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Town Specialization and the Relationships Between Occupation Employment and Industry Employment

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Abstract: This paper uses OLS regression to analyze the relationships existing between occupation jobs and industry jobs in small southwestern U.S. towns. First, occupation employment in the representative town is estimated from its industry employment. Then the towns are classified into different specialties, including the following five types: diversified, government, manufacturing, mining, and service and trade. Type-specific regression estimates follow, showing how occupation employment differentially responds to industry employment in towns having different economic bases. Using previous results from the Arizona Community Data Set, both short-run (impact) and long-run (projection) occupation employment estimates are given for basic employment changes in a hypothetical community.

I. INTRODUCTION

Numerous studies document the dramatic changes that have been experienced by nonmetropolitan areas in recent decades (Hodge 1965; Berry 1967; Beale 1975; Wardwell 1977; Todd 1983; Fuguitt 1985; Frey 1987; Stabler 1987; Power 1996). A considerable portion of this research has focused on three issues: first, analyzing the linkages and multipliers of small places (Robison and Miller 1991; Olfert and Stabler 1994; Beyers 1996; Mulligan and Vias 1996; Vias and Mulligan 1997); second, determining whether employment change is leading or lagging behind population change (Rudzitis 1993; Bao, Barkley, and Henry 1997; Vias and Mulligan 1999); and third, outlining the so-called turnaround in rural population growth (Johnson and Beale 1994; Elliot and Perry 1996; Fuguitt and Beale 1996).

In these various studies much attention has been directed to the attributes of *industry employment* in nonmetropolitan areas; however, much less attention has been given to the attributes of *occupation employment* in these areas. Analysts studying growth and change in nonmetropolitan areas have largely focused on employment shifts in industry sectors like manufacturing, retail trade, and services, but they have largely ignored the related employment shifts in occupation sectors like machine operation, sales, and management. This is unfortunate because county planners and municipal managers are sometimes more interested in a town's occupation employment profile than a town's industry employment profile. To cite one well-known example, officials overseeing rapidly growing communities often attempt to identify those particular occupations that are most

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likely to be in short supply in the near future, thereby allowing scarce retraining and recruitment resources to be deployed in an efficient manner.

This paper explores the relationships existing between occupation employment and industry employment in more than 200 small communities located throughout the southwestern U.S. Each community is located in one of the Four Corners states and each had fewer than 15,000 inhabitants during the census year 1990. In Section 3 of the paper, a simple regression model is developed that estimates the employment found in various occupation categories as a function of the employment found in different industry categories. In Section 4, this model is estimated for the data set's representative (statistically average) community. Then, later in the section, these towns are shown to have substantially different economic bases and are classified into different functional types. Five types of town economies are found to be present in fairly large numbers: diversified, government, manufacturing, mining, and service and trade. The regression model is then extended to each of these five functional types, and the new estimates show how occupation employment differentially responds to industry employment in towns having diverse economic specialties.

These last results are then used in Section 5 to estimate the changes in total occupation employment that are expected to occur whenever a community experiences either a short-run shift or a long-run change in its *basic* industry employment. Here, use is made of the Arizona Community Data Set, a body of survey data that allows small-town analysts to estimate total industry employment as a linear function of basic industry employment (Gibson and Worden 1981; Vias 1996).

The general statistical findings of the paper are interesting but not surprising. As expected, jobs in the professional, management, and technical occupations are shown to be strongly tied to the incidence of finance and service industries, while jobs in occupations like machine operation, craft production, and general labor are shown to be strongly tied to the prevalence of mining and manufacturing industries. What is novel and important, though, is that the precise nature of these relationships is uncovered, at least for this particular sample of nonmetropolitan areas. Various regional models, which typically are updated with reliable industry employment data, can then be adapted to predict any industry-driven occupation changes expected to take place in nonmetropolitan areas.

II. THE DATA

The database used in this paper, termed the Southwestern Town Data Set (SWDS), was taken from the 1990 U.S. Census of Population and Housing and includes 221 communities located in Arizona (n=67), Colorado (n=61), New Mexico (n=45), and Utah (n=48). All places had populations ranging between about 1,000 and 15,000 and employment sizes ranging between 373 and 5,501 in 1990. The towns were chosen, both in terms of location and of size, roughly to correspond to the nearly fifty communities already surveyed in the Arizona Community Data Set (ACDS).

The analysis of the paper uses ten major industries based on the nation's standard industrial classification (i.e., one-digit SIC industries). These industry groups (with their five-letter acronyms) are as follows: agriculture, forestry, and fishing (AGRIC); mining (MINIG); construction (CONST); manufacturing (MANUF); transportation, communications, and public utilities (TCPUT); wholesale trade (WTRAD); retail trade (RTRAD); finance, insurance, and real estate (FIRES); services (SERVS); and public administration (PADMN). Table 1 discloses that the representative (average) town of the SWDS had 1,989 employees, with a little under 11 percent of those employees engaged in MANUF, between 18 and 19 percent engaged in RTRAD, and more than 34 percent engaged in SERVS.

TABLE 1

Employment Attributes of the Different Types of Town Economies

Attribute	All	Agr	Div	Gov	Man	Min	S&T	Uti
Number of Towns	221	4	46	24	68	20	50	9
Employment Mean	1989	1674	1895	1763	2091	1954	2098	1911
				Industry Employment				
% AGRIC	3.37	21.16	3.66	2.45	3.51	2.08	2.78	1.60
% MINIG	2.67	0.31	1.13	0.64	1.46	16.27	1.56	2.03
% CONST	7.14	6.05	8.55	5.74	7.22	6.56	6.70	7.26
% MANUF	10.80	6.46	7.72	12.57	18.71	4.34	5.91	5.50
% TCPUT	7.18	5.79	6.05	6.07	6.07	6.88	6.58	18.58
% WTRAD	3.23	4.87	2.63	2.77	4.68	2.34	2.48	1.94
% RTRAD	18.53	19.95	20.32	14.93	16.54	19.19	20.81	19.35
% FIRES	4.99	3.62	5.64	3.38	5.25	3.55	5.71	3.78
% SERVS	34.26	27.99	36.63	29.32	29.97	33.26	41.42	33.00
% PADMN	7.81	3.77	7.66	22.11	5.20	5.51	6.03	6.96
				Occupation Employment				
% MAPS	24.46	9.94	24.05	24.06	22.86	22.56	29.62	21.84
% TSAS	29.14	22.52	29.21	32.00	29.04	25.77	30.06	27.27
% SERV	16.79	20.39	19.38	16.10	13.62	16.74	18.21	19.94
% FARM	3.00	19.79	3.10	2.01	3.31	1.64	2.40	1.73
% PROD	13.05	9.19	12.19	13.21	14.80	17.54	9.67	14.38
% OPER	13.54	18.16	12.04	12.62	16.37	15.74	10.03	14.86

Note: All refers to a town that is representative of the entire data set. The various abbreviations refer to the following seven specific types of town economies: Agr, agriculture; Div, diversified; Gov, government; Man, manufacturing; Min, mining; S&T, service and trade; and Uti, utility.

