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Market Demands for Bagged, Refrigerated Salads

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Sales of newly introduced bagged, refrigerated salads grew at over 50% annually during 1994–95. Consumption of bagged salads displayed marked seasonality despite year-round availability and uniform quality at more stable prices than head lettuce. Using scanner data from 44 areas, a single-equation demand model incorporating the effects of weather on seasonal consumption is estimated. Statistical tests of aggregation indicate that weather-induced seasonality varies significantly across areas, as do own- and cross-price elasticities. Econometric results suggest more seasonality in eating by people living in more northern latitudes, a pattern also observed by psychiatrists studying eating disorders.

Key words: fresh-cut produce, market demand, perfect aggregation tests, scanner data, seasonality

Introduction

While per capita consumption of fresh vegetables in the United States remained constant in 1995 at 146 pounds, per capita consumption of lettuce—head, leaf, and romaine—declined steadily from a high of 32.4 pounds in 1989 to 27.6 pounds in 1995 (U.S. Department of Agriculture). Yet as fresh lettuce consumption declined, sales of bagged, refrigerated salads grew vigorously at an annual pace of 51.5% in 1995, with retail sales in excess of $600 million (Information Resources, Inc.). Bagged, refrigerated salads (hereafter identified as "bagged" salads) offer consumers convenience while preserving the health benefits and palatability of fresh produce. Bagged salads of virtually identical quality can be purchased in the produce department of most local supermarkets every week of the year at less volatile prices than those of other fresh produce items. Despite year-round availability of bagged salads at stable prices, consumption varies substantially throughout the year (see figure 1).

Seasonality in the consumption of bagged salads is almost assuredly not a result of supply-related phenomena such as fluctuating availability, variable quality, or price volatility. What demand characteristics are likely to cause this seasonality? Does seasonal variation occur because climate and seasonal weather changes affect what we prefer to eat? Do we like hot, hearty meals in the dead of winter while preferring cool, light meals in spring and summer? Do consumers in San Diego, California, vary their

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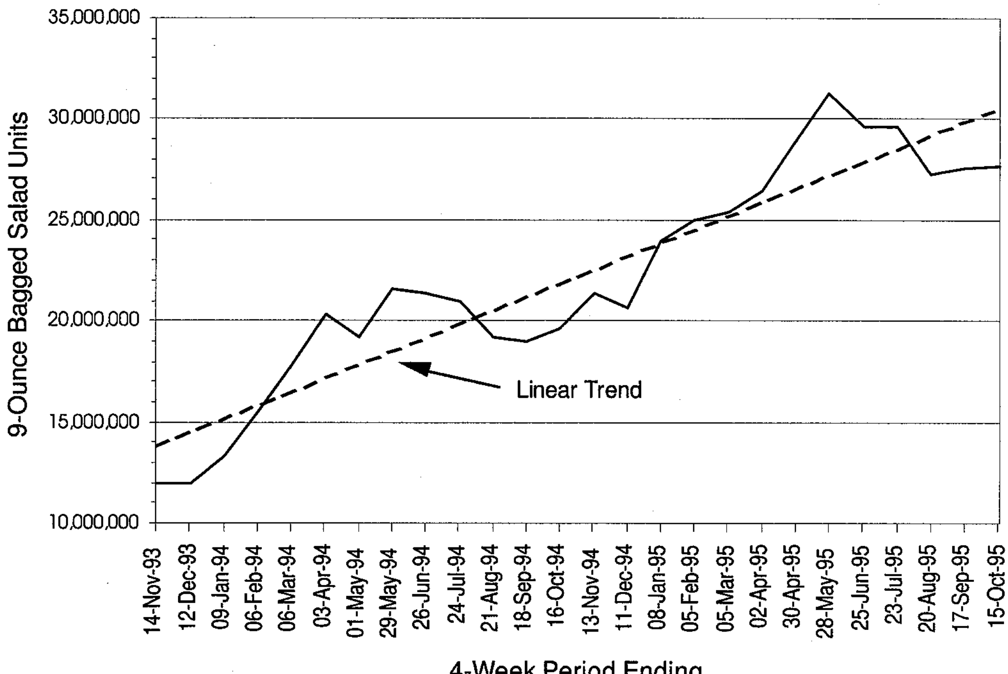

Source: IRI, *InfoScan 1995* market data.

Figure 1. Total U.S. retail volume of bagged/refrigerated salads (in four-week intervals)

diets less throughout the year than do their counterparts in Buffalo, New York? Or does the seasonal availability of fresh substitutes cause the consumption of bagged salads to fluctuate seasonally?

Explaining seasonal fluctuations in the consumption of fresh processed products is important for at least two reasons. First, from the standpoint of consumer theory, if consumer behavior regarding perishable items varies seasonally not just because of supply conditions, but because of the influence of weather on food preferences, then prediction or explanation of short-run behavior should take into account local weather conditions and regional differences in climate. Second, from an industry perspective, product shrinkage and loss can be minimized by growers, shippers, and retailers as seasonal and regional consumption patterns are understood and predicted with greater accuracy. Both retailers and fresh processors must make significant investments in fixed capital in order to process, transport, and merchandise bagged salads which typically have a shelf life of 14 to 18 days. At retail, fixed amounts of refrigerated case space are usually allocated to produce sections even though volume sold fluctuates. Minimizing product shrinkage as sales fluctuate seasonally at retail is a serious problem. Grower-shippers typically invest \$20–30 million in plant and equipment for fresh processing. They must make complex planning and logistical decisions to locate and sequence the growing of perishable raw products, and to schedule harvests, deliveries, and processing labor while coordinating sales and delivery of highly perishable final products to match seasonal and regional fluctuations in consumption.

Explanations of Seasonality

Most standard approaches to consumer theory rely on relative prices, income, and perhaps demographic variables to explain observed consumer behavior. A prominent exception to the standard approach is the energy demand literature in which regional climatic differences and outside temperature are often incorporated explicitly in theoretical models with household production functions for inside temperature (Collins and Gray), or specification of thermal relationships between indoor and outdoor temperature (e.g., Dubin). Other theoretical approaches specify temperature in demand equations in the same way socioeconomic and durable stocks are included (Hausman, Kinnucan, and McFadden). Even when temperature is not explicitly incorporated in the theoretical model, empirical implementation of energy demand models almost always includes outside temperature (e.g., Baker, Blundell, and Micklewright; Harvey and Koopman). For example, climate effects as measured by cooling and heating days were statistically significant in the seasonally and regionally disaggregated model specified by Garbacz.

