MODELING INTRAURBAN PRICE COMPETITION: AN EXAMPLE OF GASOLINE PRICING*

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1. INTRODUCTION

Economic theory explains the existence of large-scale price variation for a single homogeneous good in terms of discrete regional markets with known trading functions and nonzero transport costs between the various markets. The Cournot-Enke model assumes that each market has its own local supply and demand curves which generate local equilibrium price levels. However, the existence of intermarket price differences sets up trading relationships between the markets dependent on the costs of transport. The spatially competitive equilibrium price level in each market reflects not only local supply and demand conditions but also transport costs between the various markets [Samuelson (1952)].

However, models of this kind are unlikely to provide a satisfactory explanation of spatial price variation at subregional scales. At the intraurban scale in the retailing sector, for example, the assumption of discrete market regions with distinct local supply and demand functions would seem quite inappropriate. Nor is price variation likely to reflect transport costs either between the various trading units or with respect to an external supply source.

This paper considers a number of interacting markets models as models for intraurban retail price variation for a single homogeneous good [Henderson and Quandt (1971)]. There are, however, some important modifications. Instead of defining interacting economic sectors the models define interacting spatial markets. In addition, interaction assumptions are made only with respect to the demand function component of the models. Thus the supply function in any one market is assumed independent of price levels in other markets. In the case of the demand function, market interaction is assumed to exist because of the (local) price awareness and price sensitivity of consumers and because of the price awareness of retailers vis-à-vis their competitors. These behavioral assumptions have implications for the spatial price surface because of the considerable mobility of consumers within the urban area. The classical system of discrete market regions (characteristic of the location-theoretic tradition of spatial economics) is therefore replaced by a network of interdependent, overlapping and possibly volatile market

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regions because customers are able to search, at virtually no cost, for the particular good as part of a multipurpose trip. This high degree of consumer mobility, combined in the case of some goods with considerable variation in the timing of demand (which leads to variation in the position in the urban area from which the individual may begin a search process), also provides the justification for introducing stochastic variation into the demand function in two of the models.

The models presented here are considered most appropriate for retail price variation where the consumer is purchasing a single homogeneous good rather than a bundle of goods, but where that purchase may form part of a multipurpose trip so that the cost of that trip is spread over a large number of items. In addition, the consumer is assumed to be mobile with respect to several retail outlets and, once at a site, can quickly identify the necessary price information. The retail outlets are numerous and, ideally, in perfect competition. The models were initially investigated for a study of an intraurban gasoline market with price posting.

In the next section three interacting markets models are introduced. Two testable properties of the models are identified—first, that intraurban spatial prices possess specific spatial covariation properties. The probable structure of that covariation is given by the behavioral assumptions relating to consumers and retailers. The second property, deriving from the stochastic nature of the demand function, is that during periods of increasing consumer price sensitivity, intraurban price variation at least over the competitive range should decrease.

After presenting the three interacting markets models in the next section, Section 3 discusses the results of fitting one of the models to gasoline data for the city of Sheffield during a period of intensifying price competition in the first quarter of 1982.

2. INTERACTING MARKETS MODELS FOR INTRAURBAN PRICE VARIATION

The following notation will be used throughout. Let n denote the number of markets or retail outlets for the good. Let $\mathbf{D}_t$ denote the n-dimensional (column) demand vector at time t and let $\mathbf{S}_t$ denote the n-dimensional (column) supply vector at time t. The price at time t at each of the markets is represented by the n-dimensional column vector $\mathbf{p}_t$. The column vectors $\mathbf{c}$ and $\mathbf{e}$, also of length n, are vectors of constants. $\mathbf{A}$ and $\mathbf{B}$ denote $n \times n$ ordered matrices, their rows and columns coinciding with the labelling of the n markets. The matrix $\mathbf{A}$ is associated with the demand vector and $\mathbf{B}$ is associated with the supply vector.

