Environment and Planning A, 1990, volume 22, pages 527-549

Spatial flows and competing central places: towards a general theory of hierarchical interaction

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Received 10 October 1988; in revised form 10 March 1989

Abstract. This paper presents a variation of Fotheringham's competing destinations model using categorized information on spatial flows in a central place system. A competing central place model is developed using spatially defined choice sets for origin-destination pairs by threshold distance and central place order. The competing central place generalization is empirically tested by undertaking a comparative analysis of 1980 domestic airline passenger traffic amongst selected cities in the continental United States. A host of modeling strategies are contrasted and the effects of mass, separation, and competitive forces noted in the presence or absence of hierarchical data. The production-constrained competing central place specification is shown to exhibit not only greater explanatory power than Fotheringham's competing destinations model, but also significant reductions in potential multicollinear relations between regressors. The model is later extended to incorporate an intervening opportunities filter. Competitive flow patterns between paired origins and destinations are then delimited by geographic range, compatibility, and the impeding effects of substitute and/or intervening flows within a hierarchical network.

1 Introduction

Spatial interaction modeling using the gravity approach for the estimation of distance-decay parameters has been the focus of continuing controversy. Although the underlying importance of Newtonian principles is theoretically well founded and widely accepted (Ravenstein, 1885; Zipf, 1946; Carrothers, 1956; Niedercorn and Bechdoldt, 1969; Olsson, 1970; Wilson, 1971; Curry, 1972), concerns remain over model misspecification, the interpretation of distance-decay measures, and the actual estimation procedures that are utilized (Cliff et al, 1974; Curry et al, 1975; Ewing, 1974; Griffith and Jones, 1980; Huff and Jenks, 1968; Johnston, 1976; Sheppard, 1979; 1982; Sheppard et al, 1976). The recent literature suggests that a need exists to view the interaction process as an integrated phenomenon, composed not only of the usual mass and distance effects, but also of the elements of accessibility and competitiveness in flows (Fotheringham, 1981; 1982; 1983; 1984; Fotheringham and Webber, 1980), and feedback amongst the different interactional effects (Fotheringham, 1983; 1984; Haynes and Fotheringham, 1984). Fotheringham has labeled one such integrated arrangement as the competing destinations (CD) modeling strategy. The CD format provides an appropriate framework for simultaneously dissecting pure distance-decay-related effects from those caused by the bias of a competitive spatial structure and/or geographic layout. Yet, this CD formula should be construed as a special case of a more generalized interaction model which includes information about the stratified nature of competing central places— one that incorporates transactions amongst hierarchical alternatives in the flow pattern (Fik, 1988). This approach would certainly have a potential for reducing the statistical problems both of spatial-autocorrelated error and of internal dependence amongst regressors (otherwise known as multicollinearity).

Gravity-type formulations can only distinguish hierarchical relations through variables which represent attractiveness (for example, size or mass). The CD model allows for the indirect specification of hierarchical choice through locational accessibility, yet does not differentiate hierarchical flows in terms of nodal function or the description of service areas. The alternative model proposed in this paper not only allows for the specification of hierarchical effects in terms of mass, but by function and threshold distance as well.

The competing central place (CCP) model developed in this paper is a direct extension of the CD principle where central place logic is incorporated into the (ordered) spatial system. The focus of the CCP specification is, therefore, on hierarchical exchange. Such ordered flow considerations have gained much attention and are well documented in the current central place literature, on subjects ranging from migration to consumer shopping behavior (Huff, 1976; Mulligan, 1983; 1984a; 1984b; Parr, 1978), yet very little has been done to address the issue of spatial flows and hierarchical patterns in a general interaction theory. The purpose of this paper is to contribute to that theory by:

(1) empirically validating the strength of the CCP specification as a generalization of the CD model using 1980 airline flow data for forty-five principal US cities;

(2) embodying information on the ordered flows between central places (at the same or different hierarchical levels) (a) to lessen the potential for multicollinearity amongst explanatory variables, and (b) to increase the amount of explained variation in the flow pattern;

(3) providing alternative versions of the CCP model to account not only for hierarchical flows but also for intervening opportunities that impede those flows on the same level or between different levels.

By including information on ordered flows, the CCP model possesses the ability to correct the usual dependence encountered in the Newtonian components of the CD formula (Fotheringham, 1984). This is crucial for obtaining proper estimates of system parameters, thereby reducing the probability of making type II errors in significance testing. The inclusion both of intervening opportunities and of competitive accessibility, in the hierarchical sense, is critical to meeting this end. The underlying intent of this work is to promote the evolution of theory in hierarchical interaction modeling through an empirical validation of CCP flows.

2 The competing destinations model

It has been demonstrated that distance deterrence in flow patterns is less prominent for accessible and/or centralized nodes (origins - destinations, sources - sinks) than for inaccessible and/or peripheral nodes (Haynes and Fotheringham, 1984). This phenomenon should reinforce our suspicions about the intertwined influences of behavioral and structural components of distance decay, and has led to the belief that gravity formulations are grossly insensitive to the differentiation of behavioral and structural parameters. Many theories and methodologies have been proposed, linking distance attenuators to differentials in observed or perceived separation, symmetrical and asymmetrical network connectivity, spatial autocorrelative entities, and convolutions thereof (Berry and Marble, 1986; Curry et al, 1975; Fotheringham, 1981; 1983; Johnston, 1976; Taaffe and Gauthier, 1973).

Apparently the best example of an attempt to uncouple distance and structural components simultaneously is the CD model of Fotheringham (1983; 1984), which stands as a major advancement toward the correction of the implicit misspecification of the gravity model. The CD model can be stated as

$$I_{ij} = \alpha_i M_j^{\sigma_i} d_{ij}^{\beta_i} A_{ij}^{\delta_i} \mu_{ij} , \tag{1}$$

with

$$A_{ij} = \sum_{p=1}^{n-2} \frac{M_p}{d_{pj}} ; \tag{2}$$

where I_{ij} is the flow volume between an origin i and a destination j, M_j is the mass (attractive force) at j, d_{ij} is the distance between i and j, A_{ij} is the accessibility index for j with respect to all $(n-2)$ alternative destinations p ($p \neq i$ and $p \neq j$ for $i, j = 1, ..., n$ possible nodes), and μ_{ij} is a multiplicative disturbance term (assumed to be distributed lognormally). In this model there are four coefficients to be estimated, namely, α_i, an intercept term (restricting total interaction volume to a known total—a production constraint), and σ_i, β_i, and δ_i, the origin-specific parameters for mass, distance, and system-wide competitive accessibility, respectively. This model can also be stated in terms of an attraction or totally constrained format (Fotheringham, 1983).

Fotheringham (1984) has argued that $\delta_i < 0$ when competitive forces are dominant in the geography of alternative places, and $\delta_i > 0$ when agglomerative forces are present. If either of these influences prevails in the interaction between an origin and a destination, then the traditional gravity-type specifications would appear to be inadequate in the estimation of parameters satisfactorily capturing the attributes of place-to-place exchange.

Parameter estimates are commonly obtained via the log-linear least-squares criterion (Pindyck and Rubinfeld, 1981). The limitations of this technique have been established for improper designation of multiplicative disturbances, whereby a conversion condition is attached to the intercept coefficient during log-linear usage if the error structure is indeed additive (Haworth and Vincent, 1979). As the main concerns in this paper are over the specification and estimation of distance-decay and accessibility effects, and given that the other estimated coefficients are unaffected by the choice of error description, the intercept problem will not be explored at this time. Concerns have also been warranted as to the added distortions which arise from spatial covariation in error (Fik, 1988), another issue that will not be addressed in this paper. Instead, the focus here will be on the assessment of accessibility parameter estimates which convey information about the competitive aspects of flows. The interpretation of such estimates may be difficult when dispersed or clustered systems (or subsystems) can be identified as hierarchically separable, thereby compounding the problem of dissecting behavioral and structural influences which may exist in different magnitudes at multiple levels. Thus, Fotheringham's CD formulation may be viewed as a special case (for a single-tiered network) of a multilevel model (network) where agglomerative and/or competitive forces are both origin-destination-specific and tier-specific. Hence, any expansion of the CD argument must be couched within the realization of hierarchical competition (Fotheringham, 1983; Ingram, 1970; Shimbel, 1953; Weibull, 1980). This suggests the redefinition of the accessibility of a destination within that hierarchy in terms of competing central places.

3 Competing central places

Many researchers have suggested the pursuit of interactional modeling within a hierarchical setting (Huff, 1976; Mulligan, 1983; 1984; Parr, 1978). Central place theory (Christaller, 1966) provides a sound foundation for analyzing tier-specific agglomerative and deglomerative forces which affect hierarchical transactions. Combinations of origins and destinations and the flows between them can be classified as hierarchically competitive, depending on the direction (up or down the hierarchy), magnitude (in terms of the size of places involved), and competitive arrangements of central place exchange (which can be directly tied to the geographic distribution of those competing central places). Hierarchical flow and place information may facilitate the exposure of nested push-pull effects which would otherwise be disguised in an unstratified competitive model like Fotheringham's. The identification of hierarchical levels can yield a more accurate depiction of the flow patterns which may or may not compete at various tiers. The CCP abstraction can thus be thought of as a model which allows simultaneously for intralevel and interlevel competition in spatial flows.