Seasonal and regional variations in consumption of perishable foods have been explained in a number of analyses, though usually not using weather variables. For example, Park and Lohr employ sine and cosine terms in demand equations to account for observed seasonality in lettuce consumption. Wessells and Wilen appear to be the first to appreciate and demonstrate empirically that seasonality in food consumption may differ by region. They use monthly dummies in a demand system for fish estimated using partitioned samples of southern and northern Japan. Seasonal differences observed between the two regions were, however, largely a function of the availability of particular species of fish. Larson demonstrates the importance of varying seasonal patterns of food consumption across many markets in the United States.

Seasonality in food consumption is perhaps most apparent in econometric models employing scanner data with high frequency observations. Dummy variables of varying periodicity are usually specified to account for seasonality (Capps; Capps and Nayga; Capps, Seo, and Nichols; Cotterill; Vickner and Fulton). One of the few scanner data studies employing mean temperature in the demand equations of a simultaneous equation model is that of Cotterill. Although use of high frequency scanner data requires accounting for seasonality, the question of why seasonality occurs is not addressed in these studies.

Seasonality in consumption is usually cast as a supply phenomenon related to climatic effects on plant or animal growth. Evidence from the psychiatry literature, however, points to a physiological link between eating patterns and climate or weather. Psychiatrists studying eating disorders have documented pronounced seasonal patterns in the symptoms of such disorders. While the tendency to eat "lighter" foods such as fruits and vegetables in the summer and "heavier" foods in the winter is more conspicuous in people with eating disorders, the same tendency is observed in the general population (Brewerton et al. 1994a). Eating patterns vary significantly across latitudes, with consumers in northern locations displaying more marked seasonal eating patterns than consumers closer to the equator.

In addition to annual or "circannual" rhythms in food consumption linked to seasonally fluctuating serotonin levels, normal individuals also display daily or circadian fluctuations in serotonin levels related to the previous day's weather (Brewerton et al.

1996).[1] While daily serotonin levels in women apparently respond more to humidity, serotonin levels in men seem to respond more to the previous day's temperature. The important implication of this medical research for economic theory relating to seasonal consumption of food is that fluctuations in weather, both annual and daily, can affect human food preferences. Hence, there may be physiological grounds for including climate and weather variables as parameters affecting seasonal demand.[2]

Theoretical Approach

In order to represent the demand model, begin with the following notational conventions. Quantities of the commodities of interest—bagged salads and potential substitutes or complements like iceberg lettuce and fresh tomatoes—are represented by the n-vector $\mathbf{x}$ with corresponding price vector $\mathbf{P}$. All other commodities not of direct interest—other food and nonfood items—are represented by the m-vector of quantities, $\mathbf{z}$. The m-vector of corresponding prices is denoted $\mathbf{Q}$. Total expenditure is then defined as $\mathbf{P}'\mathbf{x} + \mathbf{Q}'\mathbf{z} \equiv y$. A linear incomplete demand system which is integrable under certain conditions is specified as

$$x_i = \alpha_i + \sum_j \beta_{ij} p_j + \gamma_i y, \tag{1}$$

where $p_j = P_j / \pi(\mathbf{Q})$, and $\pi(\mathbf{Q})$ is a suitable index (see LaFrance for details). In the present case, data are insufficient to specify (1) because observations on quantities of other goods of interest besides bagged salads are nonexistent; observations on their prices, however, are available. A single-equation alternative to (1) can be specified as

$$x = \alpha + \sum_j \beta_{ij} p_j + \gamma y. \tag{2}$$

LaFrance shows that such a model is integrable if (a) the income effect is zero ($\gamma = 0$), or (b) more complicated parameter restrictions are imposed and $\gamma \neq 0$.[3] Imposition of a zero income effect is not too onerous in the present case because per capita income changes minimally over the two years for which data are available. When the income effect is zero, the matrix of coefficients, $\mathbf{B} \equiv [\beta_{ij}]$, must be symmetric, negative semidefinite. Given the single equation (2), it is impossible to include parameters such as β_{jj} ($j \neq i$), the own-price coefficients for other commodities of interest, for assuring the negative semidefiniteness of $\mathbf{B}$. Thus the integrability conditions reduce to $\beta_{ii} \leq 0$ and $\alpha + \sum_j \beta_{ij} p_j \geq 0$ (LaFrance, p. 160).

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[1] The 1991 edition of the *Compact Oxford English Dictionary* defines serotonin (5-Hydroxytryptamine, $C_{10}H_{12}N_2O$) as a neurotransmitter active in the production of vasoconstriction and anaphylactic shock, and in the regulation of cycles of body temperature and sleep. Serotonin levels have been linked to various facets of food consumption such as satiety (Brewerton), and preference for certain macronutrients such as carbohydrates, proteins, and fat (Brewerton et al. 1994b). Not coincidentally, abnormal levels of serotonin are associated with eating disorders such as anorexia and bulimia.

[2] Recognition of the links between weather, serotonin levels, and eating preferences is consistent with Taylor's approach to consumption theory which emphasizes the effects of hierarchical brain functions on consumption activity through physiological and psychological needs.

[3] If the income effect were allowed to be nonzero, the restrictions for integrability imply that all goods would be perfect complements, an implausible result for bagged salads and iceberg lettuce, for example. Note that in specifying (2), the assumption of $m = 1$ is maintained.

For simplicity, consider introducing the effects of climate and temperature on consumption of perishables by means of a single variable, W, which subsumes the joint effects of temperature, humidity, wind speed, etc. The consumer demand literature apparently does not contain a generic approach to altering demand equations for the effects of weather and climate. Explicitly dynamic consumer models often account for longer-run phenomena such as stocks of durable goods, overheads in household production functions, fashions, or expectations, but the shorter-run effects of weather and climate variability on consumption of perishable food products are conspicuously absent. Accordingly, climate and temperature influences are incorporated into the single demand equation in an additive way as follows:

$$x = \alpha + \sum_j \beta_{ij} p_j + \delta W. \tag{3}$$

Although (3) has no explicit temporal or spatial dimensions, variations in W owing to changes in weather through time and differences in climate across regions could be incorporated.

Data and Estimation

Scanner data on units sold and total value of sales for bagged salads in 64 metropolitan areas throughout the United States were purchased from Information Resources, Inc. (IRI). Data were reported for each metropolitan area for 26 four-week periods with the last period ending on October 15, 1995.[4] Although the bagged category contains different brands, styles of salads, and bag weights, IRI standardized the units at nine ounces. Unit prices were calculated by dividing total value of sales by units sold. No information on brand-specific promotions or advertising was available from IRI.

