Food Consumption and Seasonality

Ronald B. Larson

Time-series analyses of food demand often add dummy or harmonic variables to shift intercept terms during periods when seasonal effects exist. However, variable coefficients may be influenced by seasonality and the effects may vary by region. In this paper, a cluster analysis of seasonality indices for food products shows that distinct regions exist with similar seasonal patterns. Researchers could use these clusters to test for season-region interactions when other information about seasonality is unavailable.

Seasonal forces can have profound impacts on consumption patterns, prices, and demand relationships. Waldrop and Mogelonsky (1992, p. 14) wrote: "The seasons influence not only what consumers buy, but how they feel and think during different times of the year." Many foods (e.g., candy, yogurt, and beer) have distinctive seasonal consumption patterns that marketers consider when planning their promotions and production schedules. The timing of a promotion may affect its effectiveness. For example, cycles in temperature, precipitation, and daylight appear to be related with TV viewing levels (Barnett et al., 1991). Advertisers know that television audiences shrink in the summer and adjust their advertising schedules. Ward (1985, p.9) wrote: "Daily weather changes produce large changes in consumer behavior." In test markets, he had noted changes of 50 percent to 200 percent in daily product sales rates. Radio advertising for Campbell Soup is increased whenever major storms are forecast (Waldrop and Mogelonsky, 1992). The company also ships extra soup to areas included in hurricane watches to meet increased demand (Maritato, 1991).

When categories have strong seasonal patterns, marketers can exploit these sales regularities. Totten (1991) examined two frozen novelty brands with atypical seasonalities. One, a niche product appealing to diet-conscious adults, was affected by the category's seasonal pattern and by the consumer interest in weight loss. The other brand practiced counter-seasonal promotions. Totten concluded that this brand's marketing efforts were more efficient because of less category promotional clutter and less competition for retail participation during the off-season. These examples illustrate how important understanding seasonal purchase patterns can be for firms.

Demand models often include variables to account for seasonality. Because many studies focus on the price and income coefficients, seasonal adjustments are not emphasized. Granger (1978) argued that ignoring the causes of seasonality can lead to poor choices of adjustment methods and incorrect evaluations of their performance. Analysts can enhance the quality of their parameter estimates by studying the factors that cause the seasonal variations and by improving the adjustments in their models.

Because weather patterns vary by region, region-season interactions may be important. Garbacz (1986) tested for regional and seasonal variations in electricity demand using monthly household-level data from the four Census regions. Not only did the demand elasticities differ by region and by month, each region had its own unique seasonal pattern. If region-season interactions are significant for electricity, they may also be important for food. Unfortunately, few time-series food demand studies have allowed parameters to change by season or have reported testing for region-season interactions. If regions have different seasonal consumption patterns, studies that assume one seasonal pattern exists in all markets may have biased elasticity estimates.

This paper uses cluster analysis to illustrate that seasonal food consumption patterns often differ by area and to develop regions with similar

---

Ronald B. Larson is Assistant Director, The Retail Food Industry Center, Applied Economics Department, University of Minnesota.

The author wishes to thank Dr. Jean Kinsey for her comments on this paper, and his dissertation committee, Dr. Jay T. Akridge (Chair), Dr. Daniel S. Putler, Dr. William A. Schiek, and Dr. Lee F. Schrader, for their comments on the dissertation that was the basis for this paper.

seasonal patterns. The first section reviews several causes of seasonality and common approaches for including seasonality in empirical analyses. The second section summarizes how many time-series food demand analyses have treated seasonality. In the next two sections, the Selling-Area Marketing, Inc. (SAMI) seasonality indices and the cluster analysis methodology are introduced. SAMI market areas with similar seasonal patterns are grouped using clustering techniques. If the market groups have a geographic pattern, region-season interactions may be common for food products. The paper concludes with a discussion of the several implications for marketers and demand analysts.

Methods for Considering Seasonality in Analyses

Seasonal patterns in economic time series have been studied for more than 100 years. A broad definition of the phenomenon was proposed by Hylleberg (1986, p. 23):

> *Seasonality is the systematic, although not necessarily regular or unchanging, intra-year movement that is caused by climatic changes, timing of religious festivals, business practices, and expectations and gives rise to spectral peaks around the seasonal frequency and its harmonics.*

To incorporate seasonality into models, it is often helpful to understand the causes of the cycles.

Many seasonal patterns occur in nature. Some animal behaviors change in response to day length, daylight intensity, changes in the day length, changes in food availability, and rain (Nelson, Badura and Goldman, 1990). Sunlight and weather may trigger hormonal changes that cause the behavior variations. Human birthdays have seasonal patterns that vary across countries and across regions in the U.S. Studies have speculated that weather, temperature, economic variables, holidays, misinformation on residual effects from birth control pills, the agricultural production cycle, and the timing of marriages may be related to the seasonality in births (Lam and Miron, 1991; Rodgers and Udry, 1988; Underwood, 1991; Waldrop, 1991). Some of these natural phenomena may help explain the seasonal cycles in food product demand.