Before considering the interacting markets models it is useful to consider the case of n independent markets. Supply and demand in each of the markets can be expressed as a function of price thus

$$\mathbf{D}_t = \mathbf{A}\,\mathbf{p}_t + \mathbf{c}$$

(1)

$$\mathbf{S}_t = \mathbf{B}\,\mathbf{p}_{t-1} + \mathbf{e}$$

It is assumed that supply is a lagged function of price. In the case of independence, both $\mathbf{A}$ and $\mathbf{B}$ are diagonal matrices with the entries in $\mathbf{A}$ negative and the entries in $\mathbf{B}$ positive. Assuming that clearance must take place in each market, that is

$$\mathbf{D}_t - \mathbf{S}_t = \mathbf{0}$$

then if $\mathbf{p}_e$ denotes the equilibrium price vector

$$\mathbf{p}_e = [\mathbf{A} - \mathbf{B}]^{-1} (\mathbf{e} - \mathbf{c}) \tag{2}$$

Each market is dynamically stable if $|b_{ii}| < |a_{ii}|$ for all i and convergence will be oscillatory if $b_{ii}/a_{ii} < 0$. The model suggests no systematic spatial price variation unless there is systematic variation either in the distribution of $\{(e_i - c_i)\}_i$ terms or in the distribution of $\{(a_{ii} - b_{ii})^{-1}\}_i$ terms. Such systematic variation, if present at all, is most probable in the demand elasticities, for example, across different income groups, each living in different areas of the city. This might lead to permanent spatial price variation, particularly in large metropolitan regions if there were strong disincentives to movement between city areas or if most intraurban travel was channelled along a small number of routeways and each consumer searched only along one such routeway.

Suppose that in (1) a stochastic term is added to the demand function so that

$$\begin{aligned} \mathbf{D}_t &= \mathbf{A}\,\mathbf{p}_t + \mathbf{c} + \mathbf{u} \\ \mathbf{S}_t &= \mathbf{B}\,\mathbf{p}_{t-1} + \mathbf{e} \end{aligned} \tag{3}$$

The term $\mathbf{u}$ is $IN(\mathbf{0}, \sigma^2\mathbf{I})$ where $\mathbf{I}$ is the identity matrix. So the demand function for each market is disturbed by an independent drawing from a normal distribution. The equilibrium price vector is

$$\mathbf{p}_e = [\mathbf{A} - \mathbf{B}]^{-1} (\mathbf{e} - \mathbf{c} - \mathbf{u})$$

so that $\mathbf{p}_e$ is $MVN\,[(\mathbf{A} - \mathbf{B})^{-1} (\mathbf{e} - \mathbf{c}), \sigma^2 (\mathbf{A} - \mathbf{B})^{-2}]$. In the case where all the model coefficients are constant over the n markets, as the slope of the demand function increases (or supply function increases), then the variance in spatial prices across the n markets decreases.

The introduction of a stochastic term into the demand function does not generate spatial price dependencies since each u_i is independent. However, if the $\mathbf{u}$ distribution was not independent, the pattern of its dependency would be transferred to the spatial price surface.

The discussion now turns to the interacting markets models. Some of these models have been discussed, in a different context, in Haining (1983).

A Deterministic Model of Interacting Markets

In the case of an interacting markets model the matrices $\mathbf{A}$ and $\mathbf{B}$ in (1) are no longer restricted to being diagonal. Assuming clearance in each of the markets then

$$\mathbf{p}_t = (\mathbf{A}^{-1}\mathbf{B})^t\, \mathbf{p}_0 + (\mathbf{A} - \mathbf{B})^{-1} (\mathbf{e} - \mathbf{c})$$

where $\mathbf{p}_0$ is the price vector at time $t = 0$. As before, the equilibrium price vector is given by (2) and the equilibrium is stable if the eigenvalues of $(\mathbf{A}^{-1}\mathbf{B})$ are all less than unity in absolute value.

Equation (2) is now developed further. By rearranging terms

$$\mathbf{p}_e = \mathbf{B}^{-1}\mathbf{A}\mathbf{p}_e + \mathbf{B}^{-1}(\mathbf{c} - \mathbf{e}) \tag{4}$$

To remove the self-dependence in (4) write

$$\begin{aligned} \mathbf{p}_e &= \{\mathrm{Diag}\,(\mathbf{B}^{-1}\mathbf{A}) + \overline{\mathrm{Diag}}\,(\mathbf{B}^{-1}\mathbf{A})\}\,\mathbf{p}_e + \mathbf{B}^{-1}(\mathbf{c} - \mathbf{e}) \\ &= \{\mathbf{Y} + \mathbf{Z}\}\,\mathbf{p}_e + \mathbf{B}^{-1}(\mathbf{c} - \mathbf{e}) \end{aligned} \tag{5}$$

where $\mathbf{Y}$ denotes the diagonal entries in $(\mathbf{B}^{-1}\mathbf{A})$ and $\mathbf{Z}$ denotes the off-diagonal entries in $(\mathbf{B}^{-1}\mathbf{A})$.