Employment in eleven different occupations is initially considered. These occupations, each designated by a four-letter acronym, are as follows: executive, administrative, and managerial (EXEC); professional specialty (PROF); technicians and related support (TECH); sales (SALE); administrative support, including clerical (ADMN); all services, including private household and protective (SERV); farming, forestry, and fishing (FARM); precision production, craft, and repair (PROD); machine operators (MACH); transportation and material moving (TRAN); and general labor (GENL). These are the nation's standard occupation groups with some consolidation in the service sector. The most important occupation categories were EXEC, PROF, SALE, ADMN, SERV, and PROD, accounting on average for about eight out of every ten jobs in the 221 places. In the representative community, about 235 (12 percent) persons were engaged in executive activities, 280 (14 percent) in professional specialties, 236 (12 percent) in sales, 283 (14 percent) in administrative support, 320 (16 percent) in services, and 252 (13 percent) in craft production.

III. THE MODEL

This paper assumes that a linear relationship exists between the independent variable E, industry employment, and the dependent variable O, occupation employment. In general, there are n industry categories and m occupation categories and the total workforce T in any community equals either the sum of all industry employment or the sum of all occupation employment; that is, $T = E_1 + ... + E_n = O_1 + ... + O_m$. The specific model used in the paper takes the following form for the ith occupation:

$$(1) \qquad O_i + a_{i1}E_{i1} + a_{i2}E_{i2} + ... + a_{in}E_{in} \,.$$

This holds for all m ($1 \leq i \leq m$) occupations. In general, use is made of the following theoretical model:

$$(2) \qquad O = AE \,,$$

where O is an m by 1 vector of occupation employment, A is an m by n matrix of coefficients, and E is an n by 1 vector of industry employment. The data found in O and E are taken from the SWDS while the coefficients in A are estimated as shown below. The coefficients found in matrix A simply allocate or transform the various industry jobs into related occupation jobs, much like a firm's production function transforms its inputs into outputs. From the accounting identity noted above, the coefficients in each column of A must sum to unity. On the other hand, the coefficients in each row of A indicate how a single job in a given occupation is fractionally generated by each of the n industries.

Given the linear properties of the theoretical model, ordinary least squares (OLS) regression can be used to estimate the various coefficients of matrix A. Since marginal effects are of greatest interest, the estimated regression equations are unrestricted and the intercept terms are not forced through the origin. For each occupation the statistical model can be specified as follows:

$$(3) \qquad O_i = a_{i0} + a_{i1}E_1 + ... + a_{ij}E_j + ... + a_{in}E_n + e_i \,,$$

where O_i is employment in the ith ($1 \leq i \leq m$) occupation, E_j is employment in the jth ($1 \leq j \leq n$) industry, a_{i0} is the intercept term, a_{ij} is the estimated coefficient for the ith occupation and the jth industry, and e_i is the error term. The general statistical model is then specified as follows:

(4) $O = D + AE + e$,

where D is the m by 1 vector of intercept terms (which add to zero) and e is the m by 1 vector of error terms. In this paper only the fully specified model is considered, meaning that all of the regression coefficients a_{ij} (both significant and insignificant) are estimated.

IV. REGRESSION ANALYSIS

This section of the paper presents results of two types. First, regression estimates for occupation employment are generated using all of the places in the SWDS. These estimates pertain to the data set's representative community. Then the various places are clustered together into seven different types of economies. New sets of regression estimates for occupation employment are then generated for five of these seven different types of economic specialization.

The Representative Community

First apply OLS regression procedures to all 221 places in the SWDS, setting the number of industries at n=10 and the number of occupations at m=11. The estimation results and relevant statistics are given in Table 2. To avoid any confusion in reading this table, note that for reasons of space the industries (occupations) are not arranged in columns (rows), as the matrix format of Section 2 called for, but are instead arranged in rows (columns).

Note that 70 (64 percent) of the 110 coefficients are significant at the 0.10 level using a two-tailed test. The estimates for EXEC, PROF, SALE, ADMN, and FARM all look excellent, with adjusted R-squareds exceeding 0.80, and the estimates for the remaining six occupations all look reasonably good, with adjusted R-squareds exceeding 0.60. Without doubt, the unexplained variation is due to various factors that are both internal (e.g., different adoption rates for new technologies) and external (e.g., different locations relative to larger cities) to the various places. The implications of yet another factor—economic specialization—are examined later in this section of the paper.

Note further that some occupations are clearly tied to more industries than are other occupations in the representative community. PROD is significantly related to employment in nine industries, and ADMN and SERV are each significantly related to employment in eight industries, but SALE and FARM are significantly related to employment in only two and three industries, respectively. On the other hand, the industry FIRES is significantly associated with ten of the eleven occupation sectors (a somewhat surprising result), while both MANUF and RTRAD follow close behind with nine significant occupation associations. MINIG is the industry with the weakest effect on occupation sectors, only being significantly associated in four of the eleven cases.

The main substantive findings of these regression estimates are obvious. On the one hand, white-collar occupation jobs, in sectors like EXEC, PROF, and ADMN, are strongly and positively tied to employment in tertiary and quaternary industries like FIRES and SERVS. On the other hand, blue-collar jobs, in sectors like PROD, TRAN, and GENL, are strongly and positively tied to employment in secondary industries like CONST, MANUF, and TCPUT. These are not surprising findings; as stated earlier, the real value of Table 2 lies in showing *precisely* how employment distributed across different industry sectors drives employment distributed across different occupation sectors.

TABLE 2

Regression Estimates of Occupation Employment Based on Industry Employment: Representative Town