Other systematic cycles are artificial. Annual events like Mother's Day and Halloween are associated with particular purchases. Totten (1991) showed that ready-to-eat cereal sales fell 10 to 20 percent during the week before or the week of the Thanksgiving and Christmas holidays. Piecrust mix had sales increases that ranged from 50 to 225 percent during those weeks. Seasonal patterns also have been observed within months. Carman and Figueroa (1986) found that supermarket sales in the first week of the month averaged 5.4 percent above forecast when they excluded weekly within-month dummy variables from their model. The distribution of Social Security checks, other government checks, and pay checks may explain much of the extra volume.

If important seasonal variations are not considered in a regression, the estimation error may increase and the variables correlated with the seasonality may have biased coefficients. To reduce the problem, dummy variable, time-series, harmonic variables, and deseasonalizing methods may be used. Each technique is described below along with a summary of its benefits and limitations.

Analysts often use dummy variables in their regressions when they believe that seasonality is deterministic. Dummies for weeks that tend to be far from average can be added to models to adjust for holidays and unusual events. However, dummy variables may cause sharp swings in the predicted dependent variable and influence forecasts. Wildt (1977) suggests that using dummy variables only as intercept shifters could mislead researchers because important interactions may be omitted. Because employing slope and intercept shifters may add some multicollinearity, it may be difficult to judge the value of the dummy variables. He recommends considering several seasonal forms before selecting the most appropriate specification.

Regressions constrain the dummy variable coefficients to remain fixed. To conserve degrees of freedom, some analysts collapse the set of dummy variables into a single seasonal index variable. Instability in the seasonal cycles can be a problem for both dummy variables and seasonal indices. Developing good seasonal indices and deciding when to update them can be difficult.

Some time-series models employ several lags or lag polynomials or add seasonal explanatory variables. Holidays and other seasonal purchase behaviors may be difficult to capture with standard time-series techniques. Osborn (1991) recommended using seasonally-varying parameters in time-series studies to allow behavior to change during the year.

Harmonic variables can be added to capture cyclical patterns. These sine or cosine waves provide smoother transitions than dummy variables. Because they are symmetric with similar cycle lengths and amplitudes above and below the trend line, irregular and asymmetric seasonal patterns may not fit the cycles. Deciding how many harmonic variables to include can also be a concern. If several seasonal patterns exist, more than one harmonic variable may be needed. Simmons (1990) discussed several cycle regression analysis algorithms that used stopping rules to signal when adding another wave did not significantly improve the model.

The fourth approach for handling seasonal data is to deseasonalize it before any analysis. Many government statistics are deseasonalized before publication. Kuiper (1978) and Hylleberg (1986) evaluated many techniques including several ratio-to-moving-average approaches and found that most tended to perform well. Kallek (1978) argued that deseasonalization may compound the errors when the process is imperfect or the data contain measurement errors. Hylleberg (1986) recommended that seasonality should be incorporated into the model instead of removing it from the data before the analysis and that researchers should avoid mixing deseasonalized and actual data in the same analysis. Although none of the four methods for handling seasonality is ideal for all circumstances, each captures some variation and may reduce the biases on other coefficients.

Adjusting for Seasonality in Food Demand Research

Larson (1994) reviewed how seasonality was treated in 34 U.S. food demand time-series studies that were published from 1978 to 1993. Nearly all the articles included adjustments for seasonality with little discussion of their merits or implications. Most that used weekly data added dummy variables for holiday weeks. For example, Brooker, Eastwood, and Gray (1994) analyzed weekly scanning data for beef cuts and estimated the response to price changes and promotions. Their model had dummy variables for holiday weeks, quarters, and years. They also had a week-of-the-month variable to capture seasonality within months. McNulty and Huffman (1992) employed monthly dummy variables and added an adjustment for the number of trading days per month. They considered multiplicative and additive expressions for trading days and concluded that this source of seasonality could create large biases in monthly meat demand estimates if studies failed to account for it. Their results illustrate the importance of using sound seasonality adjustments.

The influence of some variables on demand may change over time. For example, Epperson, Tyan and Huang (1981) reported that price flexibilities for fresh produce varied by market, month, and product. Almost all the studies reviewed by Larson had significant coefficients on their seasonality variables. However, only two reported testing for interactions between seasonality and the other variables. Kinnucan and Forker (1986) concluded that milk advertising productivity may vary over time. Marion and Walker (1978) reported significant interactions between price and the nearness to payday in their beef chuck, beef loin, pork loin, and fryers equations.

