RSP 14(1): 52-64.

IDENTIFICATION OF REGIONAL WAGE LEADERSHIP WITHIN A SYSTEM OF LABOR MARKETS

*William M. Syverson**

Introduction

Regional economists have for a number of years accepted the notion of a regional wage spread hypothesis by which wage changes in one region may be transmitted to another via a set of vaguely defined institutional forces. This form of wage interdependence (also referred to as coercive comparison, pattern bargaining and wage spillover) emphasizes the role which reference groups play in determining wage changes in any submarket. Union bargaining is typically ascribed as the mechanism through which this process operates, as union wage settlements set standards by which other workers seek to maintain traditional pay relativities.

Additionally, regional wage interactions are presumed to be conditioned by structural economic components as well. Regional industrial structure and interindustry linkages are suggested as determinants of the degree to which regional markets respond to wage changes among certain reference groups. This view of wage determination posits that individual labor markets respond not only to traditional supply and demand conditions, but also to external forces which exhibit differential impacts across space.

Despite the fact that no rigorous theory exists to define the structure and dynamics of the wage spread process, researchers have suggested various means for the identification of leading regions. Unfortunately, these studies have raised more questions concerning regional wage leadership than they have answered. Particularly important is the issue of the criteria which should be used in defining a leading region. The purpose of this study is to provide some verification of the importance that industrial structure plays upon wage interdependence within a system.

Previous Research

The earliest attempts to identify regional wage leaders and their impact upon wage determination follow closely in the Phillips Curve excess-demand tradition. Cowling and Metcalf [6]. Thirlwall [17] and Thomas and Stoney [18] define regional wage leaders as those labor markets which exhibit the greatest pressure of labor demand. The lowest regional unemployment rate within the system serves as a proxy for excess demand under the assumption that markets with the lowest unemployment rates will be likely to bid up wage rates more rapidly than markets of low demand. A wage transfer mechanism is suggested as wage increases in leading markets spillover into lagging regions.

* Department of Geography, University of Illinois at Urbana-Champaign

Reed and Hutchinson [16] and Weissbrod [19] provide a stronger theoretical case for a wage transfer mechanism between spatially segmented labor markets. Both studies use the highest regional wage rate change as a proxy of the highest order center in an urban hierarchy. Wage transfer is posited to move down the hierarchy from high-wage, high-order centers to low-wage, low-order centers. Implied in the theoretical discussions of their models is the notion that the transfer mechanism is in actuality a diffusion process in which spatially differentiated information levels allow for wage transmission between levels of the hierarchy.

More recently, Martin [13] suggests that institutional factors play an important role in defining wage leadership. He specifies two alternative models: one based upon high relative wages and high unionization, the other based upon high employment growth and labor market expansion. Along a similar vein, Eckstein and Wilson [7], McGuire and Rapping [11], and Mehra [15] hypothesize that wage transfer is likely to be the result of institutional factors in which reference wages in key industrial sectors will produce significant spillovers to non-key sectors. Although these studies examine industrially disaggregated markets only, the results imply that industry structure at the regional level might be important in determining wage interactions between labor markets.

While the above studies have addressed a host of issues related to earnings adjustment, they fail to either prove or disprove the regional wage leadership (RWL) hypothesis. This is due in large part to the rather ad hoc nature in which wage leaders are defined. Unanswered questions remain as to whether there is single or multi-regional leadership, whether leadership remains stable over time, and whether wage transfers are uni- or multi-directional [13]. What little theory that does exist, suggests that regional wage interaction is far more complex than can be captured in one or two variables. In addition, the previous methodologies are faulty in that they assume an a priori designation of a leading region to be correct when, in fact, it may not be so. The result may lead to biased estimates when attempting to evaluate the determinants of individual market wage rates.

Although this paper cannot hope to deal with all of the above issues, the objective is to provide a methodology to systematically identify salient interactions between labor markets, without the necessity of making prior judgements regarding those relationships. In addition, the paper will provide some empirical content as to the nature of relationships between regional industrial structure and wage interdependence.

Research Design

A number of methodologists exist as possible candidates for analyzing the RWI hypothesis. One approach might be to employ standard time-series techniques as suggested by Clark [5] in a study of national/regional fluctuations of unemployment series. This approach offers a great deal of promise in identifying lead/lag relationships of regional labor markets within the time domain and would provide insights into the stability of wage leadership over time. Unfortunately these types of models tell us very little about the actual interdependencies which exist between markets. Some recent work has been attempted to develop spatial time-series models (Martin and Oeppen, [14], and Bennett, [3]), however a number of conceptual and operational problems preclude their usefulness in the present context.