	Occupation										
Industry	EXEC	PROF	TECH	SALE	ADMN	SERV	FARM	PROD	MACH	TRAN	GENL
Intercept	-10.480	-33.750*	-10.521	11.576	-5.014	22.850*	-1.399	21.603*	-5.963	3.359	7.739
	(12.82)	(14.33)	(6.33)	(9.03)	(10.27)	(13.69)	(3.06)	(12.52)	(7.12)	(6.81)	(5.33)
AGRIC	-0.217*	-0.287*	-0.086*	-0.106*	-0.031	0.433*	0.917*	-0.153*	0.216*	0.087*	0.227*
	(0.08)	(0.09)	(0.04)	(0.06)	(0.06)	(0.09)	(0.02)	(0.08)	(0.04)	(0.04)	(0.03)
MINIG	-0.013	0.101	-0.024	-0.046	0.019	0.033	-0.002	0.511*	0.084*	0.229*	0.108*
	(0.05)	(0.06)	(0.03)	(0.04)	(0.04)	(0.06)	(0.01)	(0.05)	(0.03)	(0.03)	(0.02)
CONST	-0.133*	-0.278*	-0.041	-0.077	0.119*	0.327*	0.007	0.733*	0.035	0.134*	0.175*
	(0.07)	(0.09)	(0.04)	(0.06)	(0.06)	(0.08)	(0.02)	(0.08)	(0.04)	(0.04)	(0.03)
MANUF	0.052	0.088*	0.073*	0.009	0.171*	-0.065*	0.019*	0.219*	0.319*	0.049*	0.066*
	(0.03)	(0.04)	(0.02)	(0.02)	(0.03)	(0.04)	(0.01)	(0.03)	(0.02)	(0.02)	(0.01)
TCPUT	0.045	-0.084	0.041	0.025	0.262*	0.089	0.017	0.179*	0.088*	0.257*	0.082*
	(0.07)	(0.08)	(0.03)	(0.05)	(0.05)	(0.07)	(0.02)	(0.07)	(0.04)	(0.04)	(0.03)
WTRAD	0.261*	0.091	-0.047	0.120	0.243*	-0.211*	-0.043*	0.529*	-0.095	0.094*	0.060
	(0.10)	(0.12)	(0.05)	(0.07)	(0.08)	(0.11)	(0.02)	(0.10)	(0.06)	(0.05)	(0.04)
RTRAD	-0.029	-0.159*	-0.132*	0.348*	0.066*	0.532*	-0.008	0.129*	0.075*	0.090*	0.087*
	(0.04)	(0.05)	(0.02)	(0.03)	(0.03)	(0.04)	(0.01)	(0.04)	(0.02)	(0.02)	(0.02)
FIRES	1.158*	0.554*	0.095*	0.841*	0.118*	-0.340*	-0.011	-0.621*	-0.256*	-0.294*	-0.244*
	(0.08)	(0.09)	(0.04)	(0.06)	(0.06)	(0.09)	(0.02)	(0.08)	(0.04)	(0.04)	(0.03)
SERVS	0.150*	0.496*	0.146*	0.015	0.130*	0.098*	0.001	0.000	-0.011	-0.011	-0.014
	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(.01)	(0.02)	(0.01)	(0.01)	(0.01)
PADMN	0.174*	0.078*	0.094*	0.003	0.367*	0.082*	-0.007	0.140*	0.025	0.022	0.021
	(0.04)	(0.04)	(0.02)	(0.03)	(0.03)	(0.04)	(0.01)	(0.04)	(0.02)	(0.02)	(0.02)
Adj R^2	0.84	0.86	0.69	0.88	0.85	0.78	0.91	0.75	0.70	0.61	0.61
SEE	75.4	84.3	37.2	53.1	60.3	80.5	17.9	73.6	41.8	40.1	31.3

Note: Figures in parentheses are standard errors.
* indicates significance at the 0.10 level.
SEE indicates the standard error of the estimate.

Clustering According to Specialization

The analysis now turns to examining how economic specialization affects the relationships existing between industry employment and occupation employment. However, before the results of Table 2 can be reproduced for different functional types of places, all of the places in the SWDS must be classified into relatively homogenous groups (Smith 1965).

In order to accomplish this, a clustering procedure was applied to the percentage distribution of industry employment in each of the 221 communities. While considerable experimentation was initially carried out in four areas of the clustering exercise, the final groupings proved to be remarkably stable. This experimentation involved, first, varying the amount of industry employment detail from a minimum of ten to a maximum of twenty sectors; second, performing separate regression runs using two different versions (raw and standardized scores) of the cluster variable; third, applying a number of different clustering procedures with the Euclidean distance metric; and fourth, making different subjective choices about the final number of clusters to use for further analysis. The results of this paper are based upon the use of Ward's algorithm, which is based upon the analysis of variance principle. This algorithm was applied to a 221 by 10 matrix and clustering was terminated at fifteen groups. This seemed a reasonable termination number since the algorithm is known to create clusters having roughly the same number of members (Griffith and Amrhein 1991). Once these clusters had been identified (using descriptive statistics) and labeled, the fifteen clusters were further reduced to seven clusters, each of which is a well-known type of town economy (Table 1).

Only four towns specializing in agriculture (where the average employment in AGRIC was 21.2 percent) were found in the SWDS. These places ranged in size between 1,234 and 2,299 employees and had a mean size of 1,674 employees. Diversified places were found to be much more numerous in the data set. The forty-six places with diversified economies had an average size of 1,895 employees, where employment ranged between 493 and 4,437. As was anticipated, the typical diversified place closely resembled the representative community for the entire data set: similar percentage employment figures were especially evident in the large sectors like MANUF, RTRAD, and SERVS. A total of twenty-four government towns were identified (average employment in PADMN was 22.1 percent), and this cluster was composed of three smaller clusters having eight (low PADMN specialization of 17 percent), thirteen (moderate PADMN specialization of 22.5 percent), and three (high PADMN specialization of 34 percent) members. Government towns ranged in size between 373 and 3,862 employees with a mean size of 1,763 employees. The sixty-eight manufacturing centers (average employment in MANUF was 18.7 percent) were also composed of three smaller clusters, having membership sizes of thirty-nine (mean MANUF of 15 percent), seventeen (mean MANUF of 19 percent), and twelve (mean MANUF of 31.5 percent). These manufacturing centers ranged in size between 528 and 5,501 employees and had a mean size of 2,091 employees. The twenty mining towns (average employment in MINIG was 16.3 percent) found in the SWDS had a mean employment size of 1,954, and ranged in size between 846 and 3,765 employees. Two groups of mining towns could be identified, one group with fourteen members having low specialization (11.5 percent in MINIG) and a second group with six members showing high specialization (27 percent in MINIG). Only one cluster of trade towns (27 percent in RTRAD) could be identified in the data set and this cluster had twenty-three members. However, three different clusters of service towns, having a total of twenty-seven members, could be identified. These clusters were of sizes thirteen (42 percent in SERVS), eleven (52 percent in SERVS), and three (71 percent in SERVS). Across the twenty-seven service towns SERVS constituted 41.4 percent of employment in the average case. These service and trade towns were consolidated into one cluster having fifty members. This group of towns had a mean size of 2,098 employees and ranged in size between 531 and 4,310 employees. Finally, only nine towns specializing in transportation, communications, and public utilities (18.6 percent in TCPUT) could be found among the 221 places. These places, called utility centers, had a mean size of 1,911 employees and ranged in size between 1,143 and 3,201 employees.

Before regression procedures were applied to the various functional types, the eleven occupation categories designated above were consolidated into six new occupation categories. This was done to save space in presenting the paper's results. This consolidation was largely based upon the correlation patterns evident among the eleven occupation sectors. These six new occupation sectors, with associated acronyms, are as follows: managerial and professional (MAPS), composed of EXEC and PROF; technical, sales, and administrative support (TSAS), composed of TECH, SALE, and ADMN; services (SERV); farming (FARM); production (PROD); and operators (OPER), composed of MACH, TRAN, and GENL.