Several food demand studies have pooled cross-section and time-series data. Usually they employ one set of seasonal variables and implicitly assume that the same pattern exists in every region. If each region has unique seasonal patterns, failure to allow for these variations could produce poor estimates because of spatial error autocorrelation. Given the many causes of seasonal cycles noted in the previous section, differences between markets may be quite common. The next section explores whether adjoining markets have similar seasonal patterns.

Seasonality Data to be Clustered

Cluster analysis algorithms can use many variables to systematically classify entities based on their similarity. The seven-step cluster analysis procedure described by Milligan and Cooper (1987) was used to build regions with similar seasonality patterns. The first step was to select objects for the analysis. Grocery trading areas designed by Arbitron/SAMI, a marketing research and consulting firm, were clustered. The boundaries for these 54 SAMI markets are illustrated in Figure 1 and their names and abbreviations are listed in Table 1.

The next step was to select the variables. Arbitron/SAMI sold clients annual reports showing seasonality indices by market for each category and graciously provided the data for this analysis. These measures, based on warehouse withdrawals, compared the unit volume during each four-week period with the average annual volume in a market. Figure 2 shows the 1990 SAMI seasonalities indices for the Canned Cranberries category in two markets. In period 4, Buffalo/Rochester's index was 119, so volume during that four-week period was 19 percent above average. Buffalo's sales peaked in the period that included Thanksgiving, but Spokane/Yakima's index was twice as high during that period. Buffalo's pattern with a small increase in period 4 was similar to many other markets in the Northeast. Consumption during Easter in Buffalo represented a much higher share of their annual Canned Cranberry volume than in Spokane. Spokane's sharp spike during November was consistent with other markets in the Northwest. One source of these differences may be regional variations in the menus for traditional holiday meals.

Thirty-six SAMI food categories, listed in Table 2, were selected for the cluster analysis. They all had annual sales levels averaging at least one dollar per household, were sold in every market during each four-week period, and had wide ranges in their national seasonality indices (the Canned Cranberries category was not included because of its extreme index range). The 13 indices for each category (i.e., 468 observations for each market) will be used to group the SAMI markets based on their four-week sales trends during 1990.

Figure 1. SAMI Market Boundaries.