Let the subscript i refer to the ith element/row of the appropriate vectors/matrices. Then from (5) write

$$p_{i,e} = (1 - y_{ii})^{-1}\mathbf{Z}_i\,\mathbf{p}_e + (1 - y_{ii})^{-1}(\mathbf{B}^{-1})_i(\mathbf{c} - \mathbf{e}) \qquad (i = 1, \ldots, n) \tag{6}$$

which expresses the equilibrium price in the ith market as a function of equilibrium prices elsewhere in the system. We now develop this model further. Assume that only $\mathbf{A}$ contains both diagonal and off-diagonal terms, that is, $\mathbf{B}$ remains diagonal. (There appear to be fairly good reasons for doing this in the case of the gasoline retail study—see Section 3.) While the diagonal entries are assumed negative, the off-diagonal entries are assumed positive so that demand at any market is assumed to increase if prices elsewhere increase. By assuming that $\mathbf{B}$ is diagonal the emphasis is placed on the individual retail outlet to adjust prices in order to ensure clearance. Thus clearance is achieved at least initially by the retailer adjusting his profit margins.

Assume therefore that $\mathbf{B}$ is diagonal $(\{b_{ii}\})$; then (6) can be rewritten as

$$p_{i,e} = \sum_{\substack{j=1 \\ j\neq i}}^{n} \frac{a_{ij}}{b_{ii} - a_{ii}}\,p_{j,e} + \frac{c_i - e_i}{b_{ii} - a_{ii}} \tag{7}$$

where $a_{ij}/(b_{ii} - a_{ii}) > 0$ and the uncompetitive spatial equilibrium price is equal to the equilibrium price for the independent markets case.

An interesting variant of this model may be developed if markets are divided into price leaders and price followers. Such a division may be particularly appropriate for urban pricing. Suppose the first n_1 markets are designated as leaders, so that the remaining $n - n_1$ are followers. The matrix $\mathbf{A}$ may now be partitioned thus

$$\mathbf{A} = \left[\begin{array}{c|c} \mathbf{A}_{11} & \mathbf{A}_{12} \\ \hline \mathbf{A}_{21} & \mathbf{A}_{22} \end{array}\right]$$

The subscript 1 refers to the n_1 leader markets and the subscript 2, to the $(n - n_1)$ follower markets. Assume that $\mathbf{A}_{11}$ and $\mathbf{A}_{22}$ are diagonal and $\mathbf{A}_{12} = \mathbf{0}$. The matrix $\mathbf{A}_{21}$ describes the followers/leader dependency pattern. It may then be shown

$$(\mathbf{A} - \mathbf{B})^{-1} = \left[\begin{array}{c|c} (\mathbf{A}_{11} - \mathbf{B}_{11})^{-1} & \mathbf{0} \\ \hline -(\mathbf{A}_{22} - \mathbf{B}_{22})^{-1}\mathbf{A}_{21}(\mathbf{A}_{11} - \mathbf{B}_{11})^{-1} & (\mathbf{A}_{22} - \mathbf{B}_{22})^{-1} \end{array}\right]$$

where, again, $\mathbf{B}$ is diagonal. Then

$$p_{i,e} = \frac{c_i - e_i}{b_{ii} - a_{ii}} \qquad (i = 1, \ldots, n_1)$$

$$p_{i,e} = \sum_{j=1}^{n_1} \frac{a_{ij}}{b_{ii} - a_{ii}} p_{j,e} + \frac{c_i - e_i}{b_{ii} - a_{ii}} \qquad (i = (n_1 + 1), \ldots, n)$$

A Spatial Stochastic Model of Interacting Markets

The spatial stochastic version of the previous interacting markets model is given by (3) with $\mathbf{B}$ diagonal but $\mathbf{A}$ containing diagonal and off-diagonal terms. The demand function for each market is moved above or below the surface for the deterministic case by an amount determined by the independent drawing from the normal curve. The introduction of a random component into the process means that market clearance is now defined as a probabilistic equality, that is

$$\text{Prob}\,\{\mathbf{p}: \mathbf{D}_t(\mathbf{p}) = \mathbf{S}_t(\mathbf{p})\}$$

Under replication of this model a distribution of cutting points is obtained where the randomly-displaced demand function cuts the supply surface. Since in each replication the demand function is displaced only once for each market, it is clear that a temporal trajectory exists that ensures that if a stable equilibrium exists (as obtained from the deterministic version of the model), the price level will converge to its equilibrium. Given the earlier assumptions, this trajectory will be oscillatory.