Suppose that an m-order central place hierarchy of origins and destinations exists, such that for any paired origin i and destination j, i and j can be separately and uniquely classified within a set of m hierarchical levels denoted by S_k ($k = 1, ..., m$). Thus, $i \in S_k$ and $j \in S_k$, where $i, j = 1, ..., n$, and $\{S_1 \cup S_2 \cup ... \cup S_m\}$ is comprised of n elements belonging to m mutually exclusive and collectively exhaustive sets (that is, $S_t \cap S_w = \{0\}$ for any t and w, $t \neq w$). The proposed specification for a flow, $I_{ij}^{\star}$, between ordered places i and j may be written as

$$I_{ij}^{\star} = \Gamma_i M_j^{\alpha_i} d_{ij}^{\beta_i} V_{ij}^{\delta_i \star} \mu_{ij} , \tag{3}$$

where Γ_i is the origin-specific production-constrained balancing factor which assures that

$$\sum_{j=1}^{n} \hat{I}_{ij} = \sum_{j=1}^{n} I_{ij}^{\star}$$

(or the sum of predicted outflows, $\hat{I}_{ij}$, equals the sum of actual outflows for each origin). The variable V_{ij}, specific to different pairs of origins and destinations, can now be interpreted as a CCP accessibility component and is defined as

$$V_{ij} = \sum_{r=1}^{\theta} \frac{M_r}{d_{rj}} , \tag{4}$$

where the number of alternative or competing central places, θ, is determined by two restrictions: (1) for all competing central places r ($r \neq i$ and $r \neq j$), the condition $\{d_{rj} \leqslant d_{ij}\}$ holds (that is, only those central places within the circumscribed distance d_{ij} from destination j are considered as competing destinations); and (2) $r \in S_x$ and $i \in S_x$ (that is, i and r are elements of the same central place set S_x; and therefore, i and r are known to be of the same order). In other words, only those places which are within the paired origin-destination distance d_{ij} away from j

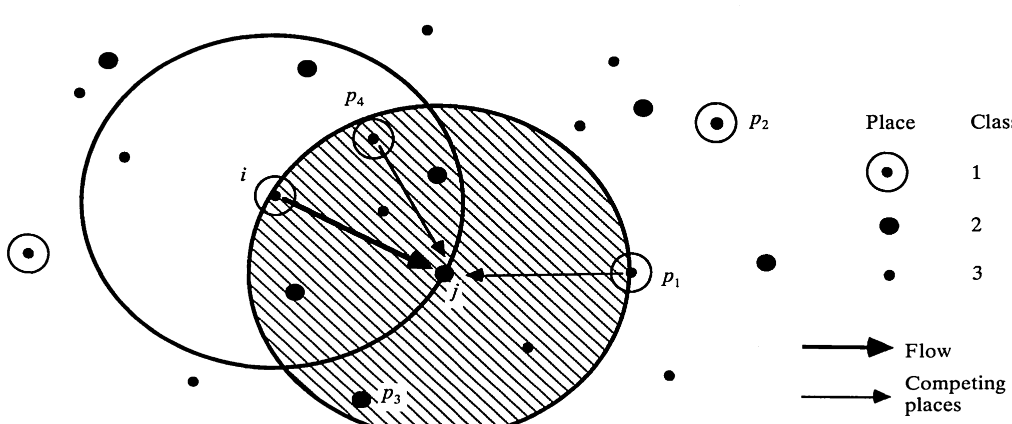

Figure 1. An illustration of competing central places to destination j from origin i.

and of like order to i are used to compute the CCP accessibility index. The central place compatibility requirement and distance restriction are illustrated in figure 1.

For example, consider figure 1 where an m-level hierarchy is trifurcated into the mutually exclusive and collectively exhaustive sets S_1, S_2, and S_3, and twenty-two (n) elements (of origins or destinations) are assigned according to size and/or function to classes 1, 2, and 3, respectively, where 1 (3) denotes the highest (lowest) central place level. The flow between an origin i (of class $x = 1$) and a destination j (of class $x = 2$) delimits a distance d_{ij}—a paired origin-destination-specific radius that encompasses competitive destinations (denoted by the cross-hatched circle whose center is j). This shaded area contains all possible central place alternatives which can be viewed as competitive in terms of distance. However, given restriction (2) above, only two central place flows are viewed as hierarchically competitive (that is, of like order to i): p_1 and p_4 to j. Because nodes like p_2 lie outside the prescribed distance, they are not viewed as competitive flow sources and are omitted from the calculation of accessibility even though p_2 satisfies the compatible order criterion. For this origin and destination combination, $\theta = 2$. Note that there will be $n(n-1)$ distinct θ values for a network composed of n nodes where $m > 1$, and θ will equal $n-2$ if and only if the number of hierarchical levels m equals 1 (as in Fotheringham's CD model) and no distance restriction is imposed. If $m \neq 1$, then we would not expect the CCP accessibility parameter $\delta_i^\star$ to equal the CD accessibility parameter δ_i. This implies that, if all places are of like order and no distance constraint is imposed, $\delta_i^\star$ must collapse to δ_i during estimation.

Because θ is unique for each origin-destination combination, the CCP accessibility index, V_{ij} (for a flow between an origin i and a destination j), can be thought of as a jointly competing origins-destinations accessibility component given that both the order of the origin and the distance between i and j play an explicit role in delimiting the range of competing flows. Thus, the CCP model can be thought of as a competing origins-destinations extension of the simpler CD case. The CCP accessibility index V_{ij} is conditional upon the spatial distribution and relative positioning (in both a hierarchical and a locational sense) of origin-destination pairings. This newly defined accessibility component distinguishes highly between competing central places in a source-sink specific basis, capturing the relative attractiveness or repulsiveness of each central place exchange. The obvious benefit of such a description is that each exchange within or between tiers can be viewed in isolation from the noncompetitive and/or incompatible places within that system. In summary, the CCP model not only allows for competitive reciprocation in a tiered spatial structure, but also employs information on the ordered characteristic of the flow which is uniquely defined from a jointly competing origins-destinations standpoint. The CD model, in contrast, is clearly a special case of the CCP formula when $m = 1$ and competitive distance thresholds are not considered.

4 Competing and intervening central places

The CD and CCP models can also be seen as subsets of an even more generalized interaction framework which comes under the heading of a competing and intervening central place (CICP) flow model, as an extension of Stouffer's intervening opportunities formula (1940). One version of this model can be stated as

$$I_{ij} = \Omega_i M_j^{\alpha_i} d_{ij}^{\beta_i} V_{ij}^{\delta_i} Z_{ij}^{\phi_i} \mu_{ij} , \qquad (5)$$

where ϕ_i is the intervening opportunities parameter attached to the intervening central place filter Z_{ij}. Although these CICP filters can take on many forms, one possible definition is as follows:

$$Z_{ij} = \frac{1}{\psi} \sum_{z=1}^{\phi} \frac{1}{d_{ij}} \frac{M_z}{d_{iz}} , \tag{6}$$

where, for all intervening opportunities z ($z \neq i$ and $z \neq j$), $d_{iz} \leqslant d_{ij}$, $d_{zj} \leqslant d_{ij}$, and z is of like order to j. This version will be labelled as CICP1 (a competing and intervening central place model which examines opportunities between i and j, for places $z, j \in S_x$ and $z \in S_x$, for intervening opportunities at equal or lesser distances than d_{ij} from i and j; $z = 1, ..., \psi$).

Alternatively, the feasible range of intervening opportunities z can take on the characteristic of being of similar or higher central place order than that of j. This can be labelled as CICP2, a generalized competing and intervening central place model which filters competitive flows moving up the hierarchy (as substitutes for j) while simultaneously accounting for the degree of competitiveness of system flows with respect to j. For CICP2, z can thus be redefined for all intervening places such that $z \in S'$ (for all opportunities at equal or lesser distances than d_{ij} which are circumscribed by the intersecting overlays of circular mapped areas whose centers are i and j with equal radii of d_{ij}), and S' is the set containing all places w which are of like order to or of higher order than j (and meet the distance or implied directional requirement).

The specification of an averaged and deflated intervening central place filter in equation (6) is necessary (a) to avoid problems of dependence or multicollinearity with M_j and d_{ij}; and (b) to avoid overstatement of the magnitude of intervening opportunities with increasing flow distance for lowest-level places. An example of the intervening opportunities filter is illustrated in figure 2. Under CICP1, nodes p_5 and p_6 can be viewed as intervening opportunities for a flow between node i and j, since they are of same order as that of j. Notice that the distance (or implied directional) restriction requires that these nodes be located within some specified region lying between nodes i and j (delineated by crosshatching). The CICP2 version would also include node p_4 as a higher order intervening central place to j.