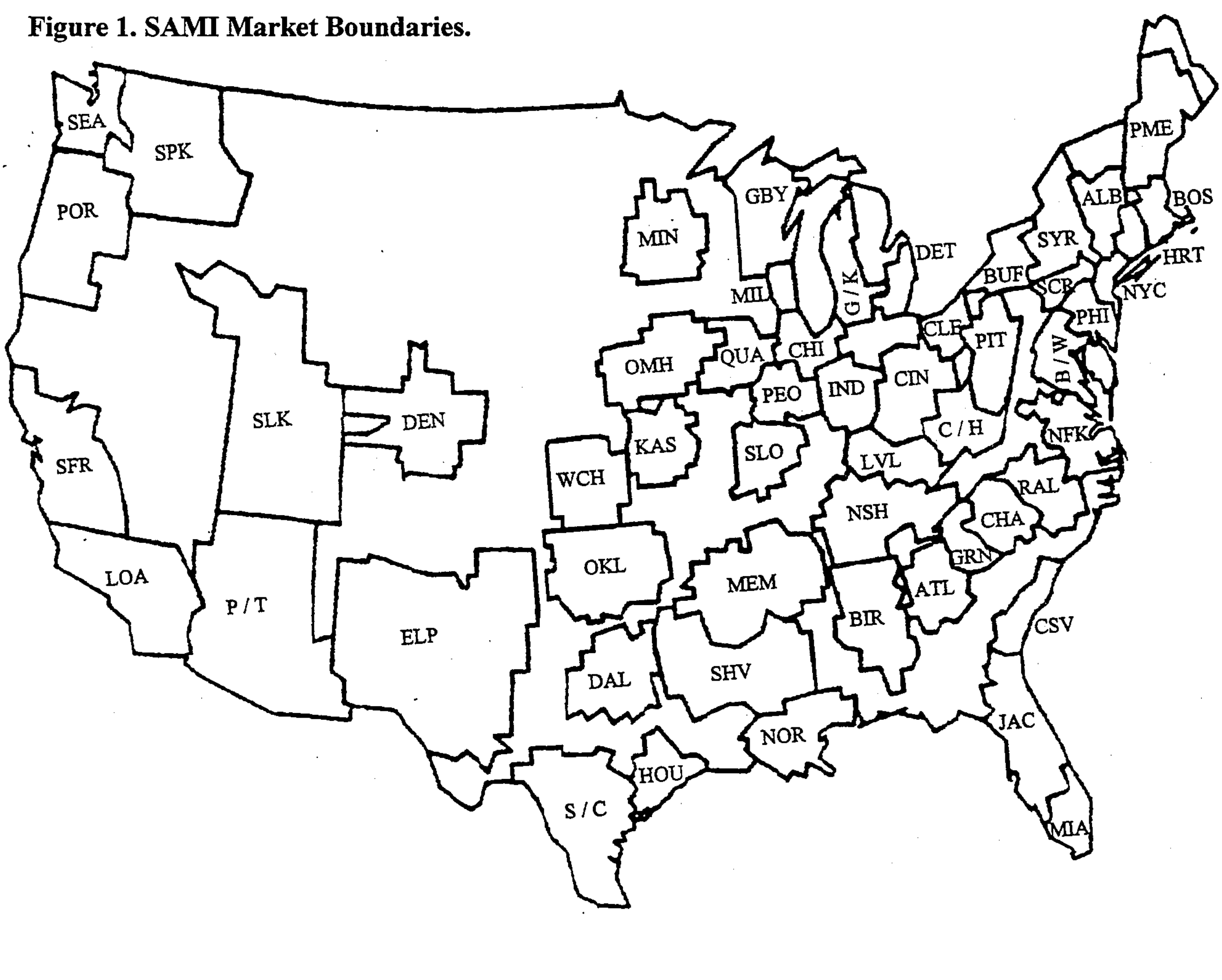

Table 1. SAMI Market Names and Abbreviations.

MKT	Market Name	MKT	Market Name
ALB	Albany-Schenectady-Troy	MIA	Miami
ATL	Atlanta	MIL	Milwaukee
BIR	Birmingham-Montgomery-Huntsville	MIN	Minneapolis-St. Paul
BOS	Boston-Providence	NFK	Norfolk-Richmond
BUF	Buffalo-Rochester	NOR	New Orleans
B/W	Baltimore-Washington	NSH	Nashville-Knoxville, TN
CHA	Charlotte	NYC	New York
CHI	Chicago	OKL	Oklahoma City-Tulsa
CIN	Cincinnati-Dayton-Columbus	OMH	Omaha-Des Moines
CLE	Cleveland	PEO	Peoria-Springfield, IL
CSV	Charleston-Savannah	PHI	Philadelphia
C/H	Charleston-Huntington	PIT	Pittsburgh
DAL	Dallas-Ft. Worth	PME	Portland, ME
DEN	Denver	POR	Portland, OR
DET	Detroit	P/T	Phoenix-Tucson
ELP	El Paso-Albuquerque-Lubbock	QUA	Quad Cities
GBY	Green Bay	RAL	Raleigh-Greensboro-Winston-Salem
GRN	Greenville-Spartanburg-Asheville, SC	SCR	Scranton-Wilkes Barre, PA
G/K	Grand Rapids-Kalamazoo	SEA	Seattle-Tacoma
HOU	Houston	SFR	San Francisco
HRT	Hartford-New Haven-Springfield, CT	SHV	Shreveport-Jackson
IND	Indianapolis	SLK	Salt Lake City-Boise
JAC	Jacksonville-Orlando-Tampa	SLO	St. Louis
KAS	Kansas City	SPK	Spokane-Yakima, WA
LOA	Los Angeles-San Diego	SYR	Syracuse
LVL	Louisville-Lexington, KY	S/C	San Antonio-Corpus Christi
MEM	Memphis-Little Rock	WCH	Wichita

Deciding whether to standardize the variables was the third step in the procedure. In this case, the index mean for each category-market combination was 100. Across all the categories and markets, the indices ranged from a peak of 519 for Canned Potatoes to a trough of 14 for Frozen Lemonade, Limeade and Orangeade. Across all the categories and periods, Philadelphia had the highest standard deviation, 47.41, while Grand Rapids/Kalamazoo had the lowest, 29.82. Across all markets and periods, Frozen Pastry Items had the highest standard deviation, 87.79, while Ready-to-Eat Cereal had the lowest, 5.44. Although these differences suggest that variable standardization may be appropriate, assigning low weights to categories with distinctive seasonalities may reduce the likelihood of developing good clusters. Therefore, unstandardized data was used in the analysis.

Before describing more of the methodology, a few data limitations should be discussed. Because the indices were developed from warehouse withdrawals, they may lead the seasonal patterns in weekly scanner data. Store inventories also buffer the indices against sharp swings. Because only one year of market-level indices was available, some spikes from regional promotions can be expected. Hopefully, the breadth of the categories involved will minimize this problem.

Figure 2. SAMI 1990 Seasonalities Indices for Canned Cranberries in the Buffalo/Rochester and Spokane/Yakima Markets.

