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The Stability of Urban Spatial Structure: An Empirical Investigation

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ABSTRACT

This study investigates the stability of urban spatial structure by first using a Goldfeld and Quandt's F-statistic to test the existence of heterogeneous residuals in estimating the relationship between population density and distance. Secondly an FHMs shifting regression technique is used to detect the possible change in the structure of an urban area. Finally, a generalized random coefficient technique is used to simultaneously detect the possible structural change and stochastic behavior of an urban area. Data for 50 United States SMSA's are used to do the empirical analyses.

THE STABILITY OF URBAN SPATIAL STRUCTURE:
AN EMPIRICAL INVESTIGATION

I. Introduction

Kau and Lee (1976a) have theoretically shown that the functional relationship between population density and distance in an urban area is not negative exponential unless the production function is Cobb-Douglas and the price elasticity of demand for housing services is a negative one.

Based upon the generalized functional form technique developed by Box and Cox (1964), Kau and Lee (1976b, 1976c) have empirically demonstrated that the functional relationship between population density and distance is not negative exponential for approximately 50% of the United States cities. Furthermore, Kau and Lee (1977) have used the random coefficient method to show that the density gradient of an urban area is generally stochastic instead of deterministic. These findings imply that the degree of stability for the density gradient should be empirically studied.

Most recently, Brueckner (1980, 1981) has theoretically and empirically developed a vintage model of urban growth. His theoretical and empirical results indicate that a growing city generally has a sawtooth-shaped spatial contour of building ages, a feature which in turn yields strikingly discontinuous contours for structural and population density. Brueckner's findings have further indicated that it is necessary to empirically investigate the stability of urban spatial structure.

The main purpose of this paper is to investigate the stability of urban structure by using three alternative econometric techniques.

This study will shed more light on the stability of the density gradient and provide new econometric techniques for researchers in urban economics. This will also supply guidelines to future researchers in using density gradients in urban planning and location theory.

The second section uses Goldfeld and Quandt's (1965) F-statistic to detect the possibility of heterostochastic behavior of the residuals. In the third section, Farley, Hinich and McGuire (1975, FHM) shifting regression technique is used to detect the possibility of structural changes in the density gradient within an urban area. In the fourth section Singh, Nagar, Choudhry and Raj (1976) generalized random coefficient method, referred to in this paper as SNCR, is used to detect the stochastic behavior and the possible structural changes in the density gradient within an urban area. This procedure would capture any changes due to population shifts or transportation routes. The fifth section discusses possible implications of the empirical results. Finally the results are summarized.

II. The Existence of Heterogeneous Residuals

Based upon the negative exponential function, the empirical relationship can be defined as

$$\log D_i(u) = \gamma_0 - \gamma U_i + \varepsilon_i \qquad (1)$$

where $D_i(u)$ = population density per square mile for each i^{th} tract,

U_i = the distance from the CBD to each tract, and

ε_i = a random error term.

To estimate γ, the density gradient, sample data was collected for each $D_i(u)$ and U_i in an urban area. One of the necessary conditions to obtain an efficient density gradient estimate is that the residual errors (ε_i) be homogeneous. A Goldfeld and Quandt's F statistic is used to test for heterosadasticity for 50 U.S. urban areas.[1] The Goldfeld and Quandt method can briefly be described as

(1) order the observations (log $D_i(u)$, u) by increasing values of u

(2) omit two control observations and run separate OLS regressions to the first (n/2-1) and the last (n/2-1) observations of (log $D_i(u)$, U)

(3) using the sum of squares from each regression compute the F-statistic as $F_j = S_{2j}/S_{1j}$.

The F-statistics for the 50 urban areas are listed in Table 1. It was found that 31 out of 50 areas had heterogeneous residuals. Therefore, the OLS estimated density gradient for these 31 urban areas are not efficient.