The distinctive properties of CICP1 and CICP2 allow the convenience of testing whether or not higher level hierarchical substitutes in flow pattern are significant from an origin-based standpoint. In addition, the expansion of CCP to CICP provides the researcher with the ability to perform sensitivity analysis of the CCP parameter estimates by comparing these estimates before and after the inclusion of information on intervening opportunities. Once the intervening opportunity filter(s)

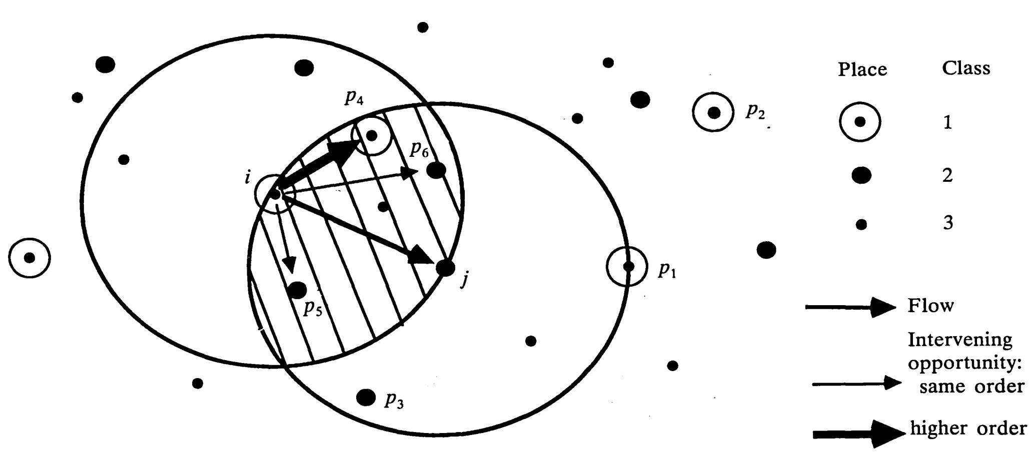

Figure 2. An illustration of intervening opportunities between an origin i and a destination j.

has (have) been interjected, the mass, distance-decay, and accessibility coefficients may be subject to change. This change may yield additional information on the statistical relevance of intervening sinks and sources in terms of their potential flow-retarding effects.

It is posited that the direction of change in the distance-decay parameter estimates (after filtering) should correspond to the true attenuating effect of those opportunities. For example, if the change is positive (negative) then it can be said that intervening opportunities are important (unimportant) attenuators of origin-based flows. This, of course, can only be true if the intervening opportunities filter is deemed statistically significant and free from collinearity. Since the filtered region will overlap the competing destinations region, it may contain redundant information to that of the CCP accessibility index. This may present problems for origin and destination pairs made up of one peripheral node and one centralized node (an urban shadow effect). With this caveat in mind (the potential for collinear relations between the intervening opportunities filter and the competitively defined accessibility index), it is apparent that CICP2 has less probability of producing an intervening opportunities filter that is collinear with CCP accessibility when higher order alternative destinations (central places) are considered. The CICP framework thus houses a series of interaction models which can be further divided into a typology of CICP models ranging from the gravity model (as the simplest case where only mass and distance variables are shown to be statistically valid in explaining the variation in flows) up to the CICP2 model—a version which is based on an integrated approach to interaction modelling which relies on statistically significant hierarchical influences (see table 1). The CICP versions presented here are only a subset of many plausible CCP models. Obviously, these prototypes may be extended beyond the production-constrained phase to include attraction-constrained and totally constrained CICP versions.

Table 1. A typology of spatial interaction models.

Model	Components	Description of hierarchical influences
Gravity model	mass distance	not applicable
Competing destinations model	mass distance locational accessibility	locational accessibility
Competing central place model	mass distance locational and hierarchical accessibility	hierarchical accessibility index
Competing and intervening central place model	mass distance locational and hierarchical accessibility intervening opportunities	hierarchical accessibility index intervening central places

5 Hierarchical interaction and spatial choice sets

The CCP and CICP approaches outlined above can be linked to the literature on patronage modeling and the definition of 'spatially based choice sets' which describe the situational characteristics of dispersed consumers in relation to the geographic distribution of competitive outlets from the perspective of a given origin (Black, 1984). Market area description and patron choice sets (the set of relevant alternatives) are determined by the competitiveness and attractiveness of outlets as a function of their relative locations (Ansah, 1977), outlet accessibility (Recker and Stevens, 1977), consumer preference, choice situation, and spatial separation of outlets and patronage (Black, 1984). Market definition is established on an outlet-specific basis through the identification of appropriate alternatives in terms of critical distances or 'threshold limits' (which are uniquely defined for each outlet). Demarcation of outlet-based choice sets allows for 'predictive efficiency' of the patronage of each outlet through an information gain because of the exclusion of irrelevant alternatives as determined by threshold limit and functional relationship (Ansah, 1977; Black, 1984).

This paper incorporates the concept of outlet-specific spatial choice sets in a slightly different context from that which is found in the research on retail patronage. Here, CCP and CICP choice limits are defined as origin and destination pair-specific choice sets. The definition of hierarchical interaction choice sets are based on the (1) service description of origin-destination pairs, (2) the relative locations and/or competitive accessibility of nodal pairs within the larger geographic setting, and (3) the constriction of spatial choice sets by simultaneously assessing the effects of threshold limits as a function of distance and assessing relevancy (or choice inclusion) as a function of central place description (compatibility). Although no new data on Newtonian components are introduced directly, the use of nodal functionality and threshold distance play an important role in the evaluation of relevant and competitive interaction alternatives. Pair-specific spatial choice sets θ and ψ are delimited by the geographic 'reach' or distance threshold d_{ij} which circumscribes a competitive information field and secondary zone of intervening nodes for flows between nodal pairs.

Ultimately, choice subsets are resolved through the assessment of hierarchical compatibility or substitutability and the sphere of influence and flow patronage by nodal pair. Similar information-field approaches to retail travel patterns and hierarchical choice modeling have already been established through empirical support (Clark, 1968; Gensch and Svestka, 1984; Hanson, 1972; Smith and Slater, 1981). In this paper, nodes will be hierarchically defined in terms of the economic diversification of their service area (that is, the highest level of the hierarchy will contain those centers which are most diverse and the lowest level will be composed of those nodes which are more specialized).

Table 2. Descriptive statistics for competing central places.

Class size	Service-area description	Obs.[a]	Population[b]		Flows[b]	
			total	average	total	average
1	national nodal	5	30013025	6002605 (2422178)	6953104	1390620 (522798)
2	regional and subregional diversified	25	41638009	1665520 (1010531	9159127	339227 (237219)
3	functional/specialty	12	16219757	1351646 (1041092)	2372461	197705 (133499)
4	consumer oriented, resort	3	2486717	828905 (523432)	920949	306983 (217393)
All			90357508	2007944 (1871748)	19309812	429107 (432995)

[a] Number of observations.

[b] All statistics are rounded to their nearest integer values. Standard deviations are given in parentheses.

6 Estimation of competing airline flows within an urban hierarchy

By means of the classification scheme of Noyelle and Stanback (1983), forty-five US cities were categorized by position in the central place hierarchy (by function) with Standard Metropolitan Statistical Area (SMSA) population data obtained from the 1980 US Census of Population and the description of those places within the national system. Attention was paid to the degree of specialization of the SMSAs in question.

Table 3. Service-area descriptions of forty-five major US cities.

City	Population (SMSA)[a]	Assigned class	Central place description
1 Albuquerque	454499	4	Consumer oriented, resort
2 Atlanta	2029710	2	Diversified/regional
3 Baltimore	2174023	2	Diversified/regional
4 Birmingham	847487	2	Diversified/subregional
5 Boston	2763357	2	Diversified/regional
6 Buffalo	1242826	3	Production center
7 Charleston (SC)	430462	3	Industrial/military
8 Chicago	7103624	1	National nodal
9 Cincinnati	1401491	2	Diversified/regional
10 Cleveland	1898825	2	Diversified/regional
11 Dallas-Fort Worth	2974805	2	Diversified/regional
12 Denver	1620902	2	Diversified/regional
13 Des Moines	338048	2	Diversified/subregional
14 Detroit	4353413	3	Specialized/functional
15 Greensboro	827252	3	Specialized/functional
16 Hartford	726114	3	Specialized/functional
17 Houston	2905353	2	Diversified/regional
18 Indianapolis	1166575	2	Diversified/regional
19 Jacksonville (FL)	737541	2	Diversified/subregional
20 Kansas City	1327106	2	Diversified/regional
21 Las Vegas	463087	4	Consumer oriented, resort
22 Little Rock	393774	2	Diversified/subregional
23 Los Angeles	7477503	1	National nodal
24 Louisville	906152	3	Specialized/functional
25 Memphis	913472	2	Diversified/subregional
26 Miami	1625781	2	Diversified/regional
27 Milwaukee	1397143	3	Specialized/functional
28 Minneapolis-St Paul	2113533	2	Diversified/regional
29 Nashville	850505	2	Diversified/subregional
30 New Orleans	1187073	2	Diversified/regional
31 New York	9120346	1	National nodal
32 Norfolk (VA)	806951	3	Industrial/military
33 Oklahoma City	834088	3	Diversified/subregional
34 Omaha	569614	3	Diversified/subregional
35 Philadelphia	4716818	2	Diversified/regional
36 Phoenix	1509052	2	Diversified/regional
37 Pittsburgh	2263894	3	Specialized/functional
38 Portland (OR)	1242594	2	Diversified/regional
39 St Louis	2356460	2	Diversified/regional
40 Salt Lake City	936255	2	Diversified/subregional
41 San Diego	1861846	3	Industrial/military
42 San Francisco	3250630	1	National nodal
43 Seattle	1607469	2	Diversified/regional
44 Tampa	1569134	4	Consumer oriented, resort
45 Washington, DC	3060922	1	Government/education

[a] SMSA Standard Metropolitan Statistical Area. Population statistics obtained from the 1980 Census of Population, Volume 1. SMSA rankings are from Noyelle and Stanback (1983).