As before, the equilibrium price vector is

$$\mathbf{p}_e = [\mathbf{A} - \mathbf{B}]^{-1} (\mathbf{e} - \mathbf{c} - \mathbf{u}) \tag{8}$$

There is evident similarity between this expression and a spatial multiplier [Haining (1978), Sheppard (1979)]. The equilibrium price level over the n markets represents the accumulation of an adjustment process (involving direct and indirect effects) across the n markets. Through such an adjustment process, shifts in price in one market trigger price changes elsewhere in the system until a new equilibrium surface is achieved.

It follows from (8) that the equilibrium price vector $\mathbf{p}_e$ is distributed MVN $[(\mathbf{A} - \mathbf{B})^{-1} (\mathbf{e} - \mathbf{c}), \sigma^2[(\mathbf{A} - \mathbf{B})^T(\mathbf{A} - \mathbf{B})]^{-1}]$. Rearranging (8) we obtain

$$p_{i,e} = \sum_{\substack{j=1 \\ j \neq i}}^{n} \frac{a_{ij}}{b_{ii} - a_{ii}} p_{j,e} + \frac{c_i - e_i}{b_{ii} - a_{ii}} + \frac{u_i}{b_{ii} - a_{ii}} \tag{9}$$

or

$$p_{i,e} \propto \sum_{\substack{j=1 \\ j \neq i}}^{n} a_{ij}\, p_{j,e} + c_i - e_i + u_i \tag{10}$$

Equation (10) describes an autoregressive spatial scheme with positive coefficients ($a_{ij} > 0$) and, hence, positive spatial autocorrelation at all lags. Since $(c_i - e_i) \neq 0$, the model implies the presence of site effects. Section 3 will return to the estimation of schemes such as (9) and (10).

Finally, note that as the slope of the demand function increases (or the slope of the supply function increases) then the variance in the distribution of equilibrium prices decreases.

A Spatial-Temporal Stochastic Model of Interacting Markets

Suppose now that instead of a single random drawing for the demand function for each market region, a new drawing is made at each time period. Thus write

$$\begin{aligned} \mathbf{D}_t &= \mathbf{A}\,\mathbf{p}_t + \mathbf{c} + \mathbf{u}_t \\ \mathbf{S}_t &= \mathbf{B}\,\mathbf{p}_{t-1} + \mathbf{e} \end{aligned} \tag{11}$$

where $\mathbf{u}_t$ is a white noise process with constant variance $\sigma^2\mathbf{I}$. Such a model implies temporal stochastic demand variation as well as spatial stochastic demand variation. Assuming market clearance gives

$$\mathbf{A}\,\mathbf{p}_t + \mathbf{c} + \mathbf{u}_t = \mathbf{B}\,\mathbf{p}_{t-1} + \mathbf{e} \tag{12}$$

Let $\Gamma = E[\mathbf{p}_t\,\mathbf{p}_t^T]$, the spatial autocovariance matrix for the price surface. Ignoring the constant terms $\mathbf{c}$ and $\mathbf{e}$ in (12) it follows that

$$\mathbf{A}\,\Gamma\,\mathbf{A}^T - \mathbf{B}\,\Gamma\,\mathbf{B}^T = \sigma^2\,\mathbf{I}$$

It appears that explicit matrix solutions of such equations are not in general available. Besag (1974) obtains a solution for the special case of a spatially stationary infinite regular lattice system where matrices **A** and **B** will commute. It then follows that

$$\Gamma = \sigma^2(\mathbf{A}\,\mathbf{A}^T - \mathbf{B}\,\mathbf{B}^T)^{-1}$$

Besag suggests fitting a conditional spatial model to the equilibrium state of such a system rather than the autoregressive (simultaneous) spatial model that was derived in the previous case.

In fact, there will be no further treatment of this case. The main reason for this, apart from the difficulty in obtaining a solution for finite irregular lattice systems, lies in the problems associated with interpreting market clearance. Since a new demand function is generated at each time period, the system is liable to be highly unstable, except in the unlikely case that it moves immediately to each equilibrium at each new time period. Otherwise, even if a stable equilibrium exists at each time period the system will no sooner move towards it than the equilibrium will move. Analytically, the clearance constraint yields the autocovariance function for the distribution of cutting points of the supply and demand functions. In practice without additional assumptions on the sampling from the white noise process it is not clear how any stable trajectory could exist—the prices in any market being subject to wild and erratic movements.

