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COMPETITION AMONG DESTINATIONS IN SPATIAL INTERACTION MODELS: A NEW POINT OF VIEW

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ABSTRACT: This paper presents a new perspective on the nature of destination competition in spatial interaction models. The concept of destinations competing with one another on the basis of their spatial proximity to each other is compared with an alternative point of view which argues that competition takes place on the basis of similarities in the spatial influences of competing destinations on decision makers at origins. Potential movers at an origin are facing a set of destinations which compete for their attention. This paper argues that the movers' choices are conditioned by the relative size and number of influences they see (where influence is directly proportional to destination size and inversely proportional to distance). A small amount of supporting empirical evidence concerning recreational day-trips, and population migration, is presented.

KEY WORDS: spatial interaction model, competing destinations, spatial proximity, spatial influence, interaction model misspecification

I. INTRODUCTION

A common viewpoint in the spatial interaction literature is that it is necessary to acknowledge spatial structure effects and/or destination competition in interaction models (Batten *et al.*, 1986; Boots *et al.*, 1988; Fik, 1988; Fik *et al.*, 1990; Getis, 1991; Guy, 1987; Haynes *et al.* 1984; Ishikawa, 1987; Jayet, 1990; Lo, 1991a, 1991b; Miller *et al.*, 1991; Pooler, 1993, 1994a, 1994b, 1995a, 1995b; Roy, 1985, 1990; Roy *et al.*, 1992). One line of thought is that the spatial proximity of destinations to one another effects the ability of spatial interaction models to forecast accurately the flows to them. The idea is that models which do not take into account such proximity effects are misspecified (Fotheringham, 1983a, 1983b; Fotheringham *et al.*, 1989). The misspecification is thought to reflect the idea that spatial decision makers do not view the destinations in a spatial cluster as individuals, but rather as a group. When it comes time to model the flows to the cluster, it does not draw trips as expected. Herein this is called the 'spatial proximity' perspective on competing destinations.

This paper presents an alternative viewpoint on competition among destinations termed the 'spatial influence' perspective. In contrast to the proximity effect described above, it argues that destinations compete for the attention of potential movers on the basis of the *spatial influence* which they have on spatial decision makers at origins. The idea is that destinations exert an 'influence' on potential movers at origins (where 'influence' consists of the combined effects of size and distance). From the point of view of the origin therefore, movers are faced with a set of destinations competing for their attention. It is hypothesized that when several of these destinations have very similar levels of influence on a particular origin, the potential movers at that origin do not differentiate among those destinations, but instead group them mentally into an 'aspatial cluster'. As a consequence, when it comes time to model the actual flows to that set of destinations, they do not draw as many trips as expected (in exactly the same way that spatially clustered destinations draw fewer movers than expected in the proximity thesis). This suggests that a traditional interaction model will overpredict the amount of interaction to the destinations in the competing set having similar influences.

The competition effect identified is a simple one, and one which is considered to occur within the confines of traditional spatial interaction models. Nevertheless, as far as this author is aware, it has not been identified previously in the context of interaction modelling.

The idea of a competition effect among spatial influences facing potential movers at an origin professes nothing more than the well known concept of the zone of indifference. Within spatial theory, the consumer who is equally distant from three equally sized facilities is considered to be indifferent with respect to spatial choice among the three destinations. The implicit idea is that if the attractivities of the three destinations at the consumer's location are uniform, there is nothing for him, or her, to choose among them. The paper essentially takes this well accepted idea and applies it to the problem of modelling spatial interaction (Pooler, 1992). In the traditional approach, spatial indifference is determined by the physical location of the decision maker. In this paper, the spatial indifference is with respect to the spatial influences, and is determined by the relative location of the decision maker.

Destinations which are widely separated in space, or which vary greatly in size and/or distance from a given origin, may exert nevertheless identical influences on decision makers at that origin. The position taken here is that competition for would-be movers takes place among such spatially diverse sets of destinations. In the tradition of Webber (1964), they could be called competing destinations without propinquity. This contrasts sharply with the spatial proximity perspective which predicts competition only by spatial association.