The implications of heteroscedasticity fall into three possible areas: (i) possible inefficient estimators, (ii) a misleading tendency to fail to reject the null in hypothesis testing, and (iii) coefficient of determination (R^2) is understated. First, since the estimators do not have the smallest variance in a class of unbiased estimator, they are inefficient. Thus, the estimators may miss the mark for any urban area more than they would if heteroscedasticity were not present. Johnston (1972, 216-217) indicates that, for a specific example the OLS estimators in the presence of heteroscedasticity were only 56-83 percent as efficient as the GLS estimators. This tendency may imply that the density gradient for some urban areas tend to be unstable over distance. Secondly, the estimated covariance matrix for estimating regression parameters is biased in the presence of heterosceadsticity. If large variances tend to be associated with large value of distance, U, then the bias will be negative and the estimated variance will be smaller, leading to narrower confidence intervals [see Kmenta (1971, p. 256)]. Consequently, hypothesis tests about the estimators will be made with a higher type I error than the assumed value. Finally, Kmenta (1971, pp. 259-264) has shown that the presence of heteroscedasticity will reduce the R^2 of OLS regression. The effect of reducing R^2 is to understate the role of distance in explaining populations distribution.

III. Structural Shifts of Population in an Urban Area

To test for possible shifts of the density gradient within an urban area the Farley, Hinich and McGuire (FHM) method is used. The FHM model is defined as

$$\log D_i(u) = \alpha_0 - \alpha_1 U_i + \alpha_2 Z(u) + \varepsilon_i \tag{2}$$

$$\text{where } Z(u) = iu \text{ and } i = \frac{1}{n}, \frac{2}{n}, \ldots 1, \tag{3}$$

n = sample size.

If the estimated α_2 is significantly different from zero, it implies that there exists some shifts of the density gradient. This indicates that the density gradient is not smooth and that other variables are important in explaining changes in the density gradient. The regression coefficients (α_2) for the 50 urban areas are listed in Table II. It was found that 20 urban areas had density gradients with structural shifts.

Possible explanation of the structural shift of the density gradient are: (i) multi-centers of an urban area and (ii) different vintage characteristics of an urban area as demonstrated by Brueckner (1980, 1981). FMH's method does give us an objective technique to detect the possible shift of urban density gradients. However, FMH method does not explicitly specify the distance variable into the functional relationship and take possible randomness of estimated γ into account. To reduce the above-mentioned weakness, a generalized random coefficient model will be used in the next section to simultaneously consider the randomness and the stationarity of an estimated density gradient.

IV. A Generalized Random Coefficient Model for Examining the Density Gradient

The possible stochasticity of the density gradient was investigated by Kau and Lee (1977) using Theil's (1971, 622-627) random coefficient model. However, Theil's method cannot take the structural shifts of the density gradient into consideration. Therefore the interpretation of Kau and Lee's results do not take into account the possible structural changes of urban areas into account.

SNCR's (1976) generalized random coefficient method is used in this paper to simultaneously correct for possible stochastic behavior and structural shifts in the density gradient. The spatial structure model is represented as[2]

$$\log D_i(u) = \alpha - \gamma(i)U_i + \varepsilon_i \tag{4}$$

$$\text{where} \quad \gamma(u) = \bar{\gamma} + \alpha_1 T_i + \eta(i). \tag{5}$$

$\eta(i)$ represents the stochasticity of the density gradient with i being the order of magnitude of the independent variable, distance (u_i). This approach is similar to SNCR's time ordering in examining the possible structural shifts of the consumption function.

The estimation procedure for estimating the parameters of equations (4) and (5) is now discussed. Substituting equation (5) into equation (4), the following is obtained:

$$\begin{aligned} \log D_i(u) &= \alpha - \overline{\gamma}U_i + \beta T_i U_i + [\eta(i)U_i + \varepsilon_i] \\ &= \alpha - \overline{\gamma}U_i + \beta T_i U_i + \omega_i . \end{aligned} \tag{6}$$

For simplicity, equation (6) can be expressed in matrix notation as:

$$D = Z\Theta + \omega, \tag{7}$$

where D is a nxl vector of observation on the dependent variable $D_i(u)$; and

$$Z = [U \quad U^*], \tag{8}$$

U and U* are nx2 and nxl matrices of regressors, $[1 \quad U_i]$ and $T_i U_i$, respectively; and

$$\Theta' = [\Lambda' \quad \beta'], \tag{9}$$

where Λ and β are colume vectors such that $\Lambda' = [\alpha \quad \overline{\gamma}]$ is a row vector. The distribution of ω is assumed to be

$$E(\omega) = 0, \text{ and} \tag{10.2}$$

$$\begin{aligned} E(\omega\omega) &= E(U\eta\eta'U') + E(\varepsilon\varepsilon') \\ &= U\Delta U' + \sigma_\varepsilon^2 I \\ &= \Omega . \end{aligned} \tag{10.1}$$