In a related approach, King, Casetti and Jeffrey [9] and Casetti, King and Jeffrey [4] use linear difference equations to analyze the leads and lags among regional unemployment series. These studies are limited because they fail to account for the processes which determine the spatial dependencies. In addition, they ignore the role that purely intraregional economic forces have in determining labor market fluctuations.

A promising alternative (and the one used in this paper) is suggested by Arora and Brown [2] and Hordijk [8] in dealing with a set of region-specific equations when spatial dependence is assumed to be significant. Under these circumstances, OLS estimation is no longer efficient, as the error terms of the estimated equations should not be expected to be uncorrelated. A method for incorporating the systematic relationship between error terms has been developed by Zellner [21] in which a two stage seemingly unrelated regression (SUR) approach is utilized. It has been shown [10] that when information regarding error terms is known to be different from zero, that SUR estimation will be more efficient than OLS. The Zellner approach pools information from individual equation estimates by using the error terms of the OLS procedure to estimate the variance-covariance matrix used in the SUR process. The formulation of the SUR subject is given in Figure 1.

It is worth noting that the gain in efficiency of using the SUR approach is related to the correlation of independent variables in individual equations as well as the correlation among their error terms. The gain in efficiency may be quite large if independent variables between equations are not highly correlated and if the error terms in different equations are highly correlated. Kmenta [10] has shown that when the error terms in different equations are uncorrelated or if the regression coefficients in each of the equations are the same as the regression coefficients in any other equation, then the SUR estimation reduces to OLS.

Apart from potential gains in estimation efficiency, the two-stage approach provides useful information through the resulting residual correlation matrix regarding spatial autocorrelation. The advantages of this approach over other attempts to model spatial interaction is that no prior assumptions are required regarding the nature of interdependence over space. Therefore, it avoids the shortcomings of previous models in defining wage leadership a priori.

Using a two stage framework similar to Marcis and Reed [12] in their study of five Western labor markets, the methodology of this study is to test the following basic Phillips Curve equation using OLS estimation:

$$W = b(0) + b(1)U + b(2)UIN + b(3)P + b(4)DIS + e$$

Where:

W = change in money wage rates.
U = change in unemployment rates.
UIN = inverse of the unemployment rate.
P = change in consumer price index.
DIS = disparity of local to national unemployment.

The unemployment and price variables serve as well established neo-classical determinants of wage adjustments based on excess demand theory. The disparity measure (DIS) is based on Archibald [1] in which it was found that the larger the disparity of unemployment rates within a system, the greater is the tendency for wage inflation. Prediction of the correct signs for

Figure 1. Seemingly Unrelated Regression

Assume a set of equations:

$$Y_1 = X_1B_1 + u_1$$

$$Y_2 = X_2B_2 + u_2$$

$$\vdots \qquad \vdots$$

$$Y_m = X_mB_m + u_m$$

Which can be expressed as:

$$\begin{bmatrix} Y_1 \\ Y_2 \\ \cdot \\ \cdot \\ \cdot \\ Y_m \end{bmatrix} = \begin{bmatrix} X_1 & & & \\ & x_2 & & \\ & & \cdot & \\ & & & \cdot \\ & & & & X_m \end{bmatrix} \begin{bmatrix} B_1 \\ B_2 \\ \\ \\ \\ B_m \end{bmatrix} + \begin{bmatrix} u_1 \\ u_2 \\ \cdot \\ \cdot \\ \cdot \\ u_m \end{bmatrix} \quad \text{where: } X_i \text{ is (txk)} \quad B_i \text{ is (kx1)}$$

In matrix notation:

$$y = X\gamma + w \qquad \text{and } w'w = \begin{bmatrix} \sigma^2_{11}I & & \sigma^2_{1m} \\ & \sigma^2_{22} & \\ & & \\ \sigma^2_{m1} & & \sigma^2_{mm} \end{bmatrix} = \phi = \Sigma \boxtimes I$$

w is distributed as n $(0,\phi)$ and ϕ is a matrix of known variances and covariances.