Table 1 indicates that the representative community in the SWDS had nearly 25 percent of its employment engaged in MAPS, over 29 percent placed in TSAS, and more than 13 percent involved in both PROD and OPER. Note, though, that across the seven different types of town economies much less variation was evident in the composition of occupation employment than was evident in the composition of industry employment. For example, the employment engaged in technical, sales, and support activities only varied between a low of 22.5 percent in agriculture towns to a high of 32.0 percent in government towns, while comprising 29.1 percent of employment in the representative community of the SWDS. Outside of the extreme employment variation apparent for farming activities (a minor category), there was only significant employment variation noticeable in two other occupation categories—MAPS (ranging from 9.9 to 29.6 percent) and PROD (ranging 9.2 to 17.5 percent).

Five Types of Town Economies

The new estimates of the OLS regression model are shown in Table 3. All of the results given here are based on n=10 industries and m=6 occupations. Note that six different sets of estimates are given and that these estimates are arranged as they were in Table 2, with industries indicated along the rows and occupations down the columns. In the first row of each set of figures, estimates are provided for the representative community of the SWDS; these estimates actually serve as benchmarks for the five other (in separate rows) economy-specific estimates given in the table. Reading across the appropriate first-row entries, the coefficients indicate that in the representative community a one-job increase in MANUF employment leads to the following occupation employment changes: an increase of 0.140 jobs in MAPS, an increase of 0.254 jobs in TSAS, a decrease of 0.065 jobs in SERVS, an increase of 0.019 jobs in FARM, an increase of 0.219 jobs in PROD, and an increase of 0.434 jobs in OPER. Note that these six occupation employment estimates sum to unity, an accounting requirement that was stipulated for each industrial sector earlier in the paper. Also note that the various intercept terms sum to zero across the six occupation sectors. Finally, note how consolidation of the occupation sectors has affected the estimates: the 0.140 coefficient generated for MAPS equals the sum of the two coefficients shown earlier in Table 2, 0.052 for EXEC and 0.088 for PROF.

TABLE 3

Regression Estimates of Occupation Employment Based on Industry Employment: Representative Town and Five Different Types of Town Economies

	Occupation					
Industry	MAPS	TSAS	SERV	FARM	PROD	OPER
Intercept	-44.230*	-3.959	22.850*	-1.399	21.603*	5.135
	-98.486*	-30.756	56.462*	1.608	28.087	43.085*
	-59.900	37.711	59.064	-3.505	-28.694	-4.676
	21.043	-10.163	-29.812	-0.818	55.889*	-36.139
	-86.606	32.854	90.784*	1.369	-73.379*	34.977
	-53.361	-15.726	44.720	10.579	10.910	2.879
AGRIC	-0.505*	-0.223*	0.433*	0.917*	-0.153*	0.531*
	-0.533	-0.131	0.677*	0.766*	-0.086	0.307*
	-0.034	-0.311	0.318	0.664*	0.160	0.203
	-0.779*	-0.043	0.377*	0.887*	-0.262	0.820*
	0.548*	-0.330	-1.282*	0.781*	0.816	0.467
	-1.033	-0.585*	0.717*	0.796*	0.068	1.038*
MINIG	0.088	-0.051	0.033	-0.002	0.511*	0.421*
	0.533	-0.977*	0.465	-0.019	0.462*	0.534*
	0.949	-1.588	0.669	-0.218	1.349	-0.161
	-0.460	-0.227	0.244	0.003	0.864*	0.575*
	0.136	-0.025	-0.078	0.001	0.545*	0.421*
	0.487	-0.580*	0.000	-0.034	0.295	0.832*
CONST	-0.411*	0.001	0.327*	0.007	0.733*	0.344*
	0.038	0.054	0.170	-0.006	0.468*	0.274
	0.352	-0.567	0.742	-0.024	0.185	0.312
	-0.643	-0.351*	0.472*	0.101*	0.809*	0.612*
	0.308	0.253	-0.203	-0.048	0.867*	-0.176
	-0.300	-0.116	0.129	0.015	0.826*	0.445*
MANUF	0.140*	0.254*	-0.065*	0.019*	0.219*	0.434*
	-0.325	0.202	-0.014	0.049	0.502*	0.585*
	0.082	0.200	-0.203	-0.024	0.418*	0.490*
	0.142	0.189*	0.036	0.009	0.197*	0.426*
	0.952*	1.520*	-0.316	-0.051	-0.066	-1.041*
	0.166	0.626*	-0.220	0.061	0.201	0.166
TCPUT	-0.040	0.328*	0.089	0.017	0.179*	0.426*
	-0.288	0.243	0.353	0.037	0.178	0.478*
	0.342	0.626*	-0.191	-0.064	-0.004	0.291
	-0.176	0.410*	-0.013	-0.005	0.164	0.620*
	0.005	0.051	-0.035	0.040	0.353*	0.585*
	0.586	0.357	0.079	-0.029	0.056	-0.049
WTRAD	0.352*	0.316*	-0.211*	-0.043*	0.529*	0.058
	2.912*	1.361*	-1.545*	-0.049	-1.006*	-0.673*
	0.579	0.877	-1.353	0.031	1.427*	-0.560
	0.012	0.129	-0.024	-0.009	0.890*	0.002
	-1.234	-0.406	1.336*	0.126	-0.644	1.821
	1.055	-0.192	-0.325	-0.024	0.062	0.424

TABLE 3 *(continued)*

Regression Estimates of Occupation Employment Based on Industry Employment: Representative Town and Five Different Types of Town Economies

	Occupation					
Industry	MAPS	TSAS	SERV	FARM	PROD	OPER
RTRAD	-0.187*	0.283*	0.532*	-0.008	0.129*	0.252*
	0.210	0.219	0.382*	0.006	0.078	0.105
	0.330	0.560*	0.008	0.009	-0.162	0.255
	-0.768*	0.526*	0.568*	0.005	0.019	0.649*
	0.338	-0.099	0.360	-0.010	0.156	0.255
	-0.123	0.341*	0.585*	-0.013	0.040	0.169*
FIRES	1.713*	1.053*	-0.340*	-0.011	-0.621*	-0.794*
	1.642*	0.606*	-0.479	-0.015	-0.271	-0.483*
	0.145	1.220	0.141	0.013	-0.095	-0.423
	1.346*	1.434*	-0.232	-0.036	-0.761*	-0.751*
	-0.031	0.951*	0.844*	-0.043	-0.398	-0.323
	1.302*	0.873*	-0.251	-0.010	-0.304*	-0.610*
SERVS	0.646*	0.291*	0.098*	0.001	0.000	-0.036*
	0.315	0.373*	0.220	-0.001	0.086	-0.006
	0.336	0.422*	0.035	0.043	0.139	0.024
	1.157*	0.208*	0.006	-0.010	-0.107	-0.254*
	0.450*	0.331*	0.199	-0.004	0.110	-0.086
	0.633*	0.300*	0.062	-0.002	0.027	-0.019
PADMN	0.252*	0.465*	0.082*	-0.007	0.140*	0.068
	0.407	0.525*	0.019	-0.029	0.081	-0.002
	0.262	0.046	0.539*	-0.015	0.113	0.055
	-0.164	0.552*	0.273	-0.041	0.645*	-0.265
	0.004	0.858*	-0.319*	0.068	0.001	0.388
	-0.317	0.674*	0.178	-0.023	0.183	0.304*
Adj R^2	0.88	0.95	0.78	0.91	0.75	0.77
	0.87	0.95	0.80	0.85	0.81	0.79
	0.92	0.96	0.72	0.89	0.79	0.87
	0.89	0.97	0.78	0.89	0.68	0.78
	0.95	0.96	0.94	0.73	0.96	0.87
	0.92	0.96	0.81	0.70	0.81	0.83
SEE	137.9	75.7	80.5	18.0	73.6	76.3
	124.4	67.6	73.6	17.0	51.8	52.2
	78.7	62.8	71.6	6.9	66.2	51.5
	141.7	68.3	68.1	19.2	86.9	87.1
	48.7	51.8	37.5	13.1	33.3	56.7
	138.6	71.8	87.7	17.8	53.9	53.0