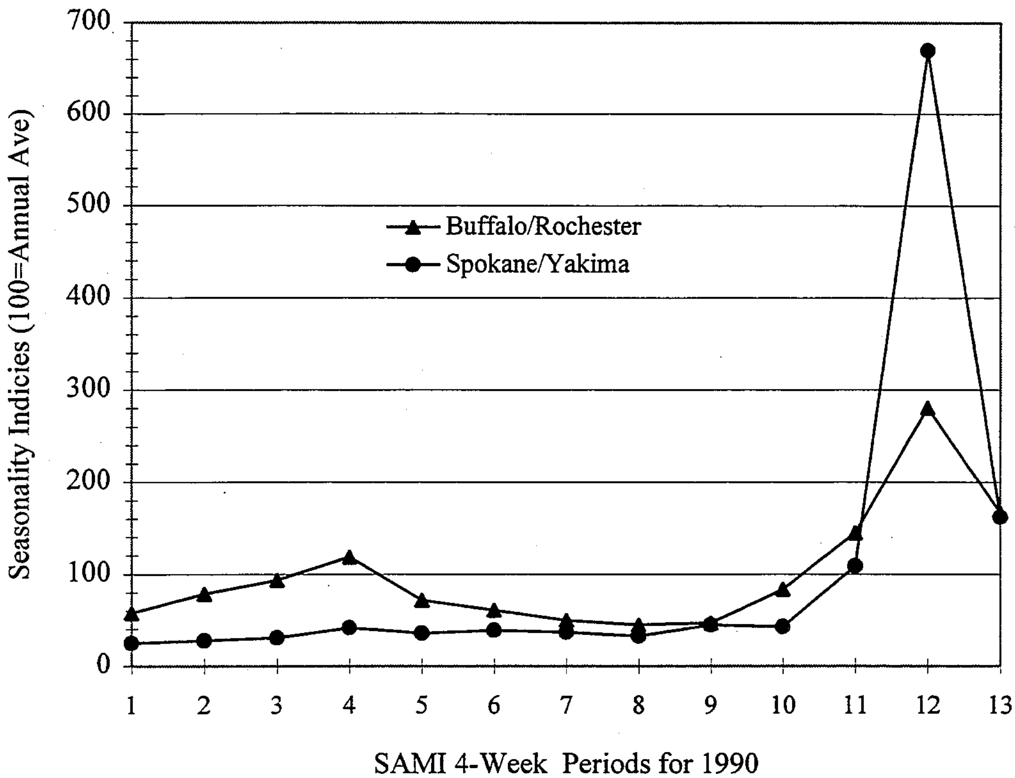

Table 2. Thirty-Six SAMI Food Categories Included in the Seasonality Cluster Analysis.

Bacon	Canned Soup	Frozen Sweet Goods
Baking Chocolate & Bits	Canned Tomatoes	Hot Cereal
Baking Nuts	Confectioners' Sugar	Milk Modifiers
Brown Sugar	Dehydrated Soup	Pancake Mixes
Canned Asparagus	Family Flour	Pasta
Canned Chili	Frozen Apple Juice/Cider	Ready-to-Eat Cereal
Canned Corn	Frozen Dinner Bread & Rolls	Refrigerated Orange Juice
Canned Green Beans	Frozen Lemonade, Limeade & Orangeade	Shelf-Stable Apple Juice
Canned Kidney & Miscellaneous Beans	Frozen Orange Juice	Shelf-Stable Juice Drinks Single Strength
Canned Meat Stew	Frozen Pastry Items	Shelf-Stable Tomato Juice
Canned Mushrooms	Frozen Pies	Tomato Paste
Canned Potatoes	Frozen Pot Pies	Tomato Sauce

Cluster Analysis Methodology and Results

The next three steps in the clustering procedure involve selecting the similarity measure, the clustering methods, and the stopping rules. Euclidean distance will be used to measure similarity. Ward's and Beta-Flexible hierarchical algorithms (with beta equal to -0.25) will be employed along with a K-means partitioning algorithm in an attempt to form a consensus on the best market grouping (Milligan, 1980; Scheibler and Schneider, 1985; Milligan, 1989). Pseudo-F and Pseudo-T^2 stopping rules will guide the selection of the number of clusters (Cooper and Milligan, 1988).

The final step in the clustering procedure is to interpret, test, and replicate the results. Figure 3 shows the tree diagram covering the level 13 to level 4 results from Ward's method. Portland, OR, Seattle/Tacoma, and Spokane/Yakima were clustered together at level 13. To create 12 groups, Salt Lake City/Boise was merged with the group of four markets headed by Dallas/Ft. Worth.