Scanner data for fresh produce substitutes and complements are not available because most produce items do not carry universal product codes (UPCs) for scanning; instead, price lookup codes (PLUs) are usually placed on produce with stickers, bands, or ties. Clerks must manually enter the PLU rather than scan the UPC. IRI did not collect price data based on PLUs because they are subject to human error.[5] A further complication with fresh produce is that some items such as lettuces are typically priced per head rather than per unit weight. Arriving at average retail prices for "random weight" products such as iceberg lettuce requires sampling and weighing procedures beyond the scope of IRI's procedures for collecting data.

The next best source of retail prices for fresh produce is the average retail price series available from the U.S. Department of Labor's Bureau of Labor Statistics (BLS). The series has two drawbacks when used in combination with IRI data: (*a*) it is collected

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[4] Data for previous periods are not available from IRI because the category of bagged salads did not exist a decade ago. Even as recently as five years ago, IRI routinely reported bagged salads in a larger category which included other "wet" salads such as cole slaw and potato salad. Increased competition among bagged salad firms has led to the demand for more refined data reporting.

[5] Errors associated with PLUs occur because of inadvertent keying mistakes as well as use of generic produce codes when individual PLUs do not register in the store's computer system. In addition to data entry errors, comparison of fresh produce prices is hampered by a lack of uniform codes across the nation. National standards for price lookup codes exist, but some innovative supermarket chains initially developed their own numerical systems. (For a detailed explanation of PLUs, see Eastwood.)

monthly rather than on IRI's four-week intervals ending at different dates each month, and (*b*) it is reported only by four major regions instead of by metropolitan area. The first drawback was remedied by using weighted average prices where weights correspond to the number of days each four-week period falls in each pair of months; e.g., for the last period ending October 15, 1995, BLS prices are weighted by (15/28) for October and by (13/28) for September. The second obstacle is more serious because even though BLS collects retail prices of selected fresh produce items in 44 metropolitan areas to calculate regional prices, sampling procedures used by BLS are not designed for reporting city-by-city price series. As a result, regional retail prices of iceberg lettuce were used in place of each metropolitan area's retail price (see the appendix for details). An analogous average price series for fresh tomatoes was also used, but continuous monthly observations for most other fresh produce items were not available. All retail prices were deflated by the appropriate regional consumer price index (CPI) for nonfood items.

Population data by IRI areas were taken from *Demographics USA, County Addition* (Bill Communications). Annual population figures were assembled by county to match exactly with those included in IRI's areas. Linear interpolation between the annual population figures for each area were calculated. Analogous household size figures were available for the same period and could have been used to calculate per household demands instead of per capita demands. The growth rates of households were virtually the same as those of the population for the two-year sample period considered. Hence, household demands are nearly indistinguishable from per capita demands in any given area.

Climate and weather variables were measured using daily values of temperature, humidity, wind speed, etc. obtained from the National Oceanic and Atmospheric Administration. Averages were then calculated to correspond to the exact dates of the four-week periods reported by IRI. To incorporate the joint effects of temperature, humidity, and wind speed, the "apparent" temperature (Steadman 1984) was used. The "apparent" temperature value combines these meteorological variables in order to capture how temperature "feels" to the human body (see the appendix for details).

A linear trend was included because growth rates in sales in the 44 areas averaged 71% during the two-year study period; growth rates of 200% or higher occurred in several areas such as Syracuse, Buffalo/Rochester, and Raleigh/Greensboro. With such pronounced growth in sales over a period of two years, inclusion of a trend was deemed important.

Dummy variables representing the effects of various holidays were also included where F-tests indicated that their effects on volume sold were statistically significant. With four-week observations, the effects of a single dummy representing Thanksgiving, for example, are expected to be attenuated. Nonetheless, in some regions holiday dummies were included. A single dummy representing the effects of the devastating flood in the Salinas, California, area in April 1995 was also included where appropriate (see appendix).

The per capita demand functions in (3) were specified as the following seemingly unrelated regressions (SURs):

$$\mathbf{y}_i = \mathbf{X}_i\boldsymbol{\beta}_i + \boldsymbol{\varepsilon}_i, \quad i = 1, 2, \ldots, m, \tag{4}$$

where $\mathbf{y}_i$ is a $\{T \times 1\}$ vector of volume sold of bagged salads in the ith metropolitan area, $\mathbf{X}_i$ represents a $\{T \times k\}$ matrix of k explanatory variables for the ith metropolitan area, and $\boldsymbol{\beta}_i$ is a conformable vector of parameters to be estimated. Each vector of error terms $\boldsymbol{\varepsilon}_i$ is a $\{T \times 1\}$ vector, and the $\{mT \times 1\}$ stacked vector of error terms, $\boldsymbol{\varepsilon}' \equiv [\boldsymbol{\varepsilon}_1' | \boldsymbol{\varepsilon}_2' | \cdots | \boldsymbol{\varepsilon}_m']$, is assumed under the null to be distributed as $\boldsymbol{\varepsilon} \sim N(\mathbf{0}, \boldsymbol{\Sigma} \otimes \mathbf{I}_T)$. The number of metropolitan areas in each region, m, varies by region, with SUR equations being estimated for each of the four regions constructed by the BLS as follows: Northeast ($m = 8$), North Central ($m = 9$), South ($m = 18$), and West ($m = 9$). Zellner efficient (ZEF) estimation procedures were employed for estimating (4) from each region.

The explanatory variables included in $\mathbf{X}_i$ were own price, average retail prices of iceberg lettuce and fresh tomatoes, apparent temperature, linear trend, and relevant holiday and flood dummies. The sample consisted of 26 observations at four-week intervals from 44 metropolitan areas.

Hypothesis Tests and Inferences

The assumptions underlying the specification of $\boldsymbol{\varepsilon}$ in (4) were subjected to various hypothesis tests. The null hypothesis of no contemporaneous correlation across equations (all off-diagonal elements of $\boldsymbol{\Sigma}$ equal zero) for each region was rejected in all regions using Breusch-Pagan tests. Likelihood-ratio tests for the presence of vector autoregressive processes (Guilkey) failed to indicate significant autocorrelation within or across equations. Multivariate tests of normality did not reject the null hypothesis of normality for $\boldsymbol{\varepsilon}$ in each region. Hausman tests did not indicate any correlation between explanatory variables and error terms. These test results jointly support the use of ZEF estimation of (4).