The hypothesized *empirical* outcome of the spatial proximity perspective on competition is that interaction is expected to be overpredicted to spatially clustered destinations (the possibility of agglomeration, rather than competition effects, is discussed in Fotheringham, 1983a). Similar ideas apply here. In the spatial influence framework, the empirical expectation is that interaction is expected to be overpredicted to aspatial sets of destinations having similar influences.

An interesting aspect of this theoretical perspective concerns the hierarchical nature of spatial interaction (Bennett *et al*., 1985; Fik, 1988; Fik *et al*., 1990). In the same way that interaction data have a skewed hierarchical structure, so too do the spatial influences. In other words, in a typical set of interaction data there will tend to be a larger number of trips over smaller distances and a smaller number of trips over larger distances. The calculated influences portray an identical pattern. The existence of such skewness in spatial interaction data allows theoretical speculation a priori as to the nature of interaction model misspecification which results from destination competition of the type proposed. This point will be elaborated on in the fifth section below.

The ideas outlined above are set out more fully in the remainder of the paper. Empirically, the argument is illustrated with respect to two types of data: a set of recreational travel data (Cesario, 1973, 1974) and a set of population migration data (Tobler, 1983, 1988). For the two sets of data, each at d different geographical scale, it is shown that interaction, for the most part, is over- and underpredicted in accordance with the hypothesis put forth.

The empirical test is a very simple one. The goal of the present paper is not to develop a more correctly specified interaction model, but rather to accomplish two other things: first, to demonstrate that a misspecification does exist in current forms of models and second, to try to account for that misspecification from the behavioral point of view that is outlined.

II. THE SPATIAL PROXIMITY PERSPECTIVE ON COMPETING DESTINATIONS

Fotheringham (1983a) argues that spatial interaction models are misspecified with respect to spatial structure and the effects of competition. In particular, the spatial proximity perspective argues that traditional models ignore competition effects among spatially grouped destinations. Explicit it this is that the models contain the IIA (independence from irrelevant alternatives) property. Golledge *et al*. (1987) define IIA as the situation where 'a new alternative entering a choice set will compete equally with each existing alternative and will obtain a share of the market by drawing from the existing alternatives in direct proportion to the original shares of the market held by these existing alternatives'. The problem of dealing with new or alternative choices of destinations in interaction models is not a new one (Stouffer, 1960).

The proximity perspective suggests that when there is competition for movers among a spatially clustered set of destinations, traditional interaction models will produce overpredictions, inasmuch as the loyalties of any set of movers electing to travel the distance to the cluster will be split among the individual members of the cluster. In other words, the spatial decision makers do not respond to the individual members of the cluster, and it does not draw as many trips as its individual members would (in total), if they were spatially dispersed. Conversely, when there are only one or a few isolated destinations available in given area, the lack of competition is seen to result in larger than expected observed flows.

The proposed solution to this problem is to insert into such models an accessibility term or population potential of the type developed by the astrophysicist Stewart (Pooler, 1987). The potential measures the accessibility of a given destination to all other destinations and its inclusion is said to make the interaction model take into account spatial structure effects. Fotheringham (1983a) presents empirical evidence to this effect. Borgers *et al*. (1988) refer to such models as having an ISS (independence of spatial structure) property. A critical commentary on the Fotheringham hypothesis is in Thill (1992).

III. AN ALTERNATIVE PERSPECTIVE ON THE DESTINATION CHOICE PROCESS

Central to the proximity perspective on destination competition discussed above, is the behavioural assumption that movers first choose a single general region with which to interact, and then choose a specific site from among many within that region. The idea is that destination choice is a two-stage hierarchical process, that is, that potential movers do not consider all destinations simultaneously, but choose broad regions before they choose specific sites. Essential to the argument is the further assumption that the specific sites are grouped *spatially* within the regions. It is easy to concur with the point of view that the decision process is hierarchical, that is, that potential movers do not consider all possible destinations simultaneously in their decision process. It is an appealing idea intuitively. The spatial choice literature recognizes also this dimension of the decision process (Eagle, 1988; Fotheringham *et al*., 1989; Lieber *et al*., 1988). Interaction modellers acknowledge also that only a portion of destinations may be considered and evaluated by movers (Horowitz, 1991).