The Ward's method results have definite regional qualities. Most of the markets in "Southwest," "Southeast," and "Northeast" clusters are adjoining. Other than including Phoenix/Tucson with the "Northwest" markets and the Michigan markets with the "Northeast," regions with similar consumption seasonalities are formed by this algorithm.

The Beta-Flexible results, shown in Figure 4, are very similar to the Ward's clusters. Nine clusters at level 13 matched and the cluster combinations are often identical. The merger order varies, leading to some differences until level 6 and level 5 when all the groups are the same. K-means was unable to improve on the seeds from the Ward's and Beta-Flexible methods. The consistency in the results from these two algorithms adds support to the hypothesis that groups of markets exist that have similar seasonal patterns.

Figure 3. Tree Diagram of Seasonality Clusters 13 to 4 Based on Ward's Method.

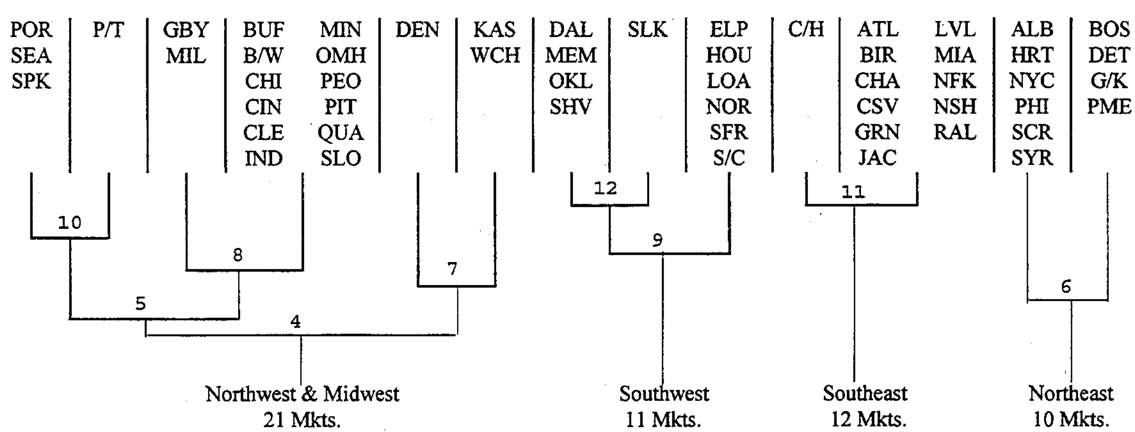

Figure 4. Tree Diagram of Seasonality Clusters 13 to 4 Based on Beta-Flexible Method.

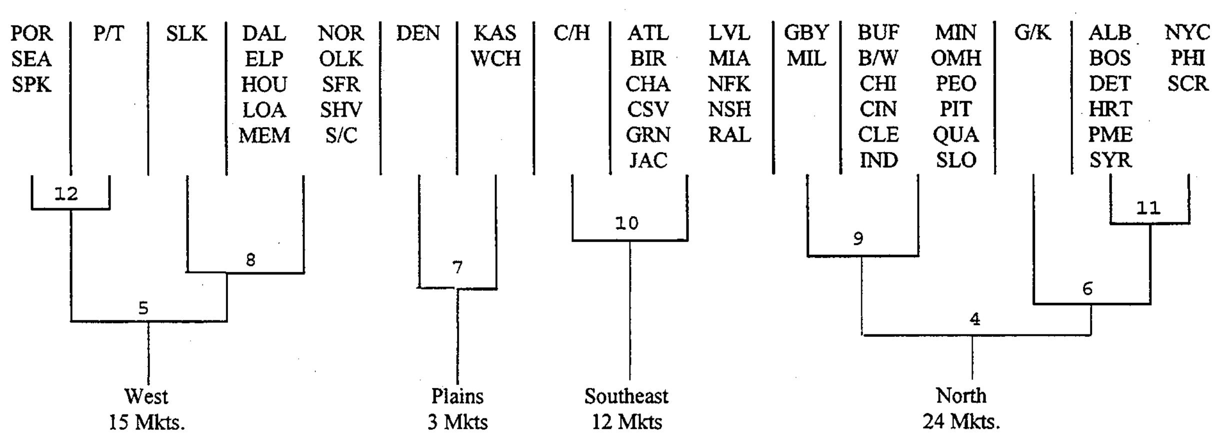

Table 3. Pseudo-T^2 Statistics for Ward's and Beta-Flexible Seasonality Clusters.

Cluster	Ward's	Beta-Flexible
13	1.82	2.10
12	1.82	1.91
11	2.55	2.06
10	1.91	2.55
9	2.06	2.28
8	2.28	1.73
7	2.75	2.73
6	2.57	1.91
5	3.02	2.81
4	3.13	3.21

Note: Underlined entries signal which levels may have good clustering.