Given the large number of metropolitan areas (44), reporting the econometric results by aggregated regions rather than by individual metropolitan areas would require less space. Aggregating metropolitan areas into regions might introduce some aggregation bias, however. Two hypothesis tests were employed to check for the admissibility of aggregating metropolitan areas into regions: (*a*) Zellner's test for aggregation bias, an F-test for equality of coefficients across equations, and (*b*) Pesaran, Pierse, and Kumar's more general test of perfect aggregation. The null hypothesis for Pesaran, Pierse, and Kumar's perfect aggregation test is

$$\text{(5)} \qquad \mathrm{H}_{\mathrm{PA}} = \sum_{i=1}^{m} \mathbf{X}_i \boldsymbol{\beta}_i = \mathbf{X}_a \mathbf{b},$$

where $\mathbf{X}_a \equiv \sum_{i=1}^{m} \mathbf{X}_i$, $\mathbf{y}_a \equiv \sum_{i=1}^{m} \mathbf{y}_i$, and $\mathbf{y}_a = \mathbf{X}_a \mathbf{b} + \mathbf{e}$ represents the aggregate or regional econometric model. If the coefficient vectors of all metropolitan areas are equal within a region ($\boldsymbol{\beta}_i = \boldsymbol{\beta}_j \; \forall \, i \neq j$), then a single regional equation could be estimated without bias (Zellner) and the null hypothesis of perfect aggregation (5) cannot be rejected. Zellner's test for aggregation bias using F-tests for equality of coefficients across equations is used in this case. The null hypothesis in (5) may not be rejected when $\mathbf{X}_i = \mathbf{X}_a \mathbf{C}_i$, where $\mathbf{C}_i$ are nonsingular matrices such that $\sum_{i=1}^{m} \mathbf{C}_i = \mathbf{I}_k$. This condition is referred to by Pesaran, Pierse, and Kumar as the "compositional stability" condition because it restricts the joint probability distribution of the regressors to be constant over time.

Table 1. Tests for Aggregation by Region

Region	Zellner's Tests of Aggregation Bias[a]						Compositional Stability Test[b]
	Own-Price	Iceberg Lettuce	Tomato Price	Apparent Temperature	Trend	All Coefficients	
NORTHEAST:							
Test-Statistic Value	4.24	31.00	4.61	13.45	17.11	169.14	1,837.20
p-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00
NORTH CENTRAL:							
Test-Statistic Value	3.95	7.12	2.52	11.57	18.27	121.92	141.66
p-Value	0.00	0.00	0.01	0.00	0.00	0.00	0.00
SOUTH:							
Test-Statistic Value	345.62	25.63	2.41	30.48	55.52	203.53	85.64
p-Value	0.00	0.00	0.00	0.00	0.00	0.00	1.00
WEST:							
Test-Statistic Value	26.80	10.81	1.23	3.65	11.26	25.94	175.55
p-Value	0.00	0.00	0.29	0.00	0.00	0.00	0.00

[a] All tests of aggregation bias use F-statistics.

[b] The test statistic [equation (5.7) in Pesaran, Pierse, and Kumar] is distributed approximately as a chi-squared random variate.

Note that this condition implies $\sum_{i=1}^{m} \mathbf{C}_i \boldsymbol{\beta}_i = \mathbf{b}$. In the special case of $\mathbf{C}_i = (1/m)\mathbf{I}_k$, the compositional stability condition indicates that the regional coefficients will equal the arithmetic mean of the metropolitan coefficients. Other restrictions between the metropolitan and regional coefficients could exist. The a-test of Pesaran, Pierse, and Kumar is employed here to test for possible violations of compositional stability.

Both the calculated values of Zellner's aggregation bias test and the compositional stability test rejected the admissibility of aggregating metropolitan areas in every region (see table 1). Tests for equality of subsets of coefficients across equations were also performed to see if individual coefficients such as those of apparent temperature might be the same across metropolitan areas. In all but one case (fresh tomato prices in the West), individual effects were not equal across metropolitan areas within a given region. Because of the significant heterogeneity detected across metropolitan areas in each region, the following estimation results are reported for individual metropolitan areas rather than regions.

Due to the large number of estimated coefficients, elasticities for each metropolitan area are presented in table 2 instead of estimated coefficients and standard errors. Estimated coefficients for holiday dummies are not presented due to space limitations. The averages of the elasticities calculated at each sample point are displayed in table 2. Each set of elasticities is discussed in turn below.

Own-Price Elasticities

Own-price elasticities for bagged salads were statistically significant in 31 of 44 metropolitan areas (see table 2). The range of statistically significant own-price elasticities (−2.45 to −0.21) indicates a considerable amount of heterogeneity across metropolitan areas and regions. Within each region, the range of own-price elasticity values was also large; the narrowest range of -0.83 (Cleveland) to -1.16 (Kansas City) occurred in the North Central region. Elastic price responses were in evidence in all regions, with at least three metropolitan areas in each region having greater than unitary own-price elasticities.

Four of the 44 metropolitan areas—Birmingham/Montgomery, Houston, Raleigh/Greensboro, and Richmond/Norfolk—displayed statistically significant *positive* own-price elasticities. These anomalous results were persistent across alternative econometric specifications not reported here. The four metropolitan areas do not appear markedly different from other areas as far as other variables such as population or retail market structure are concerned. One plausible explanation for these results is that if actual prices paid by consumers differed from the scanned prices (as could occur when coupons are redeemed or rebates are promoted), spurious positive relationships would be observed. Unfortunately, IRI did not report information on such special promotions.

Iceberg Lettuce Price Elasticities

Slightly fewer iceberg lettuce cross-price elasticities were statistically significant (28) than were own-price elasticities. With the sole exception of Raleigh/Greensboro, all statistically significant cross-price elasticities were positive, indicating some degree of substitution between iceberg lettuce and bagged salads. Cross-price elasticities for iceberg lettuce display smaller absolute values than own-price elasticities for corresponding metropolitan areas. The only cross-price elasticities in excess of unity occurred in Buffalo/Rochester and Syracuse. In the West, cross-price elasticities tended to be smaller in magnitude (ranging from 0.08 to 0.27) than in other regions. However, three Florida metropolitan areas (Tampa/St. Petersburg, Orlando, and Miami/Ft. Lauderdale) and four areas in the North Central region (Chicago, Milwaukee, Minneapolis/St. Paul, and St. Louis) displayed elasticities comparable in magnitude to those in the West (≤ 0.30). In West Coast metropolitan areas where bagged salads have been available for more years than elsewhere, substitution between iceberg lettuce and bagged salads appears less notable than in selected metropolitan areas of Texas (San Antonio/Corpus Christi, Dallas/Ft. Worth, and West Texas/New Mexico) and the Northeast (Buffalo/Rochester, Pittsburgh, and Syracuse). Despite varying levels of substitution across metropolitan areas, sales of bagged salads respond more to changes in own price than to changes in prices of iceberg lettuce.