A theoretical justification for suggesting that movers reduce the size or complexity of the choice set is to suggest that this is a behavioural mechanism for coping with uncertainty. Faced with too much information in a decision, potential movers have a need to reduce the complexity of the choice set, either by eliminating a portion of the destinations from the choice set, or by grouping them. Thus, a 'reduction of uncertainty principle' provides a theoretical rationale for saying that the destination choice process is hierarchical.

It is not easy to agree, however, that the reduced sets of competing destinations will be contiguous in space as a norm. Consider, as an example, the selection of universities by potential students. It is difficult to accept the idea that most students (withing their own country) first select a general region, or spatial cluster of institutions, and thereafter choose a specific site within the region or cluster. More likely, such decisions are based on a choice among a very large number of institutions having a variety of influences on decision makers. In this situation the 'size' variable in the calculation of influence might well be considered to represent a large number of variables such as past experience, cost, institutional image, programs available, information availability, and so on.

Nevertheless, spatial theory assumes that each institution has some overall informational, size-related ‘impact’ on the spatial decision maker which is tempered by distance. The question which arises, is how decision makers reduce complexity when faced with a choice among a large number of such spatial influences.

This paper argues that the spatial complexity is reduced by the act of mentally grouping the incoming influences into sets of like values. This is the same argument which is made within the spatial proximity viewpoint except that the grouping is not done spatially. It seems reasonable to surmise that there exists some first, large total choice set, of dozens or hundreds of potential destinations, from which potential trip makers select among some more limited choice set based on the mental grouping of destinations perceived to be similar.

It is clear that within the spatial influence perspective on competing destinations, the matter of the spatial proximity of the reduced set of destinations *to one another* may be irrelevant entirely. The choice spatial process suggested is a hierarchical one, which reduces the size of the choice set, and hence the uncertainty, but one that does not imply spatial proximity of the reduced set of destinations.

The general thrust of the spatial influence thesis being presented here is very similar to that of the traditional spatial proximity perspective. In both cases it is argued that the spatial decision making process is a hierarchical, two stage process wherein large amounts of information need to be reduced in some manner. In both cases it is agreed that this is accomplished, at least in part, by the grouping of like alternatives into sets. The principal difference is that, in the proximity thesis, the grouping is considered to be done spatially, while in the present discussion it is considered to be accomplished aspatially, according to the influences of the destination on the spatial decision makers.

IV. SPATIAL INFLUENCE

Given a geographical area with a set of n randomly distributed points, where each point may be simultaneously an origin and a destination, the predicted probability of spatial interaction p_{ij} at a location at distances $d_1, \ldots d_m$ from m potential destinations is defined as

$$P_{ij} = \alpha_j f(d_{ij}) \sum_{j=1}^{m} \alpha_j f(d_{ij}) \quad (1)$$

where α_j is the size or attractivity of the destinations and

$$\sum_{j=1}^{m} P_{ij} = 1.0 \quad (2)$$

Not all destinations interact necessarily with a particular origin, and m may be less than n. Here P_{ij} is interpretable as a prediction of the manner in which the total interaction from a single origin is proportioned among a set of m destinations. It is the probability that a trip maker at i will travel to a particular destination j. In Pooler (1992), the entropy of the P_{ij}'s measured at the origin, is defined as the ‘spatial uncertainty’ faced by the potential movers.

In the present paper, the predicted probability of interaction in equation (1) is described as the spatial influence of a destination on an origin. The phrase is employed because it is considered to represent a convenient and intuitive shorthand for the probability of interaction. Decision makers respond to information, and spatial influence is considered to be directly proportional to the information available to potential movers concerning destinations.