In the final section we consider the estimation of model (10) and then review results from the study of gasoline prices in Sheffield.

3. FITTING AN INTERACTING MARKETS MODEL

Statistical Estimation

Ord (1975) has considered the problem of estimating the parameters of mixed regressive autoregressive models of the form

$$\mathbf{Y} = \mathbf{X}\beta + \rho\mathbf{W}\,\mathbf{Y} + \mathbf{z} \tag{13}$$

where $\mathbf{z}$ is the error term, $\mathbf{X}$ is an $n \times k$ data matrix, β is a $k \times 1$ vector of parameters, $\mathbf{W}$ is a given $n \times n$ positive weights matrix (scaled so that row sums are unity) that describes the pattern of site interactions, and ρ is the interaction or spatial autocorrelation parameter. [This model should be distinguished from the case of a regression model with autocorrelated errors also considered by Ord (1975)]. In the case where $\beta = \mathbf{0}$ the model reduces to an autoregressive scheme following the joint probability formulation of Whittle (1954).

In fact, Equation (10) gives little indication as to the form of the regression component in the model. It would not be implausible, for example, to set $c_i = c$ and $e_i = e$ for all i, thus reducing the model to the statistical form $\mathbf{Y} = \mathbf{A}\,\mathbf{Y} + \beta\mathbf{1} + \mathbf{z}$. On the other hand, it would not be surprising to identify exogenous variables that did significantly affect individual retail outlet price.

Because of the absence of specific model information on the regression component of the model it was decided not to estimate the regression and autoregression components simultaneously. This would seem to minimize the effects of possible model misspecification (in the regression component) on the more important part of the analysis, that concerned with estimating the autocovariance structure. A two-step procedure was adopted:

(1) Remove the possible effects of site characteristics by regression methods. Three binary variables were measured: auto sales, auto repairs, and whether the site was on a principal radial routeway. These variables were included in a trend surface model that simultaneously tested for the presence of spatial trend in the data.

(2) Take the residuals from the significant model obtained at the first step and fit the autoregressive model using the maximum likelihood procedure [Ord (1975)]. For the second step the matrix $\mathbf{A}$ is simplified to the form $\rho\mathbf{W}$ as described in (13). The parameter ρ to be estimated may be interpreted as a competition parameter [Mead (1967)] and the model predicts that this should be positive. The $\mathbf{W}$ matrix describes the pattern of linkage. The choice of positive entries in $\mathbf{W}$ specifies the spatial nature of the interactions. Changing the rule by which these entries are determined changes the context within which significant interaction effects may be identified. Given the earlier discussion, the nonzero entries in row i (associated with retail outlet i) identify those other retail outlets that are in *direct* demand competition with site i. This competition is assumed to arise from the actions of consumers and retailers discussed in Section 1. The nonzero weights used broke the urban area into four major subregions, coinciding with the four principal routeways into the center of Sheffield. Within each of these blocks retail outlets were linked in terms of nearest neighbors (for the same routeway) and spatial proximity. Thus most retail outlets had at least two interacting neighbors (the nearest neighbors in the two directions along the routeway), and usually more, to allow for strong clustering effects of outlets near main intersections. It should be remembered from the multiplier interpretation of the model that the *indirect* competition effects extend across the entirety of the connected lattice. These effects weaken with lag order and may be identified by powering $\mathbf{W}$.

Discussion of Results

The assumptions discussed in Section 1 seem plausible in the case of gasoline purchasing. The demand for gasoline derives from mobile, price-aware, and price-sensitive consumers.[1] The availability of gasoline at any individual outlet may reasonably be considered a function of station price.[2]

Data were collected on price for 85 gasoline stations in S.W. Sheffield, on a single day, in January, February, and March, 1982. There was approximately one month between each sample. This period is marked as a period of intensifying price competition. In January the minimum price for an imperial gallon of four star (regular grade) gasoline across the 85 stations was 153.9 pence. In February the minimum was 148.7 pence and in March it was 141.0 pence. The discussion of the statistical results is in three sections.