Note: In each case the figures shown in the first row refer to a town that is representative of the entire data set. The remaining five rows of figures refer in order to the following specific types of town economies: diversified, government, manufacturing, mining, and service and trade. Estimates are not given for farming and utility towns.
* indicates significance at the 0.10 level.
SEE indicates standard error of the estimate.

Due to the limited numbers of observations, economy-specific estimates could only be provided for five of the different types of places (i.e., agriculture and utility towns could not be analyzed). The estimates for occupation employment in these different types of towns are given in alphabetical order—diversified, government, manufacturing, mining, and service and trade—immediately below the estimates for the representative community. Reading down the appropriate first-column entries, the results indicate that a one-job increase in MANUF leads to the following changes in MAPS employment: a 0.325-job loss in diversified towns, a 0.082-job increase in government centers, a 0.142-job increase in manufacturing communities, a 0.952-job increase in mining towns, and a 0.166-job increase in service and trade centers. Visual inspection of Table 3 indicates that the five economy-specific estimates are indeed distributed around the first-row estimates for the representative community of the data set. In some industries, such as CONST and RTRAD, the range of this variation is generally quite modest but in other industries, such as WTRAD and FIRES, the variation is considerable.

Furthermore, as was found earlier in Table 2, there are several instances in which estimates of the coefficients are either negative or greater than unity. This suggests that the various occupation employment shifts should probably not be strictly interpreted as marginal or one-unit shifts, but instead as shifts that would accompany significant underlying changes in a town's economic base. In other words, these occupation employment shifts should be viewed as responses to fairly large exogenous changes taking place in industry employment, perhaps changes of several hundred or more jobs. Consequently, the various regression estimates of the occupation-industry employment relationships might be more safely interpreted as being associative rather than causal.

It is also worth noting that in the case of each occupation the fits of the economy-specific regression equations are at least as good as the fit of the regression equation for the representative community. The economy-specific equations have adjusted R-squareds that are generally higher, except for FARM (a small sector) and TSAS (where they are about the same). In addition, it should be noted that when the standard estimation errors are adjusted to account for the different mean sizes of the dependent variable, the economy-specific equations invariably perform at least as well as the counterpart equation for the data set's representative community.

Collinearity among the independent variables is always a potential problem in studies of this sort. However, in the case of the representative community, the highest correlation coefficient between any pair of the ten industry employment variables was found to be $R=0.70$, between RTRAD and SERVS. Dependence among the other pairs of industries was found to be remarkably low. In any case, this figure of 0.70 is well below the danger threshold of $R=0.80$ suggested by some statisticians (Clark and Hosking 1986). This dependence between RTRAD and SERVS was exacerbated, though, by the clustering procedures: in diverse towns the correlation coefficient was $R=0.90$, in government towns $R=0.73$, in manufacturing towns $R=0.81$, in mining towns $R=0.95$, and in service and trade towns $R=0.44$. For each of the five specialties, experimentation was undertaken by dropping one of the highly interrelated variables and reestimating the regression equations (Pindyck and Rubinfeld 1991). The results indicated that collinearity was problematic for mining towns and possibly problematic for diverse towns, but only between these two industries.

Finally, it should be emphasized that the major finding of Table 2 is being simply refined or qualified by the results shown in Table 3. Clearly, once again, the estimates indicate that employment in white-collar occupations is largely driven by employment in tertiary and quaternary industries, while employment in blue-collar occupations is largely driven by employment in primary and secondary industries. But now there are various nuances in the overall trends to consider. For instance, changes in MANUF have much more dramatic effects on MAPS and TSAS in mining towns as opposed to manufacturing centers, while changes in FIRES have much more dramatic effects on MAPS and TSAS in manufacturing centers as opposed to mining towns.

V. ECONOMIC BASE APPLICATIONS

The regression results of the previous section are now combined with an interindustry employment requirements model that was previously estimated using the Arizona Community Data Set. This allows total jobs in different occupation sectors to be estimated as linear functions of *basic* jobs in different industry sectors. Employment shifts in total occupation jobs are then shown to be driven by short-run or long-run employment shifts in basic industry jobs.

Arizona Community Data Set

Economic base theory presumes that small, simple economies can be divided into two broad types of activities, a basic, or export-oriented, sector and a nonbasic, or locally oriented, sector. Individual industries have both basic and nonbasic components, although primary and secondary industries tend to be largely basic while tertiary and quaternary industries tend to be largely nonbasic. Considerable research has been carried out over the past twenty-five years on southwestern U.S. communities using the economic base approach. Much of this research has used the Arizona Community Data Set (ACDS); for full summaries of the ACDS see Gibson and Worden (1981) or Vias (1996).

The ACDS is a unique survey-based data set that captures the industry full-time equivalent employment (at the establishment level) of nearly fifty towns, most of them located in nonmetropolitan counties. At the time they were surveyed these towns had populations ranging between about 1,000 and 15,000 and employment sizes ranging between 352 and 5,828. The representative community of the ACDS is remarkably similar to the representative community of the SWDS—based on the percentage of employment distributed across the same ten industries, the two places are only 11.43 Euclidean distance units apart. Using procedures similar to those disclosed above, the ACDS has been analyzed for different types of specialization and the following functional types of towns have been identified: diversified, manufacturing, mining, service and trade, and utility.

In Mulligan and Vias (1996) and Vias and Mulligan (1997) industry employment requirements were estimated both for the representative town and for these five functional types of towns, much along the lines of an input-output model. Now, however, the so-called technical coefficients represent the total (direct, indirect, and induced) employment requirements for every one basic or export-oriented job in each of the ten industries of an ACDS community. In the upcoming discussion these industry employment requirements are merged with the occupation employment estimates shown in Table 3. Since government towns could not be identified in the ACDS and utility towns could not be found in substantial numbers in the SWDS, only four types of town economies will be used in that discussion.