The spatial influence perspective on destination competition can be portrayed in the form of a map. Fotheringham (1983a) used such a diagrammatic example to illustrate the spatial proximity perspective. As a analogous illustration of the spatial influence perspective, consider Fig. 1, where there are four destinations at given distances from a single origin.

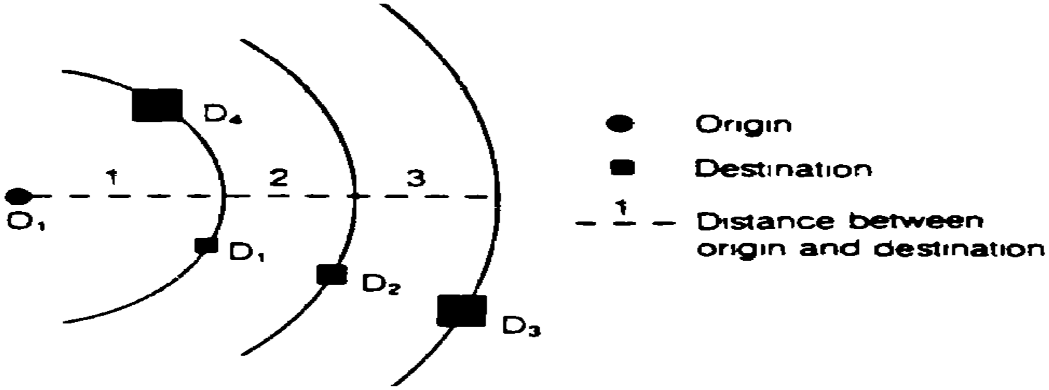

Fig. 1 Spatial competition with respect to influences of destinations on an origin

The sizes of the destinations are as follows: $D_1 = 1$, $D_2 = 2$ and D_3 and $D_4 = 3$. Given the sizes (and the distances in Fig. 1), and assuming that $f(d_{ij}) = d_{ij}^{-1}$ in equation (1), destinations 1, 2 and 3 have equal influences on the origin of $P_{ij} = 0.17$ for each, while destination 4 has a larger influence of $P_{ij} = 0.50$. Accordingly, a traditional interaction model will assign fifty percent of movers to destination 4, and 17 percent to each of the other three destinations. In contrast to this perspective on the prediction of spatial interaction, the position taken here is that movers respond differentially to particular influence levels, and therefore there will be less observed interaction than expected to the three competing destinations with equal P_{ij}.

If the spatial influence perspective is supported, the misspecification of the gravity model will show up in overpredictions of movement to the competing destinations, and in a corresponding underprediction to the other (D_4) destination. Before the discussion goes on to consider some empirical evidence of this effect, it is useful to speculate first about the nature of interaction model misspecification which is expected to result from the destination competition process outlined above.

V. INTERACTION DATA SKEWNESS AND DESTINATION COMPETITION

It is very well known that most frequency distributions of spatial interaction data are positively skewed, that is, there are a large number of shorter trips and a smaller number of longer trips. Given that the spatial influences are equivalent to spatial interactions, the same pattern of skewness can be expected in their frequency distributions. There will be normally a large number of small influences and a small number of large influences. Given the assumptions of the spatial influence point of view on destination competition, and given the skewness in the frequency distributions of the influences, what is the expected nature of misspecification? One expects to find:

(1) that there are more, smaller influences; this indicates that there are *more* destinations competing among themselves at lower P_{ij} levels, and hence there should be overpredictions associated with these smaller P_{ij}' s, and

(2) that there are fewer, larger influences; this indicates that there are fewer destinations competing among themselves at higher P_{ij} levels, and therefore flows associated with larger P_{ij}' s should be underpredicted.

The empirical test looks for evidence of these two effects.

VI. SOME EMPIRICAL EVIDENCE OF OVER AND UNDERPREDICTION

The empirical test is simply whether existing spatial interaction model predictions display the properties described in (i) and (ii) of the preceding section. If so, this may provide some indication of the presence of destination competition of the type proposed. It is important to point out, however, that such an empirical test does not support conclusively the idea put forth. There may be several other possible explanations for patterns of over- and underprediction. Such alternative explanations are discussed in the conclusion.