Fresh Tomato Price Elasticities

Relatively few cross-price elasticities for fresh tomatoes were statistically significant (12 of 44). With one exception, the elasticities indicate some degree of substitution between fresh tomatoes and bagged salads. The Northeast had the most statistically significant cross-price elasticities (five), and their magnitude ranged from 0.66 to 1.74—indicating a higher degree of substitution than in other regions. Tulsa was the lone metropolitan area in which fresh tomatoes and bagged salads are apparently complements.

Table 2. Mean Values of Elasticities by Regional Metropolitan Areas

Region/ Metropolitan Area	Elasticities				
	Own-Price	Iceberg Lettuce Price	Fresh Tomato Price	Apparent Temperature	Trend
NORTHEAST:					
Boston	-2.20***	0.49***	0.63	0.30***	0.80***
Buffalo/Rochester	-0.19	1.45***	1.54***	0.49***	0.58***
Harrisburg/Scranton	0.30	0.57***	1.24***	0.34***	0.43***
Hartford/Springfield	-1.07***	0.20	-0.04	0.12	0.56***
New York	-0.23	0.38**	0.66*	0.38***	8.31***
Philadelphia	-0.38	0.41**	0.25	0.33***	0.25***
Pittsburgh	-1.59***	0.94***	1.74***	0.56***	0.89***
Syracuse	0.55	1.43***	1.36***	0.36***	0.55***
NORTH CENTRAL:					
Chicago	-1.01***	0.19***	-0.01	0.16***	0.37***
Cincinnati/Dayton	-1.05***	0.48***	0.54**	0.10	0.71***
Cleveland	-0.83***	-0.03	-0.04	0.11**	0.22***
Columbus	-0.98***	0.15	-0.12	0.03	0.12***
Detroit	-0.95*	0.18	-0.10	0.16*	0.17**
Kansas City	-1.16***	0.45***	-0.04	0.23***	0.28***
Milwaukee	-0.04	0.25*	0.03	0.03	0.30***
Minneapolis/St. Paul	-0.24	0.23***	0.11	0.08**	0.08*
St. Louis	-0.87***	0.28***	0.31***	0.31***	0.27***
SOUTH:					
Atlanta	-0.27	0.02	-0.09	0.32***	0.31***
Baltimore/Washington DC	-0.92***	0.13	-0.14	0.11	0.48***
Birmingham/Montgomery	0.32***	0.15	-0.16	-0.10	0.49***
Charlotte	0.01	0.06	-0.46	-0.10	0.49***
Dallas/Ft. Worth	-2.33***	0.43***	0.11	0.37***	0.69***
Houston	0.53***	0.36***	-0.03	0.36***	0.37***
Jacksonville	-0.67	0.11	-0.36	0.18	0.56***
Miami/Ft. Lauderdale	-0.27***	0.21*	-0.02	-0.28**	0.75***
Nashville	-0.45***	0.12	-0.27	0.03	0.15***
New Orleans/Mobile	-0.67***	0.35	0.15	0.49***	0.54***
Orlando	-0.84***	0.27***	-0.03	0.27***	0.38***
Raleigh/Greensboro	5.22***	-0.86***	-0.61	0.64***	0.96***
Richmond/Norfolk	0.96***	-0.04	-0.59	0.15	0.94***
San Antonio/Corpus Christi	-1.73***	0.59***	0.50***	0.24	0.94***
South Carolina	-1.15***	0.02	-0.22	0.42***	0.50***
Tampa/St. Petersburg	-0.09***	0.18***	0.05	-0.36***	0.34***
Tulsa	-1.59***	0.00	-0.64**	-0.37***	0.46***
West Texas/New Mexico	-0.15	0.41***	0.34	0.24***	0.57***

(continued . . .)

Table 2. Continued

Region/ Metropolitan Area	Elasticities				
	Own-Price	Iceberg Lettuce Price	Fresh Tomato Price	Apparent Temper-ature	Trend
WEST:					
Denver	-0.48***	0.04	0.27***	0.11***	0.26***
Los Angeles	-2.45***	0.27***	-0.21	-0.01	0.65***
Phoenix/Tucson	-0.21***	0.08***	0.09	0.32***	0.22***
Portland OR	-1.73***	0.21***	0.31**	0.29***	0.31***
Sacramento	0.03	0.26***	0.13	0.11**	0.30***
Salt Lake City	-0.63	0.20	0.18	0.26***	0.34***
San Diego	-0.96***	0.15***	0.02	0.08	0.39***
San Francisco/Oakland	-0.55***	0.24***	0.14	0.06	0.29***
Seattle/Tacoma	-1.64***	0.27***	0.17*	0.22***	0.42***

Notes: Single, double, and triple asterisks (*) denote statistical significance at the 10%, 5%, and 1% levels, respectively. Coefficients on holiday and flood dummies are omitted due to space limitations. Results are available from the authors on request.

Some industry officials are interested in the potential for complementary relationships between bagged salads and other fresh produce items because they would like to harness the growth in bagged salad sales to boost sales of fresh tomatoes by using in-store "tie-in" promotions such as joint displays and special coupon offerings. The elasticities calculated for fresh tomato prices suggest that complementary relationships during the sample period were detectable only in Tulsa. Most industry-supported tie-in promotions have occurred since 1995, so that efficacy of these promotions may not be apparent in the sample period used here.

Temperature Elasticities

The effects of apparent temperature on bagged salad sales were statistically significant in 30 of the 44 metropolitan areas; in all but five of the 30 areas, temperature elasticities were significant at the 99% level. Some general patterns in temperature elasticities may be observed across regions. All temperature elasticities in the Northeast except that of Hartford/Springfield were positive and statistically significant. The only metropolitan areas with statistically significant negative elasticities (Miami/Ft. Lauderdale, Tampa/St. Petersburg, and Tulsa) were located in the South. Some of the metropolitan areas where temperature had no statistically significant effect on bagged salad sales have relatively warm, stable climatic conditions. Extremes in apparent temperature are nearly absent in Los Angeles, San Diego, and San Francisco/Oakland, for example, where temperature elasticities were not statistically significant.