For the purpose of simplifying the number of tiers, Noyelle and Stanback's classification scheme was adapted to create a four-dimensional typology according to service-area description. Descriptive statistics for these groupings are listed in table 2.

The highest-order nodes (classified as 1) are national in scope, the second level encompasses all cities which are categorized as diverse centers (regional or subregional—class 2). The two lower levels (classes 3 and 4) are comprised of nodes which specialize in either production or consumption activities, respectively. Population was not utilized as a criterion for classification because that variable is already included among the explanatory elements, and would most likely be redundant information. Service-area description furnished implicit supplementary data on the economic purpose and substitutability or differentiability of central places within the network. Separation of hierarchical level by function and the calculation of associated subsystem accessibility measures is less likely to generate collinear relations with the usual attractive and repulsive forces (for example, mass and distance).

Airline traffic flow information was taken from the 1980 Civil Aeronautics Board publication entitled "Origin-destination survey of domestic airline passenger traffic", based on a 10% sample for a twelve-month period ending 31 December 1980. All flows are origin based and represent the number of passengers in the sample, outbound plus inbound (flows between an origin and a destination). Distance is measured by total nonstop mileage between appropriate city pairs. A similar data base was used by Fotheringham (1983; 1984) in his comparison of the gravity and CD models. A list of those cities included in the study (with accompanying service-area description) is provided in table 3.

Per-capita statistics, charted in table 4, reveal a distinctive pattern of declining average interaction per capita as class size decreases from class 1 to class 3. In contrast, class 4 flows generate atypical interaction volumes for their size: no doubt this is tied to class 4's consumer orientation. Note that the regional and subregional centers exhibit the largest variation in flow patterns, followed by the national nodal, resort, and, last, the speciality centers (as would be expected).

Table 4. Per-capita flow statistics by class.

	Class				All
	1	2	3	4	
Total flows per capita	1.21724	5.66178	1.84095	1.30992	10.0441
Average flow per capita	0.24344	0.20969	0.15341	0.43664	0.2232
Standard deviation	0.04475	0.08845	0.03353	0.43240	0.1143

7 Experiment 1: a comparison of CD and CCP

Competitive accessibility indices were computed for the CD and CCP models and the two log-linear production-constrained models were then empirically tested. Next the models were contrasted for the amount of explained variation in domestic airline passenger flows accounted for by their various components. All cases were tested with the least squares (LS) linear regression criterion with individual parameter estimates evaluated at the 95% confidence level (under forty-one degrees of freedom). Parameter estimates, tests of multicollinearity (T_{i1} and T_{i2}—the least squares regression of nodal-hierarchical accessibility versus distance and mass variables, respectively), and adjusted R^2 values are displayed in tables 5, 6, and 7 (see over). Although the multicollinearity tests employed are overtly sensitive (that is, they detect statistically significant collinearity without evaluation of its severity), the results of these tests will be tabulated for the sake of completeness. Multicollinearity is not usually assumed to be severe until correlation coefficients reach 0.8 or above, yet its statistically meaningful presence may be an indicator of model misspecification or the inclusion of redundant information. Collinearity amongst explanatory variables can be reduced and/or eliminated through the use of remedial measures (for example, the use of extraneous information) (see Gujarati, 1978). Table 7 also contains adjusted coefficients of determination for the gravity (G) model for the purpose of comparison.

The CD model outperforms the gravity model by increasing the amount of explained variation in flows by approximately 9.3%. This is no surprise given the similar findings of Fotheringham (1984). The results presented here, notwithstanding the improvements of CD over G, clearly indicate that the differentiation by nodal class has a twofold effect: (1) the CCP model outperforms the CD model by increasing the amount of explained variation in flow pattern by an additional 5% (on average) or an increase of about 14.5% over the gravity model; and (2) parameter estimates of the CCP accessibility index are significant in 73% of the cases tested as opposed to 66% for CD, with far less trace of statistically significant multicollinearity amongst regressors. Inclusion of hierarchical information and the definition of nodal paired choice sets not only improves the predictive efficiency of central place flows but also increases the likelihood of producing noncollinear and statistically significant accessibility parameter estimates. In only eight out of forty-five cities the CCP accessibility index, as a function of threshold distance, exhibits a significant amount of interdependence with either population or the distance variable, whereas in the CD model the presence of multicollinearity was detected in thirty out of forty-five cases (compare tables 5 and 6). Again, this problem is not severe, yet it is obvious that the use of extraneous information on the nature of flows reduces the potential for type II errors in the significance testing of parameter estimates.

Once information on the ordering of origins and destinations was introduced, and competitive choice sets were defined, all statistically weighted CCP accessibility estimators carried negative signs (table 6). This consistent result is to be expected for two reasons: (a) because the tenets of central place theory suggest regularity in the spacing of like functional units, deglomerative as opposed to agglomerative network structures exist; and (b) the range of competition at a destination j is regulated by the reach of the information field as proxied by distance d_{ij}, thereby standardizing the extent of competitive market areas in relation to the positions both of the origin and of the destination within the larger geographic market. This assists in controlling the irregular dispersion of unordered service areas in the domestic system. By distinguishing class or functional type and nodal-pair-specific spatial choice sets, the CCP model shows an ability to reduce internal dependence among explanatory variables while simultaneously providing a more accurate depiction of flows within a complex hierarchical network (see table 7).

The CCP model shows a noticeable improvement in predicted flow volumes for those nodes which are typically associated as regional flow distribution centers or collector-sender points in major hub-spoke arrangements. Hubs such as Atlanta, Denver, Dallas-Fort Worth, Kansas City, Memphis, Minneapolis-St Paul, Phoenix, St Louis, Washington DC, and Chicago (see Grove and O'Kelly, 1986a; 1986b; O'Kelly, 1986) show the largest increases in explained variation in flows once the competitive effects of the urban hierarchy have been accentuated. The sensitivity of CCP to spatially defined choice sets confirms the competitive nature of geographically distributed central hubs which act as collection and dispersal points for the system as a whole; that is, ordered choice sets for competing origins and destinations are screened as competitive (relevant) or noncompetitive (irrelevant) in terms of their functionality and relative positioning both to collector and to sender hubs. The somewhat regular distribution of hubs within the domestic network also provides further explanation for the consistency in negative accessibility parameter estimates.

Defining the geographic reach of competitive forces and hierarchical constraints may prove useful in the location analysis of hub-spoke systems. Locational efficiency of hub-spoke networks and the restructuring of hub-spoke systems can benefit from a more comprehensive spatial interaction model such as CCP in predicting flow volume. Perhaps a further extension of this type might incorporate urban and regional economic indicators, modal competition (especially for clusters of competitive or like-order places), and demographic profiles of interactants and central places. Even though CCP flow description only marginally increases the level of explanation, it nonetheless introduces an alternative modeling strategy whose potential must be explored (particularly for those nodes classified as hubs).

In cases where the CCP model showed less explanatory power than its CD counterpart, significant multicollinearity was reported between the CD accessibility variable and distance (mostly for nodes which were highly clustered or isolated).

Table 5. Estimated coefficients for competing destinations model (ordinary least squares). t-statistics of estimated coefficients are given in parentheses.

City	Competing destinations components			Multicollinearity tests	
	M_j	d_{ij}	A_{ij}	T_{i1}	T_{i2}
Albuquerque	1.1578 (5.4039)*	0.6587 (4.1580)*	−1.7441 (−3.9400)*	1.0294 (2.4882)*	0.1750 (0.5720)
Atlanta	0.4896 (2.1410)*	0.9279 (5.8708)*	1.0562 (2.2108)*	−0.8153 (−1.8420)	0.2091 (0.6835)
Baltimore	1.0066 (4.6945)*	0.9760 (5.3405)*	1.0888 (1.6567)	−7.1224 (−7.1224)*	0.4295 (0.4295)
Birmingham	0.8633 (4.0506)*	0.5502 (3.7290)*	0.4403 (1.0118)	−0.7273 (−1.6411)	0.1836 (0.5986)
Boston	1.3737 (7.6123)*	1.1915 (9.2061)*	1.9750 (4.6680)*	−1.6692 (−3.8174)*	0.1756 (0.5599)
Buffalo	1.3923 (8.1972)*	1.0366 (7.4465)*	2.1827 (4.9375)*	−1.9859 (−5.2393)*	0.1685 (0.5425)
Charleston (SC)	1.0904 (5.1370)*	0.5709 (3.8842)*	1.2492 (2.8477)*	−0.9342 (−2.1003)*	0.1788 (0.5813)
Chicago	0.6357 (3.1210)*	1.3056 (8.9701)*	0.9228 (2.0375)*	−1.2391 (−2.7997)*	0.2478 (0.7837)
Cincinnati	1.0867 (6.4633)*	1.0594 (8.0446)*	1.6862 (4.0221)*	−1.2391 (−2.7997)*	0.2478 (0.7837)
Cleveland	1.2570 (7.3863)*	1.2594 (8.7615)*	2.1827 (4.7045)*	−2.1500 (−5.7953)*	0.1606 (0.5125)
Dallas-Fort Worth	0.4802 (2.0545)*	1.0494 (6.3664)*	−0.8821 (−1.9149)	0.4083 (0.9666)	0.1958 (0.6573)
Denver	0.7280 (3.4536)*	1.1335 (7.2383)*	−1.5524 (−3.5299)*	0.8958 (2.2063)*	0.1838 (0.6095)
Des Moines	1.1735 (5.6122)*	0.3969 (2.7356)*	−0.6304 (−1.5398)	−0.5140 (−1.1609)	0.1784 (0.5807)
Detroit	1.0609 (5.6209)*	1.3473 (8.9598)*	2.2422 (4.7081)*	−1.8871 (−4.7181)*	0.1774 (0.5569)
Greensboro	1.0228 (5.2214)*	0.6789 (4.5778)*	1.2413 (2.7002)*	−1.5701 (−3.8515)*	0.1815 (0.5881)
Hartford	1.3130 (8.6650)*	0.9026 (7.6309)*	1.5100 (3.8022)*	−2.1263 (−5.3633)*	0.1616 (0.5222)
Houston	0.7028 (3.0253)*	1.0474 (6.3624)*	−0.6604 (−1.4220)	0.4141 (0.9976)	0.1867 (0.6221)
Indianapolis	0.9731 (5.8316)*	1.0319 (7.9685)*	1.2372 (3.0481)*	−1.7032 (−4.2664)*	0.1790 (0.5777)