The analysis employs spatial interaction model predictions produced by Tobler (1988). The Tobler model is

$$M_{ij} = \frac{(k_i + k_j')\ P_i P_j}{d_{ij}} \tag{3}$$

In this model M_{ij} is the predicted movement, and P_i and P_j are the sizes of the origins and destinations respectively (a BASIC calibration program to calibrate the model is in Tobler, 1988). The k_i and k_j' terms are interpretable as pushes and pulls, or emissivities and attractivities, and act as proportionality constants in the model. They have the same normalizing effects as balancing factors in traditional constrained interaction models and are defined as

$$k_i = \left(2r_i - \sum_j \frac{P_j k_j'}{d_{ij}}\right) / \sum_j \frac{P_j}{d_{ij}} \tag{4}$$

and

$$k_j' = \left(2r_j' - \sum_i \frac{P_i k_i}{d_{ji}}\right) / \sum_i \frac{P_i}{d_{ji}} \tag{5}$$

The k values are calibrated with respect to observed in and out movement rates (r_i and r_j' respectively), and the population potential (or accessibility) of origins and destinations. In the model, Tobler sets the power term on d_{ij} to unity. Tobler (1988) states that the model yields a better fit than either doubly constrained or totally constrained models of the Wilson family (1983). The model is discussed in Fotheringham *et al*. (1989), and Golledge and Stimson (1987).

One set of data which Tobler employs in model (3) originate with Cesario (1973, 1974), and includes recreational day-trips from ten counties to five parks in northeastern Pennsylvania. The observed travel and distance data are in Cesario (1973) and Tobler (1988). The map is reproduced in Baxter and Ewing (1979) and Pooler (1992). The observed migration and distance matrices are in Cesario (1973), Slater (1974) and Tobler (1988). In the present paper, the one small correction to the distance matrix given in a footnote in Cesario (1974) is not used, although Tobler (1988) noted and used it. There are 33 461 trips over a maximum of 115 miles (one way) in a single day. These data are employed also by Slater (1974), and Baxter *et al*. (1979). The size terms in equations (3), (4) and (5) are represented by the marginal sums of the observed flows. For purposes of comparison, the observed and predicted trips are presented in Table 1.

Table 1 Observed and predicted trips from counties to parks——Pennsylvania recreational travel data

To park	From county 1	2	3	4	5	6	7	8	9	10
Big Pocono	46	50	230	307	255	376	385	17	63	8
	31	110	394	208	347	191	325	9	113	8
Gouldsboro	35	33	6970	520	3366	313	1121	7	101	20
	197	531	5019	1033	2614	737	1546	53	682	72
Hickory Run	333	1670	141	1458	4586	253	1263	26	1886	12
	211	889	2242	1071	4559	417	1292	34	876	36
Promised Land	84	71	977	315	303	150	499	87	48	124
	42	109	929	237	523	23	377	21	156	34
Tobyhanna	69	91	1917	387	595	848	981	6	40	18
	86	275	1650	438	1062	364	709	26	311	32

The upper set of numbers in each row represents the observed trips. The counties are: 1 Berks, 2 Carbon, 3 Lackawanna, 4 Lehigh, 5 Luzerne, 6 Monroe, 7 Northampton, 8 Pike, 9 Schuylkill, 10 Wayne.

The spatial influences are calculated using equation (1), where $f(d_{ij}) = d_{ij}^{-1}$, and where the total observed inflows to parks are used as the attractivity term d_j. The influences are calculated for the ten counties with respect to the influences of the five parks on them (Table 2).

Table 2 illustrates that the values of the spatial influences are highly skewed. There is a preponderance of very low values (52 percent are less than 0.100) and a scarcity of larger values (only eighteen percent are greater than 0.300).