(i) *Dispersion Properties.* Over the highly competitive price range, the dispersion in gasoline prices did fall over the three-month time period. In January 47.8 percent of the stations charged in the range 153.9 to 155.9—a range of 2 pence. In February, excluding the two cheapest outlets, 51.4 percent charged in the range 149.5 to 151.0—a range of 1.5 pence. In March, excluding the cheapest outlet, 50 percent of the outlets charged in the range 141.8 to 142.0—a range of 0.2 pence.

The rank order of stations, in terms of price, varied throughout the period, and all the brands were more or less equally represented across the full spread of prices—the right tail of which lengthened over the three months as more outlets stopped trying to compete at the lowest levels. Whereas in January brand minimum prices were spread over the two pence price range, by March all the brands had an outlet charging 141.8 or 141.9.

These results appear to extend the empirical findings of Maurizi and Kelly (1978) on the impact of price posting on intraurban gasoline price variations. They observed that price advertising increased price competition and reduced the dispersion of prices.

(ii) *Regression Properties.* Observed gasoline prices were regressed on dummy variables representing location, auto repairs, and auto sales. In addition, station coordinates were included to test for trend in the price distribution. Only the location variable was significant (at the 95 percent level) in all three months, the partial regression coefficient indicating an average price mark-up of 3.7 pence, 4.3 pence, and 2.4 pence in the three months for stations located off the principal

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[1]At the regional level, studies have confirmed the importance of price in determining the regional level of demand for gasoline [Kraft and Rodekohr (1978)]. At the scale of the individual outlet, Conoco, for example, has claimed that its researchers show that motorists "do respond to slight price differences" (report in *Sunday Times*, London, June 20, 1982) and this is facilitated by price posting. This is not surprising: in the United States gasoline stations have consistently ranked in the top four of sales of major retailing goods [Claus and Rothwell (1970)].

[2]It might be argued that in an oil glut, gasoline supply would be highly elastic and, hence, independent of price. However, the retailer, particularly if he provides a range of automotive services, might choose to vary his effort in the gasoline market dependent on prevailing profit margins. These margins would depend largely on the price level and the degree of price support to the station from the company. Except in the case of company-run outlets, where concern may be with preserving market share (over a group of outlets), the assumption that supplies to one outlet are independent of supplies to other outlets seems plausible.

routeways. In January the auto sales variable was also significant—the partial regression coefficient indicating a 1.96 pence mark-up where automobiles were sold. No other variables were significant even at the 90 percent level.

(iii) *Autocovariance Properties.* The linkage diagram, defining the nonzero components of **W** in the autoregressive model, is shown in Figure 1. A linkage system was chosen that followed the principal urban routeways that focus on the downtown area (sites 22–30), and additional linkages were permitted in terms of proximity. The downtown area was left unconnected (except for clusters) because of the congested nature of the area which would tend to discourage extensive