However, before proceeding to this analysis it is only proper to note that some differences do exist between the pairs of functional types in the two data sets. Diversified towns in the ACDS have a lot more employment in MANUF (18.3 versus 7.8 percent) and a lot less employment in SERVS (27.3 versus 36.6 percent) than do diversified towns in the SWDS. Likewise, manufacturing towns are a lot more specialized (36.6 versus 18.7 percent in MANUF) in the ACDS. Mining towns are much more specialized in the ACDS (50.3 versus 16.3 percent in MINIG) as well. However, in the service and trade specialty, the SWDS towns have greater specialization in SERVS (41.4 versus 31.6 percent) but less specialization in RTRAD (20.8 versus 31.0 percent). The Euclidean distances separating the statistically average places in both data sets are as follows: diversified, 16.56; manufacturing, 20.32; mining, 38.62; and service and trade, 15.65. These figures indicate that the worst fit between the two data sets is for mining towns and the best fit is for service and trade towns.

Interindustry Employment Requirements

As noted earlier, Mulligan and Vias (1996) provide the coefficients of a 10 by 10 interindustry employment requirements matrix B for the representative community in the ACDS. This matrix shows how a one-basic-job shift in each industry generates a shift in total jobs across the ten industries of the community. For example, an extra basic job in MANUF creates 0.009 new jobs in AGRIC, 0.003 new jobs in MINING, and so on. The total effect of this one-basic-job shift is 1.731 jobs, indicated by the column multiplier for MANUF.

For the paper at hand, a new matrix C is needed that will first transform basic industry jobs into total industry jobs and will subsequently transform total industry jobs into total occupation jobs. To accomplish this two-step process simply create the m by n matrix C by postmultiplying the m by n matrix A, established earlier in the paper, by the n by n total employment requirements matrix B for the representative community of the ACDS. That is, consider the following:

(5) $C = AB.$

The figures at the top of Table 4 indicate the various elements of the 6 by 10 matrix C for the representative community of the SWDS. This matrix shows that, for the one-basic-job increase in MANUF discussed above, the following numbers of new occupation jobs can be expected to result: 0.348 jobs in MAPS, 0.479 jobs in TSAS, 0.064 jobs in SERV, and so on. Note that the sum of these jobs across the six occupation sectors is 1.731, which equals the column multiplier for total industry employment in MANUF.

TABLE 4

Total Employment Requirements for Occupations: Different Types of Town Economies

	Industry									
Occ.	AGRIC	MINIG	CONST	MANUF	TCPUT	WTRAD	RTRAD	FIRES	SERVS	PADMN
					Representative Town					
MAPS	-0.496	0.178	-0.411	0.348	-0.040	0.352	-0.007	2.188	0.666	0.329
TSAS	-0.153	0.064	0.001	0.479	0.328	0.316	0.721	1.589	0.314	0.580
SERV	0.567	0.113	0.327	0.064	0.089	-0.211	0.762	-0.110	0.102	0.137
FARM	1.051	0.000	0.007	0.027	0.017	-0.043	0.011	0.000	0.000	-0.005
PROD	-0.124	0.538	0.733	0.308	0.179	0.529	0.282	-0.458	0.018	0.179
OPER	0.653	0.450	0.344	0.505	0.426	0.058	0.533	-0.791	-0.031	0.099
Multiplier	1.498	1.343	1.000	1.731	1.000	1.000	2.302	2.418	1.069	1.319
					Diversified Towns					
MAPS	-0.445	0.583	0.038	-0.080	-0.288	2.912	0.339	1.829	0.315	0.523
TSAS	-0.151	-0.933	0.054	0.440	0.243	1.361	0.560	0.763	0.373	0.642
SERV	0.797	0.502	0.170	0.067	0.353	-1.545	0.653	-0.364	0.220	0.044
FARM	0.825	-0.018	-0.006	0.055	0.037	-0.049	0.028	-0.014	-0.001	-0.032
PROD	-0.044	0.472	0.468	0.576	0.178	-1.006	0.202	-0.098	0.086	0.099
OPER	0.378	0.543	0.274	0.632	0.478	-0.673	0.358	-0.387	0.006	0.001
Multiplier	1.360	1.149	1.000	1.691	1.000	1.000	2.140	1.729	1.000	1.277
					Manufacturing Towns					
MAPS	-0.799	-0.510	-0.643	0.407	-0.176	0.012	-0.856	1.150	1.158	-0.164
TSAS	-0.024	-0.140	-0.351	0.521	0.410	0.129	1.124	1.564	0.266	0.552
SERV	0.377	0.319	0.472	0.204	-0.013	-0.024	0.850	0.085	0.041	0.273
FARM	0.887	0.005	0.101	0.016	-0.005	-0.009	0.018	0.004	-0.009	-0.041
PROD	-0.262	0.883	0.809	0.251	0.164	0.890	0.237	-0.433	-0.033	0.645
OPER	0.820	0.650	0.612	0.537	0.620	0.002	1.204	-0.419	-0.223	-0.265
Multiplier	1.000	1.207	1.000	1.936	1.000	1.000	2.577	1.951	1.200	1.000
					Mining Towns					
MAPS	0.548	0.215	0.308	1.345	0.005	-1.234	0.769	0.343	0.450	0.088
TSAS	-0.330	0.036	0.253	2.024	0.051	-0.406	0.438	1.360	0.331	0.943
SERV	-1.282	-0.016	-0.203	-0.127	-0.035	1.336	0.632	0.964	0.199	-0.277
FARM	0.781	0.002	-0.048	-0.051	0.400	0.126	0.023	-0.050	-0.004	0.071
PROD	0.816	0.573	0.867	0.007	0.353	-0.644	0.469	-0.031	0.110	0.070
OPER	0.467	0.457	-0.176	-1.081	0.585	1.821	0.691	-0.288	-0.086	0.448
Multiplier	1.000	1.267	1.000	2.117	1.000	1.000	3.022	2.297	1.000	1.342
					Service and Trade Towns					
MAPS	-1.526	0.501	-0.300	0.390	0.586	1.055	0.331	1.307	0.633	-0.317
TSAS	-0.763	-0.169	-0.116	0.778	0.357	-0.192	0.685	0.941	0.300	0.917
SERV	1.302	0.166	0.129	-0.188	0.079	-0.325	0.692	-0.167	0.062	0.254
FARM	1.345	-0.042	0.015	0.081	-0.029	-0.024	-0.026	-0.004	-0.002	-0.028
PROD	0.164	0.396	0.826	0.212	0.056	0.062	0.105	-0.015	0.027	0.245
OPER	1.815	0.994	0.445	0.163	-0.049	0.424	0.190	-0.437	-0.019	0.400
Multiplier	2.337	1.846	1.000	1.416	1.000	1.000	1.977	1.625	1.000	1.471

Note: The occupation employment multiplier equals the (column) sum of the coefficients for each industry. These occupation employment multipliers are identical to the industry employment multipliers shown in Table 1 of Mulligan and Vias (1996) and estimated in Vias and Mulligan (1997).