Table 2 Spatial influences of parks on counties——Pennsylvania recreational travel data

From park	On county 1	2	3	4	5	6	7	8	9	10
Big Pocono	0.080	0.021	0.012	0.126	0.017	0.273	0.123	0.101	0.025	0.022
Gouldsboro	0.056	0.011	0.765	0.162	0.268	0.149	0.262	0.039	0.036	0.077
Hickory Run	0.621	0.918	0.008	0.494	0.656	0.070	0.259	0.095	0.908	0.024
Promised Land	0.121	0.016	0.064	0.098	0.017	0.071	0.109	0.727	0.016	0.807
Tobyhanna	0.119	0.034	0.152	0.121	0.043	0.437	0.247	0.037	0.016	0.070

The counties are: 1 Berks, 2 Carbon, 3 Lackawanna, 4 Lehigh, 5 Luzerne, 6 Montoe, 7 Northampton, 8 Pike, 9 Schuylkill, 10 Wayne

In testing the hypotheses proposed here, the influences of the parks on the counties are divided into two subgroups, and the extent to which the model over or underpredicts the flows in each of the subgroups is examined. In order to accomplish this, all values of influence below 0.100 are taken as representing the small influences, and the remaining values (0.101 and above) as the large ones (this split makes the division between large and small 52 and 48 percent respectively). Examination of the Tobler model predictions indicates that for these data, of the 26 smaller influences, 84 percent have the observed interaction overpredicted, while for the remaining 24 larger influences, 75 percent are underpredicted. This difference is highly significant at 0.001 under chi square. Therefore, with these data, there exists a significant pattern of overprediction of flows when influences are small, and an underprediction when the influences are large.

As a further test of the hypothesis of model misspecification, and analysis is undertaken employing Tobler's model results with a different set of data, at a different geographical scale. Tobler (1983) calibrates the model with respect to population migration among the nine United States census regions. The data represent the 1965–1970 time period (US Bureau of the Census, 1973). The observed and predicted migrations are presented in Table 3. The spatial influences for these data are in Table 4 and they also show a definitive pattern of skew. Of 72 total influences, 82 percent have values less than 0.200, while only eighteen percent have values greater than 0.201. An examination of the over- and underpredictions in the Tobler model predictions of spatial interaction reveals a pattern which is consistent, in part, with the hypothesis being tested. Of the 58 smaller influences having values less than 0.200 in this data set, 65 percent are overpredicted by the model. Similarly, of the 34 smallest influences having values less than 0.100, an even greater proportion, 74 percent, are overpredicted. For the remaining fourteen spatial influences, with values greater than 0.200, the model underpedicts fifty percent of the interactions.

The empirical results indicate that spatial interaction is over- and underpredicted in accordance with the general hypotheses which have been set out. It was hypothesized that when the spatial influences (of destinations on origins) are relatively smaller and more numerous, spatial

Table 3 Observed and predicted united states migration between census regions

From region*	To region								
	1	2	3	4	5	6	7	8	9
1 Boston	0	180048	79223	26887	198144	17995	35563	30528	110792
	0	209775	86140	27689	167029	25378	39795	33536	89838
2 New York	283049	0	300345	67280	718673	55094	93434	87987	268458
	306706	0	263426	82075	621842	79533	125889	108356	286494
3 Chicago	87267	237229	0	281791	551483	230788	178517	172711	394481
	87609	182188	0	277992	538838	162674	257592	189358	438015
4 Omaha	29877	60681	286580	0	143860	49892	185618	181868	274629
	31343	73130	311178	0	183911	63625	177513	126355	245050
5 Charleston	130830	382565	346407	92308	0	252189	192223	89389	279739
	110542	322923	351669	118372	0	262295	215033	102517	282299
6 Birmingham	21434	53772	287340	49828	316650	0	141679	27409	87938
	24789	54939	156367	55581	384554	0	124582	50829	134408
7 Dallas	30287	64645	161645	177980	199466	121366	0	134229	289880
	30008	69399	191052	126915	253481	97062	0	107446	271136
8 Salt Lake City	21450	43749	97808	113683	89806	25574	158006	0	437255
	26682	78592	149792	98100	101026	40906	96300	0	395933
9 San Francisco	72114	133122	229764	165405	266305	66324	252039	342948	0
	57728	164864	279487	155438	233707	87749	200376	348671	0

The upper set of numbers in each row represents the observed trips. The census regions are: 1 New England, 2 Mid/Atlantic, 3 East North/Central, 4 West North/Central, 5 South Atlantic, 6 East South/Central, 7 West South/Central, 8 Mountain, 9 Pacific.