Average values of apparent temperature elasticities mask the tendency for seasonality in bagged salad sales to be highly, positively correlated to changes in apparent temperature in almost all areas. In figure 2, elasticity values of apparent temperature are plotted for selected cities from each region. The pronounced seasonal effects in

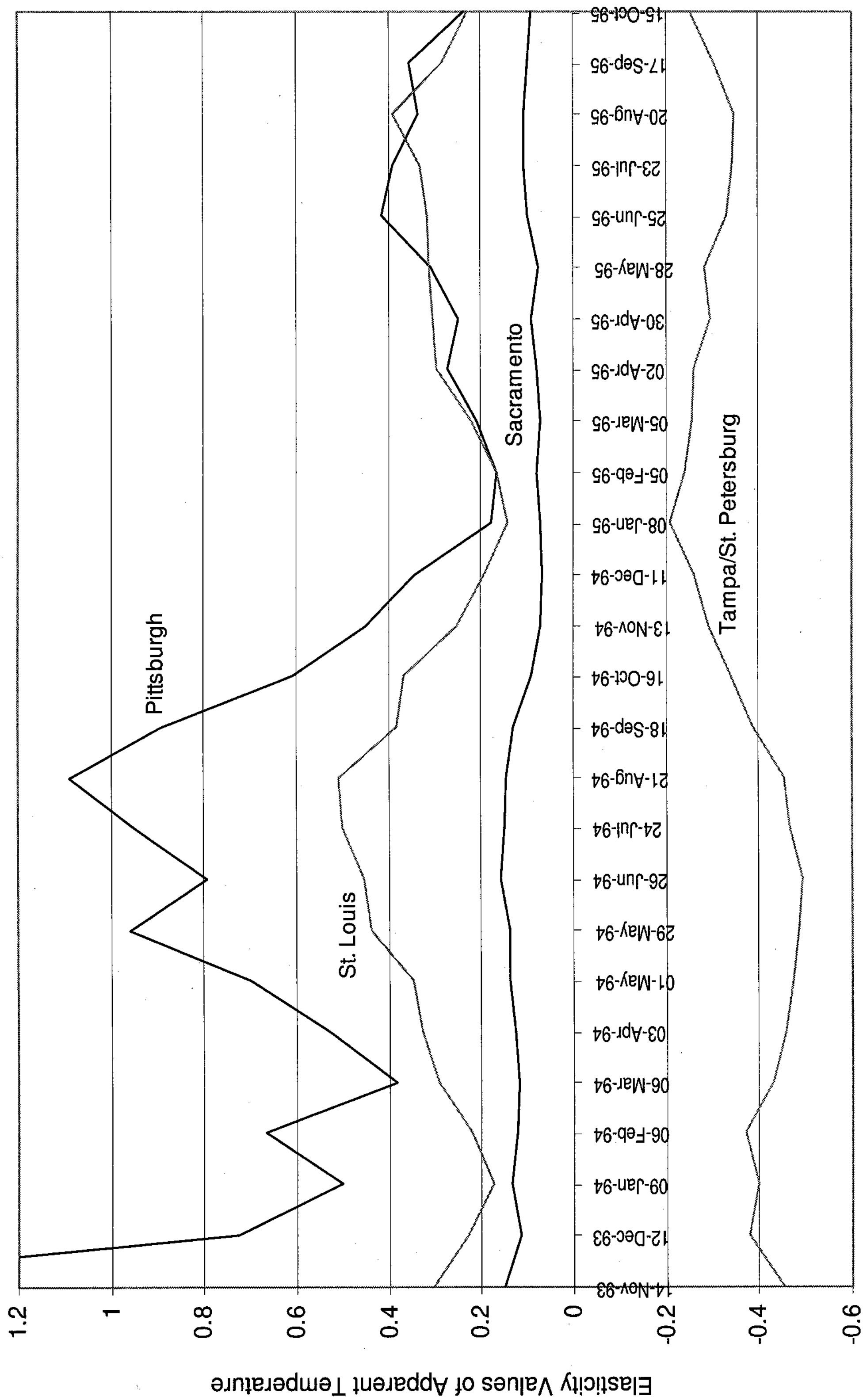

Figure 2. Temperature elasticities for selected areas at each sample point

Pittsburgh and St. Louis contrast with the more stable effects in Sacramento, even though their average elasticity values are relatively close to one another. In Tampa/St. Petersburg, where temperature variation throughout the year is much less pronounced, the apparent temperature elasticities are negative and vary much less relative to the other areas. Inter-year effects in apparent temperature are also evident: calendar year 1995 was generally a more moderate year than was 1994.

The annual patterns of seasonality in figure 2 suggest that apparent temperature increases in the summer months are generally associated with larger increases in bagged salad consumption. But peaks in temperature elasticities vary across regions: in 1994, maximum elasticities for Pittsburgh and St. Louis occurred in the four weeks ending August 21, whereas in Sacramento the maximum occurred two periods earlier. Minimum temperature elasticities usually occurred for most areas in the four weeks ending in early January. Note, however, that the differences in maxima and minima for the same areas in 1994 and 1995 suggest that inclusion of a single sine or cosine variable would not have captured inter-year differences in the same geographic areas.

In order to assess systematically the variability of temperature elasticities, the coefficients of variation of the temperature elasticities were compared with the corresponding latitude of the area (figure 3).[6] Only coefficients of variation and latitudes for statistically significant temperature elasticities are shown. Although the positive relationship between latitude and coefficients of variation is less than perfect, the positive correlation between the two is visibly evident in the scatterplot of figure 3; the correlation coefficient for the 30 observations is 0.52. A few outliers in the South are apparent: Miami/Ft. Lauderdale, Tampa/St. Petersburg, and Tulsa. In Portland and Seattle/Tacoma in the West, the moderating influences of the Pacific Ocean seem to attenuate the variability in temperature elasticities. Excluding these five areas, the correlation coefficients by region are as follows: Northeast, 0.62; North Central, 0.91; South, 0.48; and West, 0.61.

These apparent temperature elasticities provide some corroboration at a metropolitan consumption level for what psychiatrists have found for individual human beings: people residing in latitudes further north tend to display more pronounced seasonality in eating patterns. Although the temperature elasticities do indicate a considerable amount of heterogeneity across regions, they do not uniformly support an aggregate counterpart to more seasonality in the consumption of bagged salads in northern latitudes: apparent temperature elasticities in Hartford/Springfield in the Northeast, and in Cincinnati/Dayton, Columbus, and Milwaukee in the North Central region were not statistically different from zero.