To estimate Θ, the following is first obtained:

$$\hat{\omega} = M\omega, \tag{11}$$

where M is a symmetric, idempotent matrix such that:

$$M = I - Z(Z'Z)^{-1}Z. \tag{12}$$

Next, OLS is applied to:

$$\hat{\dot{\omega}} = \dot{M}\dot{U} + e = G\Delta + e, \tag{13}$$

where $\hat{\dot{\omega}}$, $\dot{M}$, and $\dot{U}$ are the vector and matrices of the squared elements of ω, M and U, respectively; and e is a vector of random error. The estimator is thus:

$$\hat{\Delta} = (G'G)^{-1}G'\hat{\dot{\omega}}. \tag{14}$$

With Δ estimated, Ω can be constructed following equation (10.2). Finally, the generalized least square estimator for Θ can be written as:

$$\hat{\Theta} = (Z'\ \Omega^{-1}Z)^{-1}Z'\ \Omega^{-1}D, \tag{15}$$

with the variance-covariance matrix:

$$\mathrm{Var}(\hat{\Theta}) = (Z'\Omega^{-1}Z)^{-1}. \tag{16}$$

Based upon the estimation procedure discussed in this section, the GLS empirical results are estimated and listed in Table III. Included in the Table are the OLS density gradients γ_1, GLS γ, GLS σ_n^2. α_1 which indicates significant structural shifts for 17 cities and σ_n which demonstrates that 28 cities have significant positive random density gradients. From Table III it is demonstrated that there exists some systematic impacts of distance on density gradient. This is determined by the t statistic associated with α_1 listed in Table IV. From the estimated σ_η, the standard deviation of the random fluctuations associated with density gradient are determined. It was found that the random coefficient approach is important for analyzing the density gradient as pointed out by Kau and Lee (1977).

The generalized random coefficient model as indicated in equations (4) and (5) allow us to decompose the OLS density gradient into three components, (i) pure density gradient, (ii) structural shift component and (iii) random component. Conceptually, only the first component indicates the relationship between population density and distance (or transportation cost). The second and the third components represent the impacts of other urban characteristics for the population density of a particular city tract. Results of Table III indicate that there are 48 out of 50 OLS density gradient estimates are negatively significant different from zero. However, there are only 20 GLS γ estimates that are negative and significantly different from zero. These results imply that the OLS estimates have misleaded researchers and planners on the importance of distance in determining population distribution in an urban area.

To our best knowledge, this is a first meaningful application of generalized random coefficient model in economic research since this model was developed.[3]

V. Implications

Previous studies [Latham and Yeates (1970), McDonald and Bowman (1976) and Mills (1970)] of spatial structure have not accounted for heteroscadasticity or structural shifts in the estimation procedure. This may lead to seriously biased and inefficient estimates leading to misguided policy conclusions. Especially, the impact of distance on the population density has been over-estimated by the traditional OLS density gradient estimates. The density gradient model has been used often by regional planners and urban economists. The results of this study suggest that other variables such as race, various amenities, school districts, mass transit and their interactions must be taken into account. A recent paper by Johnson and Kau (1980) demonstrate by using a varying coefficient model the relevance of including other variables in explaining populations shifts. Harrison and Kain's (1974) study of the influence of past development suggests that the principal differences in urban structures are due to differences in the timing of development. Many studies [Ali and Greenbaum (1977) and Kemper and Schmenner (1974)] have used density gradient specifications to obtain estimates of population or employment patterns. If the applications of the density model neglect the possible problems pointed out in this study then their empirical results will be subject to bias. The results of this paper are useful to give the researcher using this kind of model some further insight into the problems.