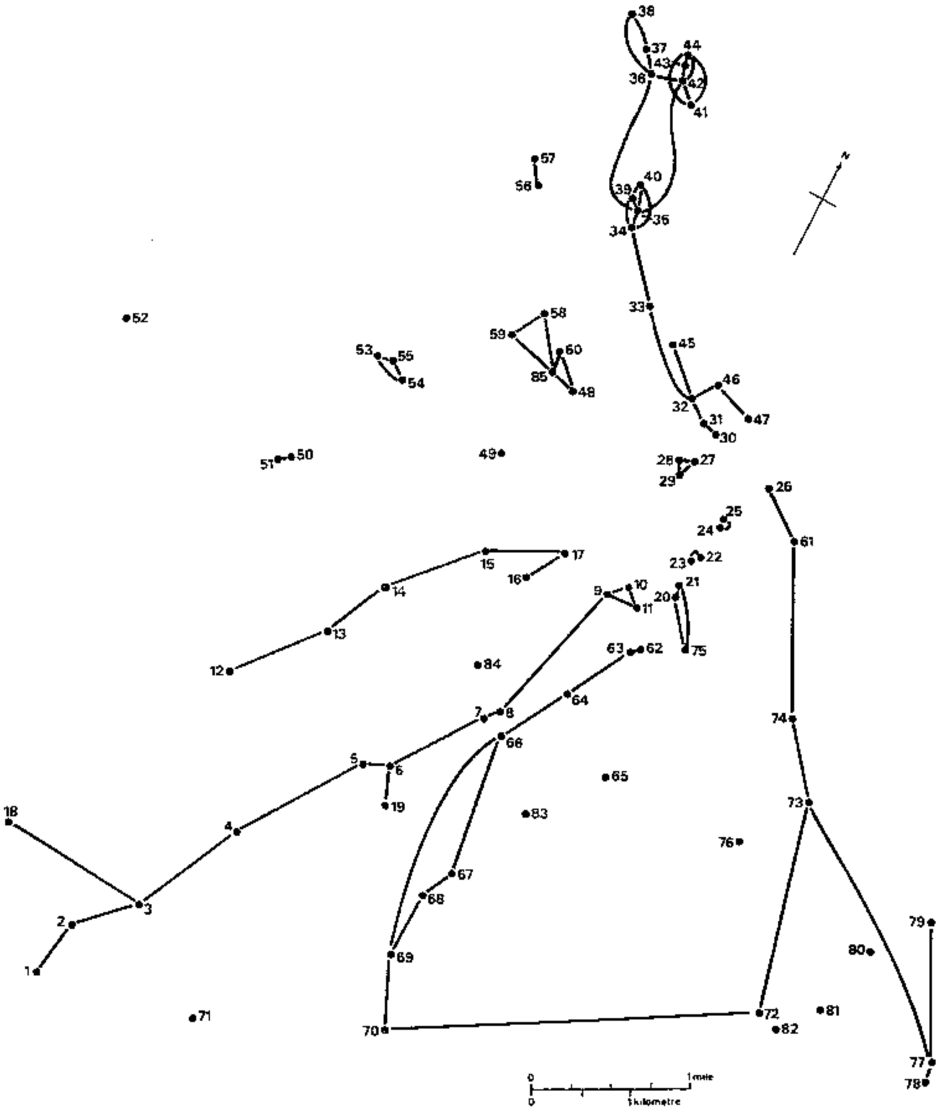

FIGURE 1: Linkage Map for the Gasoline Stations.

search. A number of peripheral stations were also left either unlinked or part of local clusters because of the difficulty of linking them to a wider reference group. It should be noted that two other weighting schemes were also used in separate analyses. One scheme was generated from an algorithm that identified the six nearest neighbors of each site and constructed the linkage map accordingly. The other scheme computed distances from a site to all others and constructed a linkage map where all sites were linked but with a weight that decreased with increasing distance. Neither of these two schemes gave any significant or theoretically consistent results.

Table 1 gives three sets of results. The first relates to the fitting of the autoregressive model to the complete set of stations. This represents an attempt to identify a single competition parameter over the entire set of outlets. Estimated values of ρ close to 0 indicate no interaction effects while values of ρ increasing from 0—up to a maximum of 1 [see Haining (1977)]—indicate, apparently, stronger interaction effects. Only in January is there evidence of significant interaction effects using a χ^2 goodness-of-fit criterion [Whittle (1954)]. Results for February and March suggest that, perhaps under the pressure of more uniform pricing, the surface has changed from being autocorrelated to being independently random.

In parts (b) and (c) of the table the same model has been estimated but on subsets of sites connected along a principal routeway. In part (b) the model has been estimated for Infirmary Road/Langsett Road (sites 30–47). In this case all the signs of the coefficients are correct but, in spite of quite large values in January and February, because of the small sample sizes only March is statistically significant. In part (c) the model has been estimated for the City Road/Ring Road/Chesterfield Road pattern (sites 26, 61–64, 66–70, 72–74, 77–79). Only January yields statistically significant results but again all the signs are consistent.

It appears from these results that although at the start of the period a contagious spatial price surface existed for the whole area, this changed as prices

TABLE 1: Parameter Estimates and Likelihood Ratio Tests for the Autoregressive Interaction Model

Month	ρ	Likelihood Function Hypotheses		χ^2	
		Null: $\rho = 0$	Alt.: $\rho \neq 0$	Value	Significance (%)
		(a) All Stations			
January	0.33	141.15	121.07	9.36	95
February	−0.021	212.90	212.79	0.03	NS
March	0.036	338.66	338.09	0.11	NS
		(b) Subset A			
January	0.29	23.02	21.41	1.01	NS
February	0.14	13.89	13.64	0.25	NS
March	0.52	32.93	21.56	5.92	95
		(c) Subset B			
January	0.43	15.91	13.34	2.46	~90
February	0.15	36.08	35.27	0.31	NS
March	0.14	36.84	36.01	0.31	NS

fell further. There is evidence, for example, that each separate routeway system began to display different competitive spatial attributes as prices fell. This may reflect the movement behavior of individual consumers and the extent of the reference group that retailers used in adjusting their prices.