Table 4. Preferred Six Cluster Solution from the Ward's (with and without K-means) and Beta-Flexible (with and without K-means) Algorithms Using Seasonality Indices.

Cluster One		Cluster Three		Cluster Five	
POR	SEA	DEN	WCH	ATL	JAC
P/T	SPK	KAS		BIR	LVL
				CHA	MIA
				CSV	NFK
				C/H	NSH
				GRN	RAL
Cluster Two		**Cluster Four**		**Cluster Six**	
BUF	MIL	DAL	OKL	ALB	NYC
B/W	MIN	ELP	SHV	BOS	PIT
CHI	OMH	HOU	SFR	DET	PME
CIN	PEO	LOA	SLK	G/K	SCR
CLE	PIT	MEM	S/C	HRT	SYR
GBY	QUA	NOR			
IND	SLO				

The stopping rules provided little guidance on the best number of market groups. The Pseudo-F statistics did not contain any spikes to signal good clustering and were not reproduced. The Pseudo-T^2 statistics, shown in Table 3, suggested that 13, 12, 10 or 8 groups might be good stopping points. Unfortunately, the results from the two algorithms differed at these levels and some markets were still separate clusters at level 8. Because the analyses produced the same clusters at level 6 and the Pseudo-T^2 statistics had a trough at this level for the Beta-Flexible results, this consensus grouping was selected as the solution. This preferred grouping of markets, shown in Table 4, had six definite geographic areas: "Northwest," "Midwest," "Plains," "Southwest," "Southeast," and "Northeast."

Implications for Researchers and Marketers

Seasonal patterns exist in many economic time series. Understanding the causes of these patterns can help analysts select an appropriate technique for seasonal adjustment. Prior to this analysis, few might have hypothesized that food sales in Denver had a different seasonal pattern than Portland, Oregon or that purchase timing in Dallas was different from Atlanta. If these markets were aggregated in an analysis, the results could bias parameter estimates and distort conclusions. Instead of being a hindrance, seasonality offers analysts unique opportunities. By exploring the underlying causes of the cycles, analysts can gain a better understanding of the market.

The examples in this paper illustrate how important seasonal variations can be for some food products. Given Totten's finding that seasonality may influence promotional effectiveness, marketers need to understand how sales tend to change over time. The cluster analysis found regions with similar seasonal patterns. This suggests that counter-seasonal promotions that are tailored for a cluster of markets may be more efficient than national promotions scheduled without considering seasonality. Omitting seasonal variables or assuming seasonal patterns are constant over time or between regions may reduce the value of the results for marketing practitioners.

The preferred grouping of markets could be used by food demand researchers to investigate whether seasonal differences by area significantly impact their results. Observations could be separated into areas. If significant differences between seasonality estimates by cluster are found, merging the areas could bias the results. Future research could examine the causes of food demand seasonality, could compare approaches to handle region-season interactions, and could explore how food marketers can use this information to improve the efficiency of the marketing plans.

References

Barnett, George A., Hsiu-Jung Chang, Edward L. Fink and William D. Richards, Jr. "Seasonality in Television Viewing," *Communication Research*. Vol. 18, No. 6 (December, 1991): 755–72.

Brooker, John R., David B. Eastwood, and Morgan D. Gray. "The Impact of Advertising on Consumer Demand for Beef: An Application of Scan Data," *Journal of Food Products Marketing*. Vol. 2, No. 1 (1994): 17–35.

Carman, Hoy F. and Enrique E. Figueroa. "An Analysis of Factors Associated with Weekly Food Store Sales Variation," *Agribusiness*. Vol. 2, No. 3 (Fall, 1986): 375–90.

Cooper, Martha C. and Glenn W. Milligan. "The Effect of Measurement Error on Determining the Number of Clusters in Cluster Analysis," *Data, Expert Knowledge and Decisions: An Interdisciplinary Approach with Emphasis on Marketing Applications*. W. Gaul and M. Schrader, editors. Berlin, NY: Springer-Verlag. (1988): 319–28.

Epperson, J. E., H. L. Tyan and C. L. Huang. "Applications of Demand Relations in the Fresh Fruit and Vegetable Industry," *Journal of Food Distribution Research*. Vol. 12, No. 1 (February, 1981): 135–42.

Garbacz, Christopher. "Seasonal and Regional Residential Electricity Demand," *Energy Journal*. Vol. 7, No. 2 (April, 1986): 121–34.

Granger, Clive W. J. "Seasonality: Causation, Interpretation, and Implications," *Seasonal Analysis of Economic Time Series*. Washington, D.C.: U.S. Dept. of Commerce, Bureau of the Census Economic Research Report ER–1. (December, 1978): 33–45.