VI. Summary

In this paper Goldfeld and Quandt's F-statistic has been used to detect the existence of heterogeneous residuals in estimating the relationship between population density and distance. FHM's shifting regressions technique has been used to detect the possible change in the structure of the density gradient. SNCR's generalized random coefficient technique has been used to simultaneously detect the possible structural change and stochastic behavior of the density gradient. In all cases significant structural shifts and bias was found. In general the OLS density gradient estimates have over-estimated the impacts of distance (transportation cost) on the population density of an urban area and understated the importance of other urban factors.

FOOTNOTES

1. There are several other methods which can be used to test the existence of heteroscedasticity. Goldfeld and Quandt's method and Bartlett's method are two more popular methods. In addition, Harvey and Phillips (1974) has found that Goldfeld and Quandt method's power is similar to other methods.

2. Alternatively, $\gamma_i(u) = \bar{\gamma} + \alpha u_i + \eta(i)$ can be estimated. The results are similar, however SNCR have shown that the estimators obtained from this specification is not consistent.

3. Lee and Chen (1981) have successfully applied this generalized coefficient model to determine the stock rates-of-return generating process.

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TABLE I

Goldfeld and Quardt F-Statistic[1] for Heteroscadasticity

$F = S_2/S_1$

City							
1.	6.366*	13.	2.124*	25.	2.855*	38.	1.838*
2.	1.744*	14.	1.856*	26.	2.207*	39.	1.347
3.	6.427*	15.	4.661*	27.	0.505	40.	1.424
4.	2.108*	16.	2.053*	28.	2.949*	41.	3.288*
5.	1.305	17.	2.356*	29.	0.615	42.	0.778
6.	0.480	18.	2.259*	30.	1.518	43.	0.618
7.	2.041*	19.	0.710	31.	5.566*	44.	1.245
8.	2.104*	20.	0.767	32.	1.141	45.	6.168*
9.	0.699	21.	6.785*	33.	1.467	46.	7.399*
10.	1.391	22.	0.916	34.	2.893*	47.	2.475*
11.	3.119*	23.	1.215	35.	3.979*	48.	1.436
12.	2.918*	24.	2.430*	36.	3.569*	49.	3.919*
				37.	3.394*	50.	3.056*

1. *Significant at the 10% significant level.

TABLE II

FHM Test for Structural Shifts in the Density Gradient

1.	-0.0707 (0.186)	14.	0.0797 (0.247)	27.	-0.1134 (0.744)	40.	-0.1568 (0.968)
2.	0.2650 (0.654)	15.	0.160 (0.927)	28.	0.0978 (0.335)	41.	-0.2862 (1.440)*
3.	0.2660 (1.539)*	16.	-0.1641 (1.307)*	29.	-0.1063 (0.605)	42.	0.1694 (0.635)
4.	-0.2346 (1.640)*	17.	-0.1554 (1.076)	30.	0.7167 (2.512)*	43.	0.4818 (2.920)*
5.	0.0245 (0.099)	18.	-0.0924 (0.878)	31.	-0.2572 (2.343)*	44.	-0.1990 (1.540)*
6.	-0.1554 (1.513)*	19.	-0.0045 (0.029)	32.	-0.2774 (0.986)	45.	0.0357 (0.124)
7.	0.2076 (1.412)*	20.	0.1525 (0.830)	33.	-0.0734 (0.497)	46.	0.1206 (0.405)
8.	0.2369 (0.844)	21.	-0.0814 (0.505)	34.	0.2365 (1.545)*	47.	0.6946 (2.696)*
9.	0.2501 (1.167)	22.	-0.0302 (0.295)	35.	0.3246 (1.015)	48.	-0.00487 (0.0170)
10.	0.1364 (1.518)*	23.	0.2793 (1.585)*	36.	0.0485 (0.325)	49.	0.1859 (0.783)
11.	-0.1641 (1.307)*	24.	0.2247 (0.919)	37.	-0.0459 (0.322)	50.	0.5306 (1.606)*
12.	-0.1263 (1.291)*	25.	0.4514 (1.906)*	38.	0.1239 (0.950)		
13.	0.3473 (1.354)*	26.	0.2113 (1.078)	39.	0.2898 (2.500)*		

*Significant at the 10% level for a one tail test.