* Distances are measured among the cities.

Table 4 Spatial influences of destinations on origins-united states migration data

From region*	On region								
	1	2	3	4	5	6	7	8	9
1 Boston	0	0.283	0.067	0.038	0.072	0.041	0.036	0.046	
2 New York	0.600	0	0.254	0.136	0.290	0.154	0.143	0.122	0.152
3 Chicago	0.140	0.254	0	0.390	0.234	0.264	0.262	0.205	0.224
4 Omaha	0.038	0.064	0.184	0	0.071	0.080	0.151	0.127	0.118
5 Charleston	0.109	0.208	0.167	0.107	0	0.268	0.159	0.097	0.128
6 Birmingham	0.037	0.065	0.113	0.072	0.161	0	0.120	0.054	0.067
7 Dallas	0.038	0.063	0.116	0.142	0.098	0.125	0	0.104	0.131
8 Salt Lake City	0.012	0.019	0.033	0.043	0.022	0.020	0.039	0	0.135
9 San Francisco	0.028	0.045	0.066	0.073	0.053	0.047	0.087	0.250	0

The census regions are: 1 New England, 2 Mid/Atlantic, 3 East North/Central, 4 West North/Central, 5 South Atlantic, 6 East South/Central, 7 West South/Central, 8 Mountain, 9 Pacific.

* Distances are measured among the cities.

interaction is expected to be overpredicted to a significant extent. This was the case in both data sets considered. Conversely, when the spatial influences are relatively larger and fewer in number, spatial interaction is expected to be significantly underpredicted. This was true of the first set of data though not of the second.

An obvious shortcoming of the empirical analysis, especially with respect to the population migration data, is that better results might be obtained with more detailed data. Nevertheless, these preliminary findings are provocative, they suggest that further empirical analyses concerning patterns of over- and underprediction are warranted.

VII. CONCLUSION

As was indicated at the outset, the purpose of this paper is not to present new models of spatial interaction but rather to demonstrate that a pattern of misspecification does exist, and to attempt to account for it. The question remains as to whether the behavioral explanation offered here for the pattern of error in the interaction models is an adequate one. The matter is open to debate. It would be interesting to see alternative attempts to interpret the pattern of over- and underprediction in the models in a competition framework.

An important cautionary note must be raised again about the interpretation of results. The hypothesis put forth here may be only one of several explanations for the pattern of over and underprediction observed. For example, simply the use of alternative forms of the distance deterrence function might lead to alternative patterns of predicted flows. Similarly the paper employs the predicted flows of Tobler's 'additive' form of interaction model, while different results might obtain from the use of the Wilson 'multiplicative' form of model. Further empirical testing is required before definitive conclusions can be drawn.

With regard to the empirical results obtained by Fotheringham (1983a) with respect to the spatial proximity point of view, it appears that the spatial competition effect may be confounded with a spatial structure effect and, as a result, it is not clear whether empirical results (e.g., Fotheringham, 1983a; Fotheringham *et al.*, 1989) reflect the behavioral postulates, or the effects of the map pattern. One means of testing for the existence of purely spatial competition effects (as opposed to map pattern effects) would be to look at a set of interaction data where there is good reason to believe that there is *no* spatial proximity, competition effect at work. Presumably, for such a data set, the usual misspecification bias found in parameter estimates could be shown not to exist.

In summary, this paper has argued that spatial interaction models are misspecified with respect to competition effects among destinations, but that these effects are not related necessarily to spatial structure or to the spatial clustering of destinations. The empirical results provide preliminary evidence which suggests that there is a competition effect at work among destinations with similar spatial influences on origins, regardless of their spatial proximity to one another.

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