Trend Elasticities

Trend elasticities were calculated in order to compare rates of per capita sales growth across metropolitan areas. Trends were statistically significant in all 44 metropolitan areas. Boston, New York, and Pittsburgh in the Northeast, and Raleigh/Greensboro, Richmond/Norfolk, and San Antonio/Corpus Christi in the South experienced the

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[6] The grouping of areas into regions was based on the regions defined by the Bureau of Labor Statistics, not on climatological or meteorological criteria. Latitude is a reasonable proxy for day length and solar intensity, two variables which affect weather patterns across these areas.

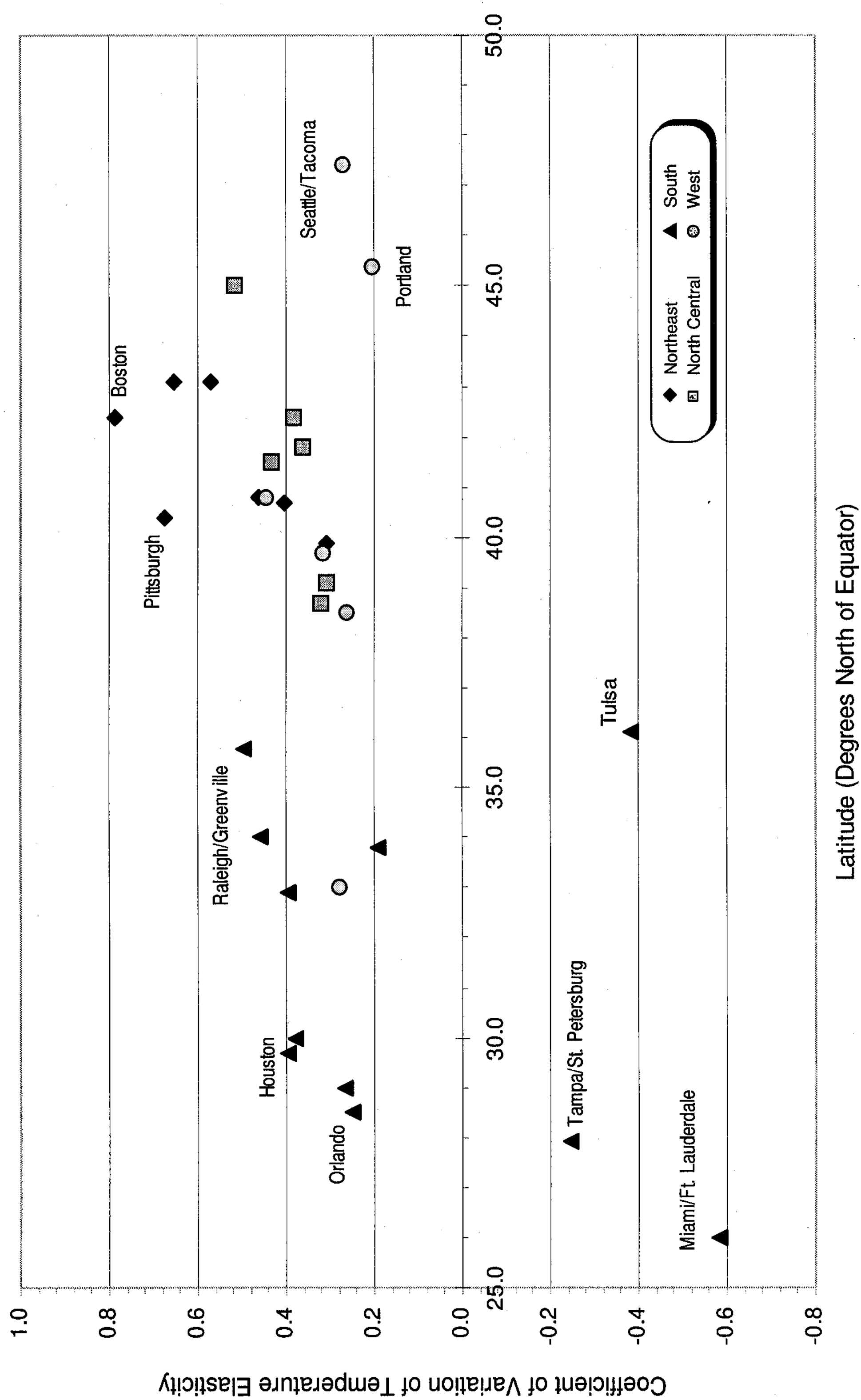

Figure 3. Coefficient of variation of temperature elasticities vs. latitude

highest rates of growth (≥ 0.80) as measured by the trend elasticity. Specifying a trend variable has no particular theoretical justification, but appears to be justified empirically as a means of accounting for the rapid growth in per capita consumption of bagged salads which were a newly introduced product with rapidly growing sales in many areas during the sample period.

Concluding Remarks

With relatively high frequency observations—four-week periods using scanner data—on bagged salad sales, seasonal consumption patterns which vary across regions can be explained reasonably well using a linear econometric model of demand behavior with standard price variables and temperature. The apparent temperature measure, which accounts for the combined temperature, humidity, and wind speed effects on humans, resulted in statistically significant, positive estimated coefficients in 30 of 44 metropolitan areas. Nearly all the metropolitan areas in which estimated coefficients were not significantly different from zero were areas in the South or the West with relatively mild winter climates. These econometric results generally accord with studies in the psychiatry literature which find more pronounced seasonality in eating patterns the further north subjects are located in the United States. From an econometric perspective, temperature or weather measures may be preferred to dummy variables in accounting for seasonality because (*a*) they are continuous variables instead of dichotomous, (*b*) degrees of freedom may be saved by using a single weather variable in place of multiple dummies, and (*c*) they reflect inter-year variability for which sine and cosine variables would not account.

Use of scanner data from 44 metropolitan areas reveals significant heterogeneity in own- and cross-price elasticities. The heterogeneity is statistically significant in the sense that various hypothesis tests rejected aggregation of these data across metropolitan areas to obtain regional models. Hence, explaining seasonality in bagged salad consumption requires accounting for differences across metropolitan areas; estimation of regional or national models would have resulted in aggregation bias. Industry officials appreciate and take advantage of heterogeneity across metropolitan areas even within regions by tailoring sale prices, promotions, merchandising campaigns, and advertising to these differences. The econometric analysis of spatially disaggregate data should be of interest to the fresh-cut produce industry, while aggregate national analysis likely would be of limited interest.