Using an Aitken estimator: $B = (Z' \phi^{-1} Z)^{-1} Z' \phi^{-1} y$
and since $\phi^{-1} = (\Sigma \boxtimes I)^{-1} = (\Sigma^{-1} \boxtimes I)$

$$B = (z'(\Sigma^{-1} \boxtimes I)Z)^{-1} Z'(\Sigma^{-1} \boxtimes I)\, y$$

the coefficients are based on the Phillips-Lipsey hypothesis with U posited as negatively related and UIN and P as positively related to W. The disparity variable is hypothesized to be non negative as increases in unemployment disparities should lead to increases in wage rate changes.

Equations are estimated for 17 SMSAs based on annual data collected from 1961-1980. Quarterly data would have been preferable (as it would have added to the degrees of freedom), but could not be obtained for all variables. Wage data were gathered from the Bureau of Labor Statistics *Employment and Earnings,* unemployment data for *Area Trends in Employment and Unemployment,* price data from the *Handbook of Labor Statistics*.

It is assumed that there is significant interaction between various labor markets due to the institutional and structural factors mentioned previously. Because of this, SUR estimation will be performed on the set of regional wage equations specified earlier. The SUR estimates will be analyzed for possible efficiency gains and, more importantly, the residual correlations matrix will be examined for potentially significant interactions.

As an extension on earlier work of this nature, the residual correlation matrix will be tested for the possibility that regional industrial structure is a key component in understanding the process of wage interdependence between regions. Based on Mehra's [15] classification of key sectors in the industrial wage-setting process, the 17 SMSAs are analyzed with respect to their industry structure for 12 2-digit SIC industries (see Table 3). Location quotients (Table 4) for each labor market are then calculated and a hierarchical grouping analysis is performed on the location quotients to determine labor markets with similar industry structure. The results of the grouping procedure can then be used to determine the correspondence between industrial structure and regional wage interdependence.

Table 1. Estimated Wage Determination Equations

		U	UIN	P	DIS	F	R^2	D.W.
Atlanta	OLS	−.0404	.0009	.2585	.0156	2.01	.423	1.576
		(−.915)	(.012)	(.573)	(1.802)			
	SUR	−.0713**	−.0427**	1.3877**	.0166**			
		(−14.241)	(−3.779)	(8.033)	(15.685)			
Baltimore	OLS	.0218	−.0835	.7181**	.0020	11.04**	.801	1.476
		(1.067)	(−1.428)	(4.302)	(.283)			
	SUR	.0061*	−.0033	.9455**	.0094**			
		(1.711)	(−.212)	(19.229)	(11.427)			
Boston	OLS	−.0019	.0233	.7097**	−.0018	8.33**	.752	1.191
		(−.071)	(.301)	(2.349)	(−.265)			
	SUR	−.0110**	.0664**	.9000**	−.0025**			
		(−4.429)	(5.334)	(23.767)	(−6.568)			
Chicago	OLS	.0110	−.0678	.5772**	−.0008	5.71**	.675	.951
		(.508)	(−1.618)	(3.267)	(−.095)			
	SUR	.0179**	−.0477**	.5382**	.0036**			
		(4.864)	(−5.057)	(12.007)	(3.984)			

Cincinnati	OLS	.0137	−.0430	.6260**	.0022	8.58**	.757	1.104
		(.501)	(−.629)	(3.479)	(.295)			
	SUR	−.0005	−.0537**	.9392**	.0062**			
		(−.148)	(−2.965)	(20.611)	(9.354)			
Cleveland	OLS	.0038	−.1084*	.5990**	−.0061	6.16**	.691	1.295
		(.188)	(−2.489)	(3.236)	(−1.239)			
	SUR	−.0024	−.0200*	.2406**	−.0009			
		(−.794)	(−1.622)	(4.209)	(−1.168)			
Detroit	OLS	−.0028	−.2404*	.6389**	−.0050	5.18**	.653	1.111
		(−.132)	(−2.253)	(2.253)	(−1.404)			
	SUR	−.0123**	−.1687**	.9830**	−.0038**			
		(−3.396)	(−13.839)	(16.176)	(−10.858)			
Houston	OLS	−.0418	−.0250	.7902**	−.0182**	26.42**	.906	1.521
		(−1.720)	(−1.188)	(7.601)	(−4.110)			
	SUR	−.0374**	.0045	1.1720**	−.0147**			
		(−9.522)	(.745)	(23.140)	(−16.381)			
Kansas City	OLS	−.0715*	−.2028	.4041**	−.0099	7.00**	.718	1.094
		(−1.951)	(−1.701)	(2.952)	(−.880)			
	SUR	−.1414**