42%	13	60	84
76	1	20	1.403	.048	3.41%	64	52	80
77	10	34	1.413	.010	0.70%	62	19	86
78	3	94	1.417	.004	0.29%	70	0	85
79	51	108	1.459	.042	2.86%	0	0	82
80	1	12	1.493	.034	2.29%	76	61	88
81	90	99	1.494	.001	0.07%	0	0	105
82	51	53	1.581	.087	5.50%	79	0	90

APPENDIX E

Cluster Analysis Dendograms and Agglomeration Schedules

Table E9.

Average Linkage Agglomeration Schedule Stage 83 to 113

	Cluster Combined					Stage Cluster First		
Stage	Cluster 1	Cluster 2	Coefficients	Difference	%Change	Cluster 1	Cluster 2	Next Stage
83	35	111	1.594	.013	0.80%	74	0	89
84	9	19	1.648	.054	3.26%	75	67	87
85	3	17	1.979	.331	**16.74%**	78	55	91
86	10	36	1.990	.011	0.54%	77	72	100
87	9	13	2.027	.037	1.84%	84	41	97
88	1	39	2.037	.009	0.46%	80	0	94
89	6	35	2.095	.058	2.79%	66	83	99
90	51	57	2.150	.055	2.55%	82	54	102
91	3	67	2.189	.039	1.77%	85	71	94
92	16	26	2.320	.131	5.66%	45	69	96
93	68	88	2.507	.187	7.46%	51	63	110
94	1	3	2.565	.058	2.27%	88	91	101
95	82	89	2.669	.104	3.89%	0	0	104
96	5	16	2.716	.047	1.72%	57	92	99
97	7	9	2.747	.031	1.12%	68	87	98
98	7	73	2.981	.235	7.88%	97	0	100
99	5	6	3.028	.046	1.54%	96	89	106
100	7	10	3.184	.156	4.90%	98	86	103
101	1	2	3.349	.165	4.92%	94	73	103
102	51	101	3.522	.173	4.90%	90	0	108
103	1	7	4.111	.589	**14.34%**	101	100	110
104	82	102	4.171	.060	1.44%	95	0	109
105	4	90	4.270	.099	2.33%	50	81	106
106	4	5	4.872	.602	12.35%	105	99	107
107	4	23	6.276	1.404	22.37%	106	0	108
108	4	51	6.814	.538	7.89%	107	102	111
109	77	82	8.028	1.214	15.13%	0	104	112
110	1	68	9.420	1.392	14.77%	103	93	111
111	1	4	14.029	4.609	32.85%	110	108	112
112	1	77	37.824	23.795	62.91%	111	109	0