Table 5 (continued)

City	Competing destinations components			Multicollinearity tests	
	M_j	d_{ij}	A_{ij}	T_{i1}	T_{i2}
Jacksonville (FL)	1.2203 (5.7349)*	0.1710 (1.2031)	0.5748 (1.3462)	−0.4786 (−1.0438)	0.1808 (0.5902)
Kansas City	0.4501 (1.8348)	0.7975 (4.6759)*	−0.1404 (−0.2877)	−0.2552 (−0.5818)	0.1958 (0.6420)
Las Vegas	1.3791 (6.9119)*	0.7295 (5.2552)*	−1.7959 (−4.1328)*	1.3265 (3.0265)*	0.1679 (0.5508)
Little Rock	0.9552 (4.7471)*	0.4531 (3.2366)*	−0.4781 (−1.2347)	−0.3184 (−0.7202)	0.1786 (0.5819)
Los Angeles	0.9951 (4.2045)*	1.3842 (8.0956)*	−2.6882 (−5.7127)*	1.4902 (4.1261)*	0.1545 (0.5923)
Louisville	0.9169 (5.4150)*	0.9000 (7.0039)*	1.2815 (3.1977)*	−1.6165 (−1.6165)	0.1834 (0.1834)
Memphis	0.7290 (3.3060)*	0.6739 (4.3950)*	0.3549 (0.8005)	−0.5871 (−1.3319)	0.1899 (0.6196)
Miami	1.1070 (5.3996)*	0.9155 (6.6864)*	0.6992 (1.6976)	0.0758 (0.1658)	0.1825 (0.5977)
Milwaukee	1.0209 (5.1873)*	0.8341 (5.6975)*	0.1274 (0.2842)	−1.3926 (−3.3583)*	0.1557 (0.5048)
Minneapolis-St Paul	0.8527 (3.8707)*	0.9675 (6.2477)*	−0.0641 (−0.1438)	−0.2922 (−0.6839)	0.1908 (0.6246)
Nashville	0.8280 (3.9013)*	0.7382 (4.8161)*	0.7310 (1.5992	−1.1357 (−1.1357)	0.1853 (0.1853)
New Orleans	0.8397 (3.9373)*	0.8434 (5.6779)*	−0.1055 (−0.2485)	0.0038 (0.0086)	0.1808 (0.5923)
New York	1.0218 (3.6907)*	1.3419 (6.6202)*	1.6512 (2.3008)*	−2.1919 (−4.6754)*	0.1373 (0.4000)
Norfolk (VA)	0.9544 (5.9728)*	−0.1002 (−0.8098)	0.4608 (1.1569)	−1.8522 (−4.6389)*	0.1763 (0.5700)
Oklahoma City	0.8360 (3.9266)*	0.6866 (4.5590)*	−1.4310 (−3.4066)*	0.2532 (0.5870)	0.1771 (0.5805)
Omaha	0.9713 (4.6777)*	0.5651 (3.9452)*	−0.8999 (−2.2265)*	−0.1759 (−0.3958)	0.1828 (0.5963)
Philadelphia	0.9901 (4.1039)*	1.2503 (6.1713)*	1.6539 (2.3664)*	−2.5476 (−6.5509)*	0.0850 (0.2604)
Phoenix	0.9809 (4.0928)*	0.8943 (5.1615)*	−1.6879 (−3.2118)*	1.3112 (3.1527)*	0.1733 (0.5765)
Pittsburgh	1.1979 (7.3364)*	1.3622 (9.6732)*	2.8447 (6.2003)*	−2.2465 (−6.1511)*	0.1720 (0.5462)
Portland (OR)	1.1194 (5.5226)*	0.9127 (6.0572)*	−2.4550 (−5.2579)*	1.6076 (3.9955)*	0.1632 (0.5459)
St Louis	0.6008 (2.8833)*	0.9848 (6.5700)*	0.4325 (0.9824)*	−0.8691 (−2.0413)*	0.2044 (0.6675)
Salt Lake City	1.1470 (5.4545)*	0.8378 (5.3139)*	−2.2212 (−4.7820)*	1.3090 (3.2334)*	0.1732 (0.5708)
San Diego	1.0609 (5.0638)*	0.8458 (6.0457)*	−2.2644 (−5.1988)*	1.1793 (2.6855)*	0.1171 (0.3995)
San Francisco	1.2084 (5.8558)*	1.3024 (8.5108)*	−2.4150 (−5.2187)*	1.5640 (3.9446)*	0.1556 (0.5326)
Seattle	1.1298 (5.6690)*	1.0761 (7.2038)*	−2.3611 (−5.1505)*	1.5954 (4.0114)*	0.1694 (0.5684)
Tampa	0.9012 (4.1583)*	0.7846 (5.4575)*	1.2770 (2.9513)*	−0.0779 (−0.1700)	0.1861 (0.6123)
Washington, DC	0.9214 (4.0912)*	1.3639 (7.0260)*	2.0203 (2.9081)*	−2.6558 (−7.0010)*	0.1617 (0.4946)

* Significant at 95% confidence level.

Given collinear relations, it is possible that the adjusted R^2 values of CD are most likely marginally distorted, as is the significance of those accessibility parameters. Subsequently, the overall improvement in adjusted R^2 coefficients (of CCP over CD) may be somewhat underrepresentative in the comparison of the explanatory strengths of the models, reinforcing the argument that the CCP model (the spatially and hierarchically defined choice set approach) is superior in its predictive efficiency to that of Fotheringham's CD model (which does not distinguish hierarchical patterns and/or the range of competing influences).

For situations in which multicollinearity persisted after the inclusion of nodal-pair-specific choice sets, there were dramatic reductions in the degree of regressor dependence. In particular, these nodes portrayed a tendency to be either highly clustered and/or peripherally located (that is, isolated) in their network position (for example, Detroit, Hartford, Baltimore, New York, Philadelphia, Portland, and Seattle). Those places whose results exhibited no multicollinearity under the CD formula were less responsive to changes in parameter estimates of distance decay

Table 6. Estimated coefficients for competing central place model (ordinary least squares). *t*-statistics of estimated coefficients are given in parentheses.