TABLE III

Generalized Random Coefficient Model Results

	OLS γ	GLS Const.	GLS γ	GLS α_1	GLS σ_η
1	-0.23 (4.86)*	8.926 (20.58)*	0.094 (0.26)	-0.0063 (0.79)	0.0343 (1.52)*
2	-0.19 (13.12)*	10.418 (20.56)*	-0.390 (2.41)*	0.00434 (1.21)	0.00059 (0.94)
3	-0.19 (6.76)*	9.832 (22.37)*	-0.504 (3.12)*	0.00685 (1.92)*	0.004767 (2.44)*
4	-0.12 (2.91)*	9.638 (29.30)*	0.0268 (0.17)	-0.0056 (1.75)*	0.00144 (0.52)
5	-0.24 (8.27)*	9.539 (12.88)*	-0.289 (1.03)	0.00278 (0.53)	0.00622 (1.68)*
6	-0.04 (1.64)*	8.939 (14.05)*	0.158 (1.07)	-0.00361 (1.36)*	-0.00116 (1.02)
7	-0.16 (4.96)*	10.139 (34.51)*	-0.413 (2.81)*	0.0054 (1.65)*	0.00382 (1.30)
8	-0.14 (4.08)*	10.342 (19.43)*	-0.473 (1.51)*	0.00536 (0.85)	-0.00264 (0.12)
9	-0.13 (3.07)*	10.943 (20.66)*	-0.449 (1.74)*	0.00582 (1.13)	-0.00264 (0.55)
10	-0.13 (4.56)*	10.164 (37.37)*	-0.309 (3.42)*	0.00351 (1.77)*	0.00181 (1.39)*
11	-0.18 (4.64)*	10.023 (32.06)*	-0.390 (2.59)*	0.00375 (1.09)	0.00942 (2.19)*
12	-0.21 (5.53)*	8.729 (52.60)*	0.239 (3.88)*	-0.00719 (4.37)*	0.00564 (5.29)*
13	-0.07 (4.02)*	9.739 (28.40)*	-0.366 (1.09)	-0.00041 (0.58)	0.0139 (4.96)*
14	-0.38 (7.03)*	9.450 (17.95)*	-0.367 (1.09)	-0.000402 (0.58)	0.00971 (1.69)*

TABLE III (continued)

	OLS γ	GLS Const.	GLS γ	GLS α_1	GLS σ_η
15	-0.06 (2.42)*	8.254 (30.64)*	0.0248 (0.19)	-0.00209 (0.678)	0.00642 (3.48)*
16	-0.15 (5.94)*	8.771 (22.42)*	-0.0557 (0.49)	-0.00147 (0.58)	0.00487 (1.84)*
17	-0.24 (6.79)*	8.798 (34.26)*	-0.151 (1.23)	-0.00409 (1.42)*	0.00717 (1.94)*
18	-0.10 (3.54)*	9.247 (29.62)*	-0.151 (1.55)*	0.000544 (0.231)	0.00549 (2.43)*
19	-0.02 (0.96)	8.928 (24.43)*	-0.116 (0.71)	0.00020 (0.057)	0.00217 (0.723)
20	-0.14 (7.16)*	9.082 (15.35)*	-0.317 (1.44)*	0.00355 (0.81)	-0.000710 (0.49)
21	-0.17 (6.56)*	9.534 (27.37)*	-0.214 (1.30)*	0.00099 (0.27)	0.00508 (1.84)*
22	-0.14 (6.26)*	9.206 (20.10)*	0.00604 (0.045)	-0.000703 (0.27)	-0.00123 (1.21)
23	-0.20 (6.31)*	11.277 (18.37)*	-0.647 (3.07)*	0.00805 (2.08)*	0.00228 (1.58)*
24	-0.27 (8.61)*	10.16 (28.12)*	-0.771 (4.05)*	0.00535 (1.02)	0.0069 (1.15)
25	-0.51 (10.79)*	9.859 (22.20)*	-0.718 (2.79)*	0.00945 (1.69)*	0.0037 (1.68)*
26	-0.19 (4.62)*	9.252 (27.05)*	-0.423 (2.43)*	0.00652 (1.72)*	0.0102 (2.03)*
27	-0.17 (4.00)*	9.503 (19.37)*	0.0496 (0.22)	-0.00264 (0.62)	-0.006001 (1.909)*
28	-0.10 (2.46)*	9.0754 (17.83)*	-0.248 (0.82)	0.00264 (0.41)	0.00535 (0.54)
29	-0.20 (6.22)*	10.28 (15.99)*	-0.0768 (0.37)	-0.00247 (0.57)	-0.00241 (0.89)