Lack of scanner data on other fresh produce items which do not carry UPCs for scanning seriously hampers econometric testing of potential substitution and complementarity relationships with bagged salads. Some fresh produce items which are not processed now carry stickers, bands, or tags with UPC codes which allow scanning. Random weight items such as heads of iceberg lettuce still present problems for scanning. Until sufficient scanner data become available for a wide range of unprocessed fresh produce items, estimating cross-price elasticities will be based on sampled data such as regional average prices collected by the Bureau of Labor Statistics.

The results of this seasonal analysis point to some important challenges to future empirical studies of new fresh-cut products such as bagged salads. Although seasonal consumption of bagged salads can be explained reasonably well, much of the heterogeneity observed across metropolitan areas may be explained by demographic variables which change slowly over the short sample period of two years used in this study. For newly introduced products such as bagged salads, econometric analysis of a single, annual cross-section, or of panel data with only a few annual cross-sections, can incorporate demographic variables which may help explain heterogeneity in bagged salad consumption.

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Appendix: Data Collection and Development

Retail Prices

The Bureau of Labor Statistics (BLS) samples prices of selected fresh produce items monthly in 44 metropolitan areas. These prices are aggregated and averaged for four regions: Northwest, North Central, South, and West. Average retail prices are not reported monthly by metropolitan areas because BLS sampling procedures do not always guarantee sufficient observations within a metropolitan area to calculate sample variances.

Matching monthly average retail prices for the four regions with the 64 metropolitan areas used by Information Resources, Inc. (IRI) was accomplished by first deleting the 20 metropolitan areas not included in BLS samples. The remaining 44 metropolitan areas sampled by BLS and covered by IRI were then compared carefully to determine if the same counties were included in each pair of metropolitan areas. The counties included in BLS and IRI areas coincided exactly in many, but not all, cases. But as BLS's average prices are calculated for the entire region, the average retail prices for the region were matched to each IRI metropolitan area.

Temperature Measures

The temperature measure used to reflect the influences of weather on consumption was apparent temperature (AT) as defined by Steadman. Apparent temperature is a measure of human perception of temperature well suited both for wind chill (wind and low temperatures) and for sultriness (humidity and high temperatures). In fact, tabled values of apparent temperature cover dry-bulb temperatures over the range of $-40°C \leq T \leq 50°C$. Steadman (1994, 1984) has developed and calibrated a sophisticated procedure for calculating apparent temperature based on ambient weather conditions as well as human activity levels, clothing surface area, and clothing thickness. Given certain "base conditions" for body size, human activity, and apparel, apparent temperature can be closely approximated by the following linear function of ambient temperature (T_a), ambient vapor pressure (P_a), and wind speed (v_{10}):

(A1) $$AT_{pv} = T_a + 3.3P_a - 0.7v_{10} - 4.0.$$

The fitted relationship in (A1) provides a good approximation to more exact tabled values of AT (Steadman 1994, p. 6). An even more sophisticated measure of apparent temperature accounts for "extra radiation" in addition to vapor pressure and wind speed. However, calculations including measures of extra radiation require numerous assumptions regarding ambient conditions, human activity, and clothing—all beyond the scope of this study.

In (A1) temperature is measured in degrees Celsius, while vapor pressure is given in kiloPascals (kPa). Wind speed measured in meters/second is an average based on continuous measurement during one minute at 10 meters above the ground. The fitted equation in (A1) indicates that the marginal effect of an increase in vapor pressure, ceteris paribus, is to increase apparent temperature. Put more intuitively, as humidity increases, so does apparent temperature. The marginal effect of an increase in wind speed is to lower apparent temperature.

The raw data required for calculating AT_{pv} were retrieved from the National Oceanic and Atmospheric Administration's (NOAA's) online file transfer protocol server. Daily values from October 18, 1993 through October 15, 1995 were obtained for selected weather stations in the 44 metropolitan areas. The raw data series used were as follows: TMAX, daily maximum temperature in whole degrees Fahrenheit; AWND, average daily wind speed in tenths of a mile per hour; and DPTP, average daily dew-point temperature in tenths of degrees Fahrenheit. Because NOAA does not report vapor pressure, values for vapor pressure were calculated with the following equation using dew-point temperatures:

(A2) $$P_a = 1013.25e^{[13.3185S - 1.9760S^2 - 0.6445S^3 - 0.1229S^4]},$$

where $S \equiv 1 - (373.16/10 \times DPTP)$, and $DPTP$ is average daily dew-point temperature in tenths of degrees Fahrenheit (Sellers).

Holiday and Flood Dummies

Each holiday occurred twice over the sample period. Holiday dummies were constructed with zero values for all observations except the two four-week periods in which the holiday occurred; different holiday dummies were not constructed in each year due to limited degrees of freedom. For example, a single Thanksgiving dummy was constructed to account for that holiday in both years. Dummies for the following holidays were tested: Super Bowl, Easter, Memorial Day, Fourth of July, Labor Day, Thanksgiving, and Christmas.

The Salinas Valley in California experienced a devastating flood in April 1995 which shocked fresh vegetable prices substantially. Although retail prices of fresh-cut products were not as volatile as those of unprocessed commodities, some temporary price increases did occur in bagged salads. A dummy representing the flood, with a value of one only for the four-week period ending April 30, 1995, was included with the holiday dummies in the following testing sequence.

The initial hypothesis (H1) tested was that all dummies for each metropolitan area within a region were jointly different from zero. For example, all Thanksgiving dummies in the eight areas within the Northeast were tested for being different from zero. The second hypothesis tested (H2) for each set of holiday dummies was whether their effects were equal across areas within a region. In the Northeast, for example, the null hypothesis was that Thanksgiving had the same coefficient across all eight areas. The last null hypothesis tested (H3) was whether a single coefficient, equal across equations for the holiday under consideration, was different from zero.

Inferences were drawn from these tests as follows. Failure to reject H1 suggests that no holiday dummies be included. Rejection of H1 and H2 jointly suggests separate dummies for each area within the region should be included. Rejection of H1 and H3 while failing to reject H2 suggests that a holiday dummy with a single coefficient constrained to be equal across equations should be included.

Using the foregoing sequence of F-tests for each holiday dummy in turn produced the following results: an Easter dummy with no cross-equation restrictions and single dummies for Labor Day and the Salinas flood in the Northeast; a single Memorial Day dummy in the North Central region; all holiday and the flood dummies with no cross-equation restrictions in the South; and in the West, Thanksgiving and Super Bowl dummies restricted across equations with Christmas, Easter, Fourth of July, Labor Day, and flood dummies unrestricted across equations.