City	Competing central places components			Multicollinearity tests	
	M_j	d_{ij}	V_{ij}	T_{i1}	T_{i2}
Albuquerque	1.2783 (5.9424)*	0.4069 (2.7428)*	−0.1881 (−3.9946)*	−0.0085 (−0.1709)	0.0257 (−0.7462)
Atlanta	0.7058 (3.1752)*	0.8905 (6.0854)*	−0.2316 (−3.0415)*	0.0759 (0.9918)	0.0785 (1.5590)
Baltimore	0.9612 (4.4404)*	0.8044 (6.0923)*	−0.0700 (−1.2308)	0.1433 (2.2781)*	−0.0229 (−0.5973)
Birmingham	0.9236 (5.0090)*	0.5874 (4.6646)*	−0.2363 (−3.7472)*	0.0888 (1.1613)	0.0256 (0.4911)
Boston	1.4221 (6.5868)*	0.9360 (6.9337)*	−0.1948 (−1.9379)	0.1115 (0.9803)	0.0512 (0.7206)
Buffalo	1.4238 (7.2651)*	0.5893 (4.6737)*	−2.8459 (−2.8459)*	−0.0337 (−0.3879)	0.0096 (0.1715)
Charleston (SC)	1.2045 (5.2908)*	0.4364 (2.8955)*	−0.0434 (−0.7371)	0.0297 (0.4874)	0.0192 (0.4763)
Chicago	0.8658 (4.6566)*	1.3255 (10.8172)*	−0.1187 (−4.1779)*	0.0466 (1.352)	0.0337 (1.4847)
Cincinnati	1.1749 (6.0174)*	0.7808 (6.0251)*	−0.0507 (−0.8655)	0.1038 (1.5461)	0.0073 (0.1651)
Cleveland	1.1798 (5.8611)*	0.8751 (6.7637)*	−0.1336 (−2.2544)*	0.1045 (1.5473)	−0.0493 (−1.1351)
Dallas-Fort Worth	0.4692 (2.5679)*	1.1398 (8.7454)*	−0.0350 (−5.6093)*	0.0894 (1.2454)	0.0117 (0.2286)
Denver	0.7642 (4.0380)*	1.0488 (7.8020)*	−0.4058 (−5.0564)*	0.0824 (0.9151)	0.0425 (0.6649)
Des Moines	1.1138 (6.5406)*	0.5457 (4.5974)*	−0.2677 (−4.7884)*	0.0902 (1.2198)	0.0142 (0.2770)
Detroit	0.9460 (3.9656)*	0.9637 (6.3543)*	0.0933 (1.1200)	−0.1167 (−1.4580)	0.1022 (2.0097)
Greensboro	1.2697 (6.2706)*	0.4494 (3.5400)*	−0.1909 (−2.7114)*	−0.0177 (−0.2185)	0.1022 (2.0009)
Hartford	1.2602 (6.6743)*	0.6378 (5.9476)*	−0.0571 (−0.9851)	0.0980 (1.3141)	−0.1194 (−2.8193)*
Houston	0.7222 (3.7003)*	1.0628 (7.7219)*	−0.3892 (−4.4271)*	0.0521 (0.5392)	0.0263 (0.3851)
Indianapolis	0.9814 (5.3770)*	0.8525 (7.1442)*	−0.0712 (−1.4928)	0.0793 (1.3527)	−0.0503 (−1.3187)

Table 6 (continued)

City	Competing central places components			Multicollinearity tests	
	M_j	d_{ij}	V_{ij}	T_{i1}	T_{i2}
Jacksonville (FL)	1.2486 (5.0339)*	0.5670 (3.4026)*	−0.0452 (−0.6419)	0.0856 (1.3390)	0.0322 (0.7495)
Kansas City	0.5842 (2.7806)*	0.7841 (5.4391)*	−0.6886 (−3.9885)*	−0.0049 (−0.0271)	0.1388 (1.1086)
Las Vegas	1.1848 (6.6004)*	0.6450 (5.6059)*	−0.2607 (−5.7512)*	0.0796 (1.3453)	−0.0343 (−0.9058)
Little Rock	0.9593 (5.2194)*	0.5054 (3.9680)*	−0.2498 (−3.0822)*	0.0636 (0.6251)	0.0431 (0.6105)
Los Angeles	1.0878 (6.4615)*	1.3184 (11.8805)*	−0.3672 (−10.2343)*	0.1263 (2.7490)*	0.0279 (0.9228)
Louisville	1.0393 (5.5015)*	0.6856 (5.6751)*	−0.0276 (−0.7838)	0.0193 (0.4432)	0.0383 (1.3807)
Memphis	0.9109 (4.3734)*	0.6651 (4.8313)*	−0.2701 (−2.8511)*	0.0717 (0.6988)	0.1292 (1.9030)
Miami	1.1834 (5.9285)*	0.9215 (6.9199)*	−0.5618 (−2.3163)*	0.0155 (0.0561)	0.1190 (0.6446)
Milwaukee	1.0584 (5.7059)*	0.8139 (6.6281)*	−0.0979 (−2.3075)*	−0.0025 (−0.0492)	0.0180 (0.5191)
Minneapolis–St Paul	0.9249 (5.2458)*	0.9008 (7.2536)*	−0.9228 (−4.7907)*	−0.1789 (−0.7596)	0.0958 (0.5776)
Nashville	0.9924 (5.0633)*	0.5512 (4.1522)*	−0.6902 (−3.1653)*	−0.3021 (−1.2180)	0.1472 (0.8767)
New Orleans	0.8820 (4.6123)*	0.7781 (5.7662)*	−0.7434 (−3.1556)*	−0.2544 (−0.9573)	0.0688 (0.3669)
New York	0.8934 (3.8902)*	1.2637 (8.8254)*	−0.2641 (−4.8876)*	0.1231 (2.1180)*	−0.0274 (−0.7582)
Norfolk (VA)	0.9683 (6.1664)*	−0.1627 (−1.6182)	−0.0711 (−1.4782)	0.0667 (0.9235)	−0.0116 (−0.2522)
Oklahoma City	0.6674 (3.6222)*	0.7421 (5.6836)*	−0.4348 (−5.4610)*	0.0671 (0.7130)	−0.0396 (−0.5951)
Omaha	1.0401 (6.5570)*	0.7253 (6.5381)*	−0.3188 (−6.1617)*	0.1102 (1.5579)	0.0587 (1.1882)
Philadelphia	0.7251 (2.3939)*	0.9533 (6.6115)*	−0.1367 (−1.9548)	0.1245 (1.7543)	−0.0897 (−2.1619)
Phoenix	0.9545 (5.4081)*	0.9591 (7.8147)*	−0.3312 (−7.2937)*	0.1264 (2.3822)*	0.0095 (0.2587)
Pittsburgh	1.1502 (5.2173)*	0.7533 (5.4124)*	−0.1350 (−1.6378)	−0.0310 (−0.3404)	−0.0181 (−0.3154)
Portland (OR)	0.8594 (4.8778)*	0.7886 (6.6745)*	−0.4365 (−7.1533)*	0.1710 (2.3192)*	−0.0398 (−0.8064)
St Louis	0.7710 (4.2933)*	0.8493 (6.8755)*	−0.8260 (−4.1202)*	−0.2684 (−1.1195)	0.2072 (1.2568)
Salt Lake City	1.0251 (5.6457)*	0.7071 (5.6225)*	−0.3984 (−6.7094)*	0.1082 (1.5315)	−0.0131 (−0.2678)
San Diego	1.0639 (7.4729)*	0.8764 (9.4291)*	−0.2900 (−10.2884)*	0.0972 (2.2170)*	0.0087 (0.3059)
San Francisco	0.9169 (4.2652)*	1.0069 (7.2458)*	−0.2860 (−4.5819)*	0.0955 (1.4319)	−0.0390 (−0.9053)
Seattle	1.0298 (6.2973)*	0.9747 (8.6935)*	−0.5853 (−7.6375)*	0.2404 (2.4640)*	0.0009 (0.0148)
Tampa	0.8704 (5.7300)*	0.7803 (7.7350)*	−0.2463 (−7.7380)*	0.0020 (0.0424)	−0.0162 (−0.5086)
Washington, DC	0.7989 (3.7933)*	1.0408 (8.2429)*	−0.1400 (−3.9044)*	0.0570 (1.3247)	−0.0178 (−0.6902)

* Significant at 95% confidence level.

after the inclusion of the CCP accessibility index. For example, Atlanta and Oklahoma City exhibited no collinearity problems and only a slight change in their estimated regression coefficients for distance (where the estimated distance

Table 7. Adjusted goodness-of-fit measures for the gravity (G), competing destinations (CD), and competing central place (CCP) models.

City	Adjusted R^2 values			R^2 values for collinear regressors[a]	
	G	CD	CCP	CD	CCP
Albuquerque	0.4415	0.5494	0.5979	0.125 *a*	*
Atlanta	0.4139	0.4763	0.5218	*	*
Baltimore	0.4926	0.5278	0.5141	0.541 *a*	0.107 *a*
Birmingham	0.4388	0.4525	0.5819	*	*
Boston	0.5881	0.7310	0.6226	0.253 *a*	*
Buffalo	0.5538	0.7202	0.6274	0.387 *a*	*
Charleston (SC)	0.4871	0.5718	0.4938	0.093 *a*	*
Chicago	0.6145	0.6499	0.7296	0.154 *a*	*
Cincinnati	0.6104	0.7206	0.6174	0.134 *a*	*
Cleveland	0.5776	0.7257	0.6242	0.439 *a*	*
Dallas-Fort Worth	0.4456	0.4911	0.6863	*	*
Denver	0.4789	0.6003	0.6790	0.102 *a*	*
Des Moines	0.5256	0.5515	0.6957	*	*
Detroit	0.5028	0.6772	0.5175	0.341 *a*	0.085 *b*
Greensboro	0.4771	0.5560	0.5566	0.256 *a*	*
Hartford	0.6480	0.7397	0.6561	0.401 *a*	0.156 *b*
Houston	0.4867	0.5108	0.6527	*	*
Indianapolis	0.6402	0.7066	0.6587	0.297a	*
Jacksonville (FL)	0.4445	0.4680	0.4847	*	*
Kansas City	0.3735	0.3747	0.5486	*	*
Las Vegas	0.5259	0.6653	0.7376	0.176 *a*	*
Little Rock	0.5013	0.5192	0.5951	*	*
Los Angeles	0.3402	0.6057	0.8008	0.284 *a*	0.149 *a*
Louisville	0.5964	0.6770	0.6024	0.268 *a*	*
Memphis	0.4459	0.4544	0.5376	*	*
Miami	0.6203	0.6452	0.6642	*	*
Milwaukee	0.5805	0.5813	0.6287	0.208 *a*	*
Minneapolis-St Paul	0.5415	0.5417	0.7060	*	*
Nashville	0.4841	0.5144	0.5854	0.141 *a*	*
New Orleans	0.5424	0.5431	0.6318	*	*
New York	0.4498	0.5127	0.6523	0.337 *a*	0.094 *a*
Norfolk (VA)	0.4532	0.4705	0.4809	0.334 *a*	*
Oklahoma City	0.3947	0.5282	0.6496	*	*
Omaha	0.4913	0.5462	0.7358	*	*
Philadelphia	0.4561	0.5215	0.5025	0.500 *a*	0.098 *b*
Phoenix	0.3583	0.4873	0.7207	0.188 *a*	0.117 *a*
Pittsburgh	0.5854	0.7447	0.5358	0.468 *a*	*
Portland (OR)	0.3395	0.6055	0.7062	0.271 *a*	0.111 *a*
St Louis	0.5306	0.5414	0.6680	0.088 *a*	*
Salt Lake City	0.3801	0.6020	0.7045	0.195 *a*	*
San Diego	0.3160	0.5877	0.8090	0.144 *a*	0.103 *a*
San Francisco	0.4482	0.6684	0.6351	0.266 *a*	*
Seattle	0.4098	0.6416	0.7564	0.272 *a*	0.123 *a*
Tampa	0.4792	0.5706	0.7884	*	*
Washington, DC	0.5044	0.5891	0.6387	0.533 *a*	*
Average	0.4893	0.5824	0.6342		