Hylleberg, Svend. *Seasonality in Regression*. Orlando, FL: Academic Press, Inc. 1986.

Kallek, Shirley. "An Overview of the Objectives and Framework of Seasonal Adjustment," *Seasonal Analysis of Economic Time Series*. Washington, D.C.: U.S. Dept. of Commerce, Bureau of the Census Economic Research Report ER–1. (December, 1978): 3–19.

Kinnucan, Henry and Olan D. Forker. "Seasonality in the Consumer Response to Milk Advertising with Implications for Milk Promotion Policy," *American Journal of Agricultural Economics*. Vol. 68, No. 3 (August, 1986): 562–71.

Kuiper, John. "A Survey and Comparative Analysis of Various Methods of Seasonal Adjustment," *Seasonal Analysis of Economic Time Series*. Washington, D.C.: U.S. Dept. of Commerce, Bureau of the Census Economic Research Report ER–1. (December, 1978): 59–76.

Lam, David A. and Jeffry A. Miron. "Seasonality of Births in Human Populations," *Social Biology*. Vol. 38, Nos. 1–2 (Spring/Summer, 1991): 51–78.

Larson, Ronald B. "Seasonality of Food Consumption." Paper presented at the 1994 Annual Meeting of the Food Distribution Research Society in Seattle, WA. November.

Marion, B. W. and F. E. Walker. "Short-Run Predictive Models for Retail Meat Sales," *American Journal of Agricultural Economics*. Vol. 60, No. 4 (November, 1978): 667–73.

Maritato, Paul. "Maximizing Regional Marketing Effectiveness via Scanner Sales Analysis," *Proceedings of the Third Annual Advertising Research Foundation Behavioral / Scanner Data Workshop*. (June, 1991): 209–18.

McNulty, Mark S. and Wallace Huffman. "Trading-Day Variation: Theory and Implications for Monthly Meat Demand," *American Journal of Agricultural Economics*. Vol. 74, No. 4 (November, 1992): 1003–09.

Milligan, Glenn W. "An Examination of the Effect of Six Types of Error Perturbation on Fifteen Clustering Algorithms," *Psychometrika*. Vol. 45, No. 3 (September, 1980): 325–42.

Milligan, Glenn W. "A Study of the Beta-Flexible Clustering Method," *Multivariate Behavioral Research*. Vol. 24, No. 2 (April, 1989): 163–76.

Milligan, Glenn W. and Martha C. Cooper. "Methodology Review: Clustering Methods," *Applied Psychological Measurement*. Vol. 11, No. 4 (December, 1987): 329–54.

Nelson, Randy J., Lori L. Badura and Bruce D. Goldman. "Mechanisms of Seasonal Cycles of Behavior," *Annual Review of Psychology*, Vol. 41 (1990): 81–108.

Osborn, Denise R. "The Implications of Periodically Varying Coefficients for Seasonal Time-Series Processes," *Journal of Econometrics*. Vol. 48, No. 3 (June, 1991): 373–84.

Rodgers, Joseph L. and J. Richard Udry. "The Season-of-Birth Paradox," *Social Biology*. Vol. 35, Nos. 3–4 (Fall/Winter, 1988): 171–85.

Scheibler, Dieter and Wolfgang Schneider. "Monte Carlo Tests of the Accuracy of Cluster Analysis Algorithms: A Comparison of Hierarchical and Nonhierarchical Methods," *Multivariate Behavioral Research*. Vol. 20, No. 3 (July, 1985): 283–304.

Simmons, L. F. "Time-Series Decomposition Using the Sinusoidal Model," *International Journal of Forecasting*. Vol. 6, No. 4 (1990): 485–95.

Totten, John C. "Seasonality Adjustments for Weekly Scanner Data," Paper presented at the 1991 TIMS Special Interest Conference on Scanner Data at UCLA. January.

Underwood, Jane H. "Seasonality of Vital Events in a Pacific Island Population," *Social Biology*. Vol. 38, Nos. 1–2, (Spring/Summer, 1991): 113–26.

Waldrop, Judith. "The Birthday Boost," *American Demographics*. Vol. 13, No. 9 (September, 1991): 4.

Waldrop, Judith and Marcia Mogelonsky. *The Seasons of Business: The Marketer's Guide to Consumer Behavior*. Ithaca, NY: American Demographic Books. 1992.

Ward, Fred. "Weather, Behavior Correlated in New Market Test," *Marketing News*. Vol. 19, No. 12 (June 7, 1985): 9.

Wildt, Albert R. "Estimating Models of Seasonal Market Response Using Dummy Variables," *Journal of Marketing Research*. Vol. 14, No. 1 (February, 1977): 34–41.