The results given here must be interpreted with some caution however. Two points are particularly important. First, the results are drawn from an analysis comparing only a limited number of weighting schemes. A second problem concerns the behavior of the estimates of ρ. These estimates depend on the ratio of covariances to variances in the data. Now variances are not constant over the three time periods and are generally decreasing. This tends to reduce covariances too. So, changes in ρ estimates will depend on changes in the ratio of these reductions.

4. CONCLUSIONS

This paper has investigated interacting markets models as models of intraurban pricing with specific reference to gasoline retailing. Two sets of conclusions are drawn here of increasing generality.

First, with respect to gasoline price modeling, evidence has been presented that supports both independent and interacting markets models though at different intraurban scales. The nature of the interaction seems to be defined in terms of the principal routeways. Two further developments would seem to be of interest: (a) investigation of price leader/price follower models and (b) investigation of company-level models. The first group of models would recognize that certain service stations act as leaders in price setting and thus initiate the adjustment process in the spatial price surface. Such a study would require a more detailed investigation of the reference group used by each retailer. The second group of models would recognize that for company outlets, clearance is defined not so much on a station-by-station basis but with respect to groups of retail outlets of the same company. Price adjustment is possibly led not only by price cutters but also by those company outlets that contribute most to retaining market share, since these outlets might be offered more favorable price discounts by the parent company [Allvine and Patterson (1972)]. The models presented here and these extensions would seem of importance in developing models of the spatial structure of many intraurban retailing markets, not only gasoline.

The second conclusion relates to the development of interaction models such as (10) in the study of spatial-temporal processes. Interaction models are models of spatial structure, though such structure evolves in response to associated flow patterns. In the present discussion urban search models and models of intraurban flow might provide a stronger theoretical foundation for constructing the matrix **A** and hence the matrix **W** in the statistical model. As a longer-term objective we require an integrated theory of structure and flow as noted by Curry (1978). The study of relationships between fast- (flow) and slow- (pattern) moving spatial structures is an important area of research at the interface between static and dynamic spatial problems [Haining (1983)].

REFERENCES

Allvine, F. C. and J.M. Patterson. *Competition Ltd.: The Marketing of Gasoline.* Bloomington, Indiana: Indiana University Press, 1972.

Besag, Julian. "Spatial Interaction and the Statistical Analysis of Lattice Systems," *Journal of the Royal Statistical Society B*, 36 (1974), 192–236.

Claus, R. James and D. C. Rothwell. *Gasoline Retailing*. Vancouver, Canada: Tantalus, 1970.

Curry, Leslie. "Position, Flow and Person in Theoretical Economic Geography," in T. Carlstein, D. Parkes, and N. Thrift (eds.), *Time and Regional Dynamics*. New York: Wiley, 1978.

Haining, Robert P. "Model Specification in Stationary Random Fields," *Geographical Analysis*, 9 (1977), 107–129.

———. "Statistical Tests and Process Generators for Random Field Models," *Geographical Analysis*, 11 (1978), 45–64.

———. "Spatial Structure and Spatial Temporal Processes," in D. Griffith and A. Lea (eds.), *Evolving Geographical Structures*, Proceedings of the NATO Advanced Studies Institute, San Miniato, July 1982. The Hague, The Netherlands: Martinus Nijhoff, 1983, pp. 323–345.

Henderson, James M. and Richard E. Quandt. *Microeconomic Theory: A Mathematical Approach*, 2nd Edition. New York: McGraw-Hill, 1971.

Kraft, John and Mark Rodekohr. "Regional Demand for Gasoline: A Temporal Cross Section Specification," *Journal of Regional Science*, 18 (1978), 45–55.

Maurizi, A. and T. Kelly. "Prices and Consumer Information," Washington, D.C., American Enterprise Institute for Public Policy Research, 1978.

Mead, Richard. "A Mathematical Model for the Estimation of Interplant Competition," *Biometrics*, 23 (1967), 189–205.

Ord, J. Keith. "Estimation Methods for Models of Spatial Interaction," *Journal of the American Statistical Association*, 70 (1975), 120–126.

Samuelson, Paul A. "Spatial Price Equilibrium and Linear Programming," *American Economic Review*, 42 (1952), 283–303.

Sheppard, Eric. "Geographic Potentials," *Annals, Association of American Geographers*, 69 (1979), 438–447.

Whittle, Peter. "On Stationary Processes in the Plane," *Biometrika*, 41 (1954), 434–449.