* No collinearity detected at 95% confidence level.

[a] Collinearity type: collinearity of accessibility with *a* distance, and *b* mass.

parameter declined by 0.0374 for Atlanta and increased by 0.0555 for Oklahoma City), whereas Cincinnati and Cleveland, nodes which showed marked collinear relations, had changes in distance-decay parameter estimates that far exceeded the average (note the decrease in the estimated coefficients for distance of 0.2786 and 0.3843 for Cincinnati and Cleveland, respectively). These results are commentaries on the distortions which can exist in estimations involving multicollinear regressors.

8 Experiment 2: a comparison of CCP, CICP1, and CICP2

The original data base utilized in experiment 1 was then expanded to include a fourth explanatory variable, namely the intervening opportunities filters for CICP1 or CICP2. The CCP and CICP models were calibrated, and contrasts noted in estimated parameter changes and the overall significance of intervening opportunity measures (tables 8 and 9). Only CICP models which were free of additional multicollinearity between the intervening opportunities filter and the other independent variables were listed (twenty-eight out of forty-five cases). For the remaining cases, the CICP specification produced either a statistically insignificant intervening opportunities filter or a filter that usually was highly correlated with the competing accessibility measure. The former condition is most probably explained by the lack or irrelevance of intervening places; the latter finding, no doubt, is connected to a redundancy of information because of a concentration of competing places found in the overlapping circular market areas which are used to calculate the indices (the crosshatched area in figure 2). This is not to say that intervening opportunities are not important for those nodes excluded from the comparison, because the accessibility index may in fact contain this information (depending on the hierarchical level of the place in question and its relative position in the domestic network).

The most striking feature of the CICP approach is its ability to increase further the amount of explained variation in flows. The CICP type (that is, CICP1 or CICP2) is chosen by its capacity to fail to reject the null hypothesis of collinearity and its potential to maximize the adjusted R^2. For the 62% of the cases which fit this description, the CICP model showed an increase of 9.91% in explained variation in flow pattern over the unfiltered CCP model and an overall improvement of 11.34% over CD. For CICP models exhibiting significant intervening central place filters, there was an average of accuracy in explained flows of approximately 70% (that is, average adjusted $R^2 \approx 0.70$). For the remainder of places studied, the unfiltered CCP formula provides the greatest amount of explanation and the least number of collinear relations as before. In twenty four of the twenty-eight cases which proved to be sensitive to the intervening central-place filter, the CCP accessibility index retained significance and was tested as noncollinear to the intervening opportunities filter (that is, 86% of the CICP runs observed had all four explanatory variables register as significant at the 95% confidence level with forty degrees of freedom). Most places responded more successfully under CICP2 (when higher order intervening central places were counted). This highlights the importance of modeling the hierarchical aspects of competition in flows for functionally ordered places. Definition of spatially constrained and hierarchically divisible choice sets (for places ranked or classed in accordance with their relative diversification of activities) proves to be an efficient method in the accounting of flow patterns amongst competing origins and destinations.

For those cities responding to the filtering process, further attention was paid to the changes in parameter estimates for mass, distance, and accessibility (that is, how these coefficients were altered by the inclusion of the intervening central place filter) (table 9). Some geographical similarities exist in the breakdown of estimated parameter changes. For instance, midwestern cities (for example, Kansas City,

Table 8. Estimated coefficients of competing central place intervening opportunities model CICP(1, 2) for cities exhibiting no multicollinearity among regressors[a]. t-statistics of estimated coefficients are given in parentheses.

City	CICP	M_j	d_{ij}	V_{ij}	z_{ij}	Adjusted R^2 [b]
Atlanta	1	0.5416 (2.6664)*	0.9129 (7.0129)*	−0.2798 (−4.0501)*	0.5658 (3.4551)*	0.6139 (0.016)
Baltimore	2	1.0840 (6.5094)*	0.8284 (8.2221)*	−0.0516 (−1.1861)	0.4136 (5.5264)*	0.7112 (0.197)
Boston	2	1.2836 (7.2305)*	0.9728 (8.8628)*	−0.2846 (−3.3997)*	0.5197 (4.7259)*	0.7462 (0.083)
Charleston (SC)	2	1.0182 (4.8621)*	0.4643 (3.4598)*	−0.0729 (−1.3752)	0.6437 (3.4505)*	0.5911 (0.097)
Denver	2	0.7532 (4.1413)*	1.0111 (7.7554)*	−0.4035 (−5.2336)*	0.5588 (2.1042)*	0.6971 (0.018)
Detroit	2	1.0333 (4.6835)*	0.9983 (7.1567)*	0.0725 (0.9456)	0.3736 (2.9670)*	0.5854 (0.068)
Hartford	2	1.0300 (6.9153)*	0.6810 (8.3380)*	−0.1259 (−2.7581)*	0.4193 (5.5967)*	0.7978 (0.141)
Houston	1	0.8176 (4.4818)*	1.0775 (8.5078)*	−0.4260 (−5.2075)*	0.4958 (2.9145)*	0.6997 (0.047)
Indianapolis	2	1.0168 (6.0950)*	0.8586 (7.8895)*	−0.0905 (−2.0574)*	0.2962 (3.0520)*	0.7098 (0.051)
Kansas City	2	0.7681 (3.8755)*	0.6996 (5.2679)*	−0.8592 (−5.2163)*	0.5881 (3.2074)*	0.6236 (0.075)
Little Rock	2	1.0861 (6.6974)*	0.4754 (4.3085)*	−0.3242 (−4.4624)*	0.5369 (3.8624)*	0.6908 (0.095)
Louisville	2	1.0409 (6.1142)*	0.6788 (6.2336)*	−0.0296 (−0.9331)	0.3506 (3.2386)*	0.6997 (0.097)
Memphis	1	0.8925 (4.5985)*	0.6674 (5.2059)*	−0.3228 (−3.5721)*	0.3982 (2.6973)*	0.5898 (0.052)
Miami	1	1.1374 (6.2895)*	0.9162 (7.6174)*	−0.7259 (−3.2269)*	0.9073 (3.2042)*	0.7199 (0.055)
Milwaukee	2	1.0728 (6.5266)*	0.8169 (7.5097)*	−0.1206 (−3.1604)*	0.3008 (3.4992)*	0.7020 (0.073)
Nashville	2	0.9913 (5.3736)*	0.4999 (3.9487)*	−0.7213 (−3.5081)*	0.3487 (2.5063)*	0.6244 (0.039)
New Orleans	2	1.0131 (5.9632)*	0.7440 (6.3217)*	−0.7853 (−3.8277)*	0.7785 (3.7709)*	0.7152 (0.083)
New York	2	1.0365 (6.2763)*	1.3569 (13.167)*	−0.3393 (−8.4267)*	0.5788 (6.3854)*	0.8195 (0.167)
Oklahoma City	2	0.8427 (4.9809)*	0.6980 (6.0441)*	−0.4746 (−6.6943)*	0.5893 (3.6058)*	0.7227 (0.073)
Philadelphia	2	0.9334 (6.7374)*	1.0674 (13.200)*	−0.1140 (−2.9335)*	0.6360 (9.6536)*	0.8433 (0.340)
Phoenix	1	0.8847 (5.8481)*	1.0238 (9.6835)*	−0.3263 (−8.4334)*	0.6654 (4.0655)*	0.7928 (0.072)
Pittsburgh	1	1.1006 (5.1753)*	0.7539 (5.6494)*	−0.1810 (−2.2101)*	0.2676 (2.1433)*	0.5635 (0.027)
Portland (OR)	2	0.8200 (8.0501)*	0.8730 (12.674)*	−0.4151 (−11.749)*	0.9432 (9.1026)*	0.8997 (0.193)
St Louis	2	0.8461 (5.3172)*	0.8146 (7.4766)*	−1.0354 (−5.5852)*	0.4269 (3.6216)*	0.7379 (0.069)
Salt Lake City	2	1.0298 (7.1290)*	0.7658 (7.6021)*	−0.3761 (−7.9269)*	0.7304 (4.9787)*	0.8087 (0.104)
San Francisco	2	1.0143 (9.2543)*	1.1833 (16.333)*	−0.2896 (−9.1323)*	0.8179 (10.898)*	0.9036 (0.268)
Seattle	2	1.1278 (10.928)*	1.0414 (14.720)*	−0.5179 (−10.623)*	0.8360 (8.0257)*	0.9021 (0.145)
Washington, DC	1	0.7505 (3.7507)*	1.0894 (9.0000)*	−0.1620 (−4.6157)*	0.2708 (2.4367)*	0.6697 (0.031)

* Parameter estimate significant at 95% confidence level.