Table 4 also provides information regarding four other C matrices, one for each of the four functional types that are commonly found in both the SWDS and the ACDS. It is worth stressing that *both* A and B are somewhat different in each of the four types of communities. Consequently, as an examination of Table 4 makes very evident, the composition of this matrix C can vary significantly from one type of town specialization to another. Note, too, how the various occupation-industry coefficients for the different functional types are distributed around the corresponding coefficient for the representative community. In the case of the effect of a one-basic-job increase in MANUF on employment in PROD, for instance, note that the four coefficients 0.576, 0.251, 0.007, and 0.212 are distributed around 0.308, the corresponding coefficient for the representative community.

Short-Run Impacts

First, consider the case of estimating a short-run impact where one or more industries experience a change in basic employment. Table 5 provides initial employment data for a hypothetical town that has a total of 1,400 basic workers. Note that this town initially qualifies as a service and trade town, since 800 (57 percent) basic jobs are concentrated into those two industries alone. Now suppose the basic employment in MANUF increases from 100 to 1,300 but the basic employment in each of the remaining industries remains constant. Since this town would now have 50 percent of its basic employment in MANUF, the economic base of the town would shift from a service and trade specialty to a manufacturing specialty.

TABLE 5

Industry Employment Data and Functional Weights for Community Economic Base Study

	Basic (Export) Employment		
Industry	Initial Conditions	Short-Run Impact	Long-Run Projection
AGRIC	50	50	50 (0%)
MINIG	0	0	0 (0%)
CONST	50	50	55 (10%)
MANUF	100	1300 (+1200)	110 (10%)
TCPUT	50	50	55 (10%)
WTRAD	50	50	55 (10%)
RTRAD	400	400	480 (20%)
FIRES	50	50	60 (20%)
SERVS	400	400	480 (20%)
PADMN	250	250	300 (20%)
Total	1400	2600	1645 (17.5%)
	Functional Weights w		
Diversified	0.08858	0.19618	0.43259
Manufacturing	0.02111	0.75286	0.07202
Mining	0.01044	0.01192	0.03019
Service & Trade	0.87987	0.03904	0.46519
Total	1.00000	1.00000	1.00000

Note: The short-run and long-run cases are not related. The short-run case depicts a one-time shift of 1,200 basic jobs in one sector only (i.e., manufacturing). The long-run case depicts different amounts of growth (percentages are indicated in parentheses) occurring in the basic employment of the ten industries. Detailed procedures for calculating the functional weights are given in Mulligan (1994) and Mulligan and Vias (1996).

In order to incorporate the structural changes that always occur in impacted small-area economies, Mulligan (1994) has outlined a distance-weighting methodology that controls estimates of basic-nonbasic employment relationships for the functional type of the economy, both before and after the impact. This allows traditional multiplier effects to be adjusted for underlying shifts taking place in the economic structure of the small-area economy.

Using this procedure, the community shown in Table 5 is allocated the following functional weights for its pre-impact specialization: $w_{DI} = 0.08858$, $w_{MA} = 0.02111$, $w_{MI} = 0.01044$, and $w_{ST} = 0.87987$ (where all four weights sum to unity). In a sense, this means that the pre-impact community is 87.9 percent like the typical ACDS service and trade town. However, after the basic employment impact is experienced this community is allocated the following weights: $w_{DI} = 0.19618$, $w_{MA} = 0.75286$, $w_{MI} = 0.01192$, and $w_{ST} = 0.03904$. Clearly, it now closely resembles a manufacturing town in the ACDS.

Suppose the analyst is interested in estimating the effect of this specific industry employment change on, first, overall occupation employment and, second, employment specifically involved in executive, managerial, and professional occupations (MAPS). Then there are four different possibilities or models to consider. These can be ordered, from simplest to most complex, depending upon the amount of information the analyst would need for the model's application. If in Model 1 the analyst could not differentiate between town types, then the first matrix (for the representative community of the SWDS) in Table 4 would be used. From this matrix the estimate for the total occupation employment impact is 2,077.2 (1.731 x 1,200) new jobs, where 417.6 (0.348 x 1,200) of these new jobs are found in MAPS. In Model 2 the analyst can differentiate between towns according to specialization of the town economy. Now the last (service and trade) matrix in Table 4 is used and the estimate for the total impact is 1,699.2 (1.416 x 1,200) new jobs, where 468 (0.390 x 1,200) of these new jobs are allocated to MAPS. In Model 3 the four functional weights are used by the analyst; however, these weights are applied only to the *initial* employment conditions of the community. The MANUF column multiplier of the community is now estimated to be 1.459 = .08858 (1.691) + 0.02111 (1.936) + 0.01044 (2.117) + 0.87987 (1.416) and the coefficient for MAPS is now estimated to be 0.357 = 0.08858 (-0.080) + 0.02111 (0.407) + 0.01044 (1.345) + 0.87987 (0.390). So, in Model 3 the total impact is 1,750.8 new jobs, where 428.4 of these new jobs are allocated to MAPS. Model 4, however, accounts for the underlying shift in the entire economic base of the community and makes use of *both* the pre-impact and the post-impact functional weights. First, compute the results as in Model 3 but instead use the post-impact weights shown in Table 5. The estimate of the column multiplier is now 1.869 = 0.19618 (1.691) + 0.75286 (1.936) + 0.01192 (2.117) + 0.03904 (1.416) and the estimate of the MAPS coefficient is now 0.322 = 0.19618 (-0.080) + 0.75286 (0.407) + 0.01192 (1.345) + 0.03904 (0.390). The Model 4 estimate of the total impact is 2,242.8 new jobs but the estimate of the specific allocation to MAPS is only 386.4 new jobs. A brief comparison between Models 3 and 4 is in order. With the shift in the underlying economic base of the town economy from a service and trade specialization to a manufacturing specialization, the column multiplier for manufacturing (the industry of impact) shifts from 1.459 to 1.869. So, there is a total occupation employment shift of 1,750.8 new jobs due to the multiplier effect and a further 492 new jobs due to the underlying structural shift in the employment requirements of the town economy. In the specific case of MAPS, however, the multiplier-induced effect is 428.4 new jobs but a loss of 42 jobs is incurred as the economic base of the town changes. Of course, this decrease is compensated for by increases in the five other occupation employment categories of the town.

Long-Run Projection

Now consider the case of an analyst making a long-run projection about changes in occupation employment based on expected changes in the basic employment of the town's various industries. Return to the hypothetical town shown in Table 5 and note that primary industries are projected to remain flat, secondary industries, along with WTRAD and TCPUT, are expected to grow by 10 percent, and all other activities (including government) are projected to grow by 20 percent. Thus, the town is expected to experience a 17.5 percent increase in its overall basic industry employment. Also note that this long-run scenario does not incorporate the short-run impact considered immediately above; however, the methodology could be easily modified to accommodate this impact. If this were the case, the long-run projection could be called the baseline scenario and the aforementioned impact scenario would be added to it.