TABLE III (continued)

	OLS γ	GLS Const.	GLS γ	GLS α_1	GLS σ_η
30	-0.10 (3.94)*	11.138 (18.86)*	-1.010 (2.90)*	0.1667 (2.59)*	-0.000394 (0.073)
31	-0.11 (2.50)*	8.680 (101.76)*	-0.0322 (0.616)	-0.00126 (0.82)	0.00786 (4.62)*
32	-0.14 (4.49)*	8.649 (14.38)*	0.08179 (0.278)	-0.00479 (0.76)	0.00184 (0.847)
33	-0.13 (4.46)*	9.012 (24.58)*	-0.0504 (0.314)	-0.00187 (0.56)	0.000225 (0.098)
34	-0.22 (6.80)*	9.262 (23.63)*	-0.433 (3.07)*	0.00484 (1.48)*	0.00712 (3.20)*
35	-0.35 (10.95)*	10.295 (20.82)*	-0.608 (1.85)*	0.00610 (0.81)	0.00959 (4.19)*
36	-0.12 (5.13)*	9.018 (30.74)*	-0.173 (1.31)*	0.00151 (0.48)	0.00327 (1.91)*
37	-0.13 (5.27)*	9.095 (34.35)*	-0.102 (0.75)	-0.00233 (0.78)	0.00578 (1.50)*
38	-0.18 (6.36)*	9.393 (32.22)*	-0.176 (1.46)*	0.00234 (0.92)	0.00288 (3.08)*
39	-0.05 (2.48)*	10.133 (25.66)*	-0.457 (3.67)*	0.0067 (2.59)*	0.000077 (0.06)
40	-0.01 (0.27)	8.744 (26.66)*	-0.00465 (0.031)	-0.00101 (0.31)	0.0075 (1.58)*
41	-0.13 (5.73)*	8.745 (142.2)*	-0.141 (2.20)*	-0.000043 (0.02)	0.0178 (3.67)*
42	-0.17 (7.75)*	9.227 (19.85)*	-0.335 (1.26)*	0.00452 (0.77)	0.00156 (0.438)
43	-0.25 (5.02)*	11.56 (18.55)*	-0.696 (3.39)*	0.01121 (2.76)*	-0.00190 (0.89)
44	-0.49 (15.63)*	9.375 (19.62)*	0.0248 (0.17)	-0.00399 (1.39)*	0.000702 (0.64)

TABLE III (continued)

	OLS γ	GLS Const.	GLS γ	GLS α_1	GLS σ_η
45	-0.18 (4.30)*	8.739 (16.23)*	-0.227 (0.802)	-0.000903 (0.141)	0.01189 (2.01)*
46	-0.36 (8.27)*	9.9945 (30.59)*	-0.520 (1.68)*	0.000510 (0.069)	0.00851 (2.22)*
47	-0.13 (3.41)*	10.099 (24.76)*	-0.949 (3.30)*	0.01615 (2.71)*	-0.00118 (0.27)
48	-0.37 (5.70)*	9.829 (21.28)*	-0.320 (1.12)	0.00018 (0.029)	0.00221 (0.311)
49	-0.14 (4.08)*	8.865 (17.88)*	-0.346 (1.38)*	0.00378 (0.72)	0.00698 (0.885)
50	-0.29 (6.17)*	10.294 (23.61)*	-1.0622 (3.11)*	0.0138 (1.89)*	0.0128 (1.36)*

1. t-values (absolute values) are in parentheses, *, significant at the 10% level for a one tail test.