[a] All cases are void of statistically significant levels of multicollinearity between the CICP accessibility or intervening opportunity filter and the remaining regressors (at the 95% confidence level). [b] Increase in adjusted R^2 values (over CCP) given under coefficient.

Oklahoma City, and St Louis) show an increase in destination-bound flows with respect to destination mass and a decrease with respect to distance (along with a consistent increase in the negative coefficient which measures CCP accessibility). The hierarchical intervening opportunities filter yields a similar reaction in parameter changes for those cities of a particular locational trait, as would be expected if these cities are significantly influenced by the geography of central place alternatives. In the case of the midwestern cities listed above, intervening central places are less important than for cities showing increases in flows over a given distance once the intervening alternatives are filtered (like those of the northeast: Washington DC, Boston, Philadelphia, and Pittsburgh). One explanation for this phenomenon may lie in the spatial variation in the intervening central place density function (that is, the responsiveness of paired origins and destinations to both the design of the intervening central place filter and the geographic distribution of places). This is likely to change with the specification of equation (6).

Regional patterns also emerge in the behavior of the competing central place accessibility parameter once the intervening filter is added. For instance, there is a tendency for those western (midwestern and southern) cities to show an increase (decrease) in their accessibility parameters once intervening destinations are

Table 9. Changes in estimated mass, distance, and competing central place coefficients from inclusion of intervening opportunities filter for cities exhibiting no multicollinearity among regressors and intervening opportunity filter (CICP1 or CICP2).

City	Mass M_j	Distance d_{ij}	Accessibility V_{ij}	Geographic location[a]
Atlanta	−0.1642	+0.0224	−0.0474	S (4)
Baltimore	+0.1228	+0.0240	+0.0184	S (4)
Boston	−0.1385	+0.0368	−0.0898	NE (1)
Charleston (SC)	−0.1863	+0.0279	−0.0295	S (4)
Denver	−0.0119	−0.0377	+0.0023	W (8)
Detroit	+0.0873	+0.0346	−0.0208	MW (3)
Hartford	+0.2302	+0.0432	−0.0688	NE (1)
Houston	+0.0954	+0.0147	−0.0368	S (6)
Indianapolis	+0.0354	+0.0061	−0.0193	MW (3)
Kansas City	+0.1839	−0.0845	−0.1706	MW (7)
Little Rock	+0.1268	−0.0300	−0.0744	S (6)
Louisville	+0.0016	−0.0068	−0.0200	S (5)
Memphis	−0.0184	+0.0023	−0.0527	S (5)
Miami	−0.0460	−0.0089	−0.1641	S (4)
Milwaukee	+0.0144	+0.0030	−0.0227	MW (3)
Nashville	−0.0011	−0.0513	−0.0311	S (5)
New Orleans	+0.1311	+0.1928	−0.0951	S (6)
New York	+0.1431	+0.0932	−0.0752	NE (2)
Oklahoma City	+0.1753	−0.0441	−0.0398	S (6)
Philadelphia	+0.2083	+0.1141	+0.0227	NE (2)
Phoenix	−0.0698	+0.0647	+0.0049	W (8)
Pittsburgh	−0.0496	+0.0006	−0.0460	NE (2)
Portland (OR)	−0.0394	+0.0844	+0.0214	W (9)
St Louis	+0.0751	−0.0077	−0.2094	MW (7)
Salt Lake City	+0.0047	+0.0587	+0.0223	W (8)
San Francisco	+0.0974	+0.1764	−0.0036	W (9)
Seattle	+0.0980	+0.0667	+0.0674	W (9)
Washington, DC	−0.0484	+0.0486	−0.0220	S (4)

[a] By major census division: (1) New England, (2) Middle Atlantic, (3) East North Central, (4) South Atlantic, (5) East South Central, (6) West South Central, (7) West North Central, (8) Mountain, (9) Pacific; S south, NE northeast, MW midwest.

accounted for (see table 9). An opposite trend is present for the estimated effects of mass, but this relationship is not as strong. These patterns are even less visible for the distance-decay parameter. Such consistencies and inconsistencies reinforce the need to view interaction between places on a pair-specific basis. It would be interesting to see how these conditions would change under alternative sampling frameworks and/or grouped estimation.

Notice that in all cases reported in table 8, the parameter estimates for hierarchical accessibility remained negative and those associated with intervening opportunities were shown to be positive. Moreover, after the inclusion of information on intervening forces, peripherally located cities showed the greatest increase in their adjusted coefficients of determination. This is most likely because the peripherally based flows are more sensitive to the effects of centrally located destinations. The CICP model has thus simultaneously dissected the impacts of competitive and agglomerative forces.

Although the design of the intervening opportunities filter chosen above is only one of many plausible specifications, this component can be viewed as an origin-based complement of the destination-based competing accessibility index. Each measure displays opposing tendencies in its statistical properties, with the intervening central place filter promoting positive parameter estimates and the competing accessibility index showing a consistently negative influence once the hierarchical features of competitive network flows are properly identified. Together, these pair-specific operators can be seen as surrogate measures of the latent competitive (push and pull) effects of ordered and dispersed central places from the perspective of an origin-destination pair. Since the CICP model is largely void of collinear relationships, it proves to be an efficient mechanism for assessing the importance of intervening impediments to flows.

Clearly, the CICP framework can be generalized as a synchronized version of a competing origins and competing destinations model given that spatial choice sets are strictly defined by both the origin and the destination under consideration. The modeling of competitive and ordered flows by variable threshold distance and hierarchical designation with respect to each origin and destination pair demonstrates a superior approach in the extraction of accurate flow descriptors. A summary of the effectiveness of this approach for domestic airline passenger data is listed in table 10 below.

Further research endeavors which examine patterns of hierarchical interaction must fully illuminate, and distinguish between, the properties of competitive accessibility and intervening opportunities. Much more needs to be done in

Table 10. Summary statistics for experiments 1 and 2.

Model[a]	$\overline{R}^2$		Significantly multicollinear cases[b]	
	average	% increase over G	number	%
G	0.4893	na[c]		
CD	0.5824	9.31	30	66
CCP	0.6342	14.49		
CICP	0.6959	20.66	8	17

[a] G gravity model, CD competing destinations model, CCP competing central places model, CICP competing and intervening central places model.

[b] Number of cases with significant levels of potential multicollinearity among regressors.

[c] Not applicable.

redefining the concepts of accessibility and intervening forces within a hierarchical setting. Additional experimentation is also necessary to evaluate the predictive advantages of delimiting relevant spatial choice sets for origin and destination pairs which are uniquely defined in geographic and relational spaces. Then and only then can the groundwork for hierarchical interaction models be said to be adequately laid.

9 Conclusion

A competing central place interaction model was introduced as a generalization of Fotheringham's competing destinations model, incorporating information on the nature of flows in a hierarchical system. The analysis of ordered and competing flows has been linked to the literature on defining the limitations of spatial choice sets. This approach is viewed as a jointly competing origins and destinations modeling strategy because the extent of spatial choice is highly dependent upon the pairwise definition or hierarchical positioning of individual origin and destination pairs in relation to competitive forces at similar or higher levels. Predictive efficiency in flow patterns is gained through the ordering of network nodes and pair-specific threshold distances (the circumscription of competitive information fields).

From a priori knowledge of nodal description or class, a series of interaction models were established and shown to be highly effective in exposing the direct effects of mass and distance and the latent effects of competing and intervening central places. The development of hierarchical interaction modeling is seen as fundamental in overcoming the deficiencies of simple gravity-type approaches, given that traditional gravity formulations do not accurately capture the effects of system competition, compatibility, and/or substitutability in ordered network flows. Only when the dampening or accelerating effects of hierarchical exchange are differentiated through the functional classification of nodes and the identification of spatial choice sets can accurate parameter estimates of interaction components be found. By ordering the nodes of a network and delimiting a competitive threshold distance for each origin and destination pair, the competing and intervening central place model offers the flexibility to do just that. In short, the competing and intervening central place models are shown to be appealing both in their statistical properties and in their overall predictive efficiency.

Acknowledgements. The authors would like to thank David A Smith (SUNY at Buffalo) for contributing the data base on domestic airline traffic. Also, our thanks go out to Edward J Malecki (University of Florida), Luc Anselin (UCSB), David A Plane (University of Arizona), and anonymous referees for their comments and suggestions. An earlier version of this paper was presented at the International Geographical Union's Committee on Mathematical Models' Special Session II: Spatial Models and Methods, at the 28th Annual Meeting of the Western Regional Science Association, San Diego, California (22 February 1989).

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