In designing Model 4 for these expected employment changes, the analyst would have to compute new functional weights reflecting the expected distribution of basic employment at the end of the study period. These new weights are shown in the right-hand column near the bottom of Table 5. The community is expected to resemble both a service and trade town (w_{ST}=0.46519) and a diversified town (w_{DI}=0.43529) about equally at the end of this period of growth. So, using the same methodology outlined above, column multipliers and specific occupation-industry coefficients can be computed for both the pregrowth and postgrowth cases. Then expected occupation employment changes can be estimated very easily. For instance, the column multiplier for MANUF is expected to shift from 1.459 to 1.594 (+0.135) while the column multiplier for PADMN is expected to shift from 1.442 to 1.349 (-0.093). This means that a total occupation employment shift of 15.94 jobs can be expected to follow the increase of 10 basic jobs in MANUF while a total occupation employment shift of 67.45 jobs can be expected to follow the increase of 50 basic jobs in PADMN. If the underlying changes in the town economy were not accounted for, the analyst would underpredict the first change by 1.35 jobs and overpredict the second change by 4.65 jobs. It is then a relatively simple matter to disaggregate each of these industry-specific total employment changes into the six occupation categories as indicated along the rows of each matrix in Table 4.

VI. CONCLUSIONS

This paper develops a simple regression model that estimates occupation employment in small towns as a linear function of industry employment. This estimation is first done for the representative community of a small-town data set. Then the estimates are redone for five different types of town economies—diversified, government, manufacturing, mining, and service and trade. Four of these specialties (not government) are then used for further analysis. In each case a six-occupation by ten-industry matrix is generated that shows how one new basic (export) job in any industry generates, through the familiar multiplier process, a body of total occupation employment that is distributed across the ten industries of the town. The sum of these occupation employment coefficients equals the usual column multiplier for industry employment, as in input-output analysis. Finally, two applications of the estimates were given in the area of economic base analysis.

The linear model obviously needs further examination in other parts of the nation and in other nations to see if it has potential for general application. Furthermore, historical studies could be done to discern how the occupation-industry employment relationships have been changing over time. Another fruitful area of inquiry relates to the sizes of places used in this study: obviously, larger places should be examined to see whether these linear relationships between occupation employment and industry employment appear to hold up over different-sized centers. Of course, further extension of the well-known Arizona Community Data Set would also be nice as this would shed more light on the accuracy of the various industry employment matrices used to compute the occupation employment matrices found in this paper.

REFERENCES

Bao, S., D. Barkley, and M. Henry. "The Hinterland's Stake in Metropolitan Growth: Evidence from Selected Southern Regions." *Journal of Regional Science* 37 (1997), 479-502.

Beale, C.L. *The Revival of Population Growth in Nonmetropolitan America*. Washington, D.C.: U.S. Department of Commerce, 1975.

Berry, B.J.L. *Geography of Market Centers and Retail Distribution*. Englewood Cliffs, NJ: Prentice-Hall, 1967.

Beyers, W. "Lone Eagles and High Fliers in Rural Producer Services." *Rural Development Perspectives* 11 (1996), 2-10.

Clark, W.A.V., and P.J. Hosking. *Statistical Methods for Geographers*. New York: John Wiley, 1986.

Elliot, J.R., and M.J. Perry. "Metropolitanizing Nonmetro Space: Population Redistribution and Emergent Metropolitan Areas, 1965-90." *Rural Sociology* 61 (1996), 497-512.

Frey, W. "Migration and Depopulation of the Metropolis: Regional Restructuring or Rural Renaissance." *American Sociological Review* 52 (1987), 240-257.

Fuguitt, G.V. "The Nonmetropolitan Turnaround." *Annual Review of Sociology* 11 (1985), 259-280.

Fuguitt, G.V., and C.L. Beale. "Nonmetropolitan Migration: Toward a New Turnaround." *Growth and Change* 27 (1996), 156-174.

Gibson, L.J., and M.A. Worden. "Estimating the Economic Base Multiplier: A Test of Alternative Procedures." *Economic Geography* 57 (1981), 146-159.

Griffith, D., and C. Amrhein. *Statistical Analysis for Geographers*. Englewood Cliffs, NJ: Prentice-Hall, 1991.

Hodge, G. "The Prediction of Trade Center Viability in the Great Plains." *Papers and Proceedings of the Regional Science Association* 15 (1965), 87-115.

Johnson, K.M., and C.L. Beale. "The Recent Revival of Widespread Population Growth in the Nonmetropolitan Areas of the United States." *Rural Sociology* 54 (1994), 301-326.

Mulligan, G.F. "Multiplier Effects and Structural Change: Applying Economic Base Analysis to Small Economies." *Review of Urban and Regional Development Studies* 6 (1994), 3-19.

Mulligan, G.F., and A.C. Vias. "Interindustry Employment Requirements in Nonmetropolitan Communities." *Growth and Change* 27 (1996), 460-478.

Olfert, M.R., and J.C. Stabler. "Community Level Multipliers for Rural Development Initiatives." *Growth and Change* 25 (1994), 467-486.

Pindyck, R.S., and D.L. Rubinfeld. *Econometric Models and Economic Forecasts*. New York: McGraw-Hill, 1991.

Power, T.M. *Lost Landscapes and Failed Economies*. Washington, D.C.: Island Press, 1996.

Robison, H.H., and J.R. Miller. "Central Place Theory and Intercommunity Input-Output Analysis." *Papers in Regional Science* 70 (1991), 399-417.

Rudzitis, G. "Nonmetropolitan Geography: Migration, Sense of Place, and the American West." *Urban Geography* 14 (1993), 574-585.

Smith, R.H.T. "Method and Purpose in Functional Town Classification." *Annals of the Association of American Geographers* 55 (1965), 539-548.

Stabler, J.C. "Trade Center Evolution in the Great Plains." *Journal of Regional Science* 27 (1987), 225-244.

Todd, D. "The Small-Town Viability Question in the Prairie Context." *Environment and Planning A* 15 (1983), 903-916.

Vias, A.C. "The Arizona Community Data Set: A Long-Term Project for Education and Research in Economic Geography." *Journal of Geography in Higher Education* 20 (1996), 243-258.

Vias, A.C., and G.F. Mulligan. "Disaggregate Economic Base Multipliers in Small Communities." *Environment and Planning A* 29 (1997), 1055-1074.

________. "Integrating Economic Base Theory with Regional Adjustment Models: The Nonmetropolitan Rocky Mountain West." *Growth and Change* 30 (1999), 507-525.

Wardwell, J.M. "Equilibrium and Change in Nonmetropolitan Growth." *Rural Sociology* 42 (1977), 156-179.