TABLE III (continued)

	OLS γ	GLS Const.	GLS γ	GLS α_1	GLS σ_η
30	-0.10 (3.94)*	11.138 (18.86)*	-1.010 (2.90)*	0.1667 (2.59)*	-0.000394 (0.073)
31	-0.11 (2.50)*	8.680 (101.76)*	-0.0322 (0.616)	-0.00126 (0.82)	0.00786 (4.62)*
32	-0.14 (4.49)*	8.649 (14.38)*	0.08179 (0.278)	-0.00479 (0.76)	0.00184 (0.847)
33	-0.13 (4.46)*	9.012 (24.58)*	-0.0504 (0.314)	-0.00187 (0.56)	0.000225 (0.098)
34	-0.22 (6.80)*	9.262 (23.63)*	-0.433 (3.07)*	0.00484 (1.48)*	0.00712 (3.20)*
35	-0.35 (10.95)*	10.295 (20.82)*	-0.608 (1.85)*	0.00610 (0.81)	0.00959 (4.19)*
36	-0.12 (5.13)*	9.018 (30.74)*	-0.173 (1.31)*	0.00151 (0.48)	0.00327 (1.91)*
37	-0.13 (5.27)*	9.095 (34.35)*	-0.102 (0.75)	-0.00233 (0.78)	0.00578 (1.50)*
38	-0.18 (6.36)*	9.393 (32.22)*	-0.176 (1.46)*	0.00234 (0.92)	0.00288 (3.08)*
39	-0.05 (2.48)*	10.133 (25.66)*	-0.457 (3.67)*	0.0067 (2.59)*	0.000077 (0.06)
40	-0.01 (0.27)	8.744 (26.66)*	-0.00465 (0.031)	-0.00101 (0.31)	0.0075 (1.58)*
41	-0.13 (5.73)*	8.745 (142.2)*	-0.141 (2.20)*	-0.000043 (0.02)	0.0178 (3.67)*
42	-0.17 (7.75)*	9.227 (19.85)*	-0.335 (1.26)*	0.00452 (0.77)	0.00156 (0.438)
43	-0.25 (5.02)*	11.56 (18.55)*	-0.696 (3.39)*	0.01121 (2.76)*	-0.00190 (0.89)
44	-0.49 (15.63)*	9.375 (19.62)*	0.0248 (0.17)	-0.00399 (1.39)*	0.000702 (0.64)

TABLE III (continued)

	OLS γ	GLS Const.	GLS γ	GLS α_1	GLS σ_η
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47	-0.13 (3.41)*	10.099 (24.76)*	-0.949 (3.30)*	0.01615 (2.71)*	-0.00118 (0.27)
48	-0.37 (5.70)*	9.829 (21.28)*	-0.320 (1.12)	0.00018 (0.029)	0.00221 (0.311)
49	-0.14 (4.08)*	8.865 (17.88)*	-0.346 (1.38)*	0.00378 (0.72)	0.00698 (0.885)
50	-0.29 (6.17)*	10.294 (23.61)*	-1.0622 (3.11)*	0.0138 (1.89)*	0.0128 (1.36)*

1. t-values (absolute values) are in parentheses, *, significant at the 10% level for a one tail test.

TABLE IV

List of Sample Cities

1.	Akron	18.	Kansas City	35.	Rochester
2.	Baltimore	19.	Los Angeles	36.	Sacramento
3.	Birmingham	20.	Louisville	37.	Salt Lake City
4.	Boston	21.	Memphis	38.	San Antonia
5.	Buffalo	22.	Miami	39.	San Diego
6.	Chicago	23.	Milwaukee	40.	San Jose
7.	Cincinnati	24.	Nashville	41.	Seattle
8.	Cleveland	25.	New Haven	42.	St. Louis
9.	Columbus	26.	New Orleans	43.	Spokane
10.	Dallas	27.	Oklahoma City	44.	Syracuse
11.	Dayton	28.	Omaha	45.	Tocoma
12.	Denver	29.	Philadelphia	46.	Toledo
13.	Detroit	30.	Phoenix	47.	Tucson
14.	Flint	31.	Pittsburgh	48.	Utica
15.	Fort Worth	32.	Portland	49.	Washington, D.C.
16.	Houston	33.	Providence	50.	Wichita
17.	Jacksonville	34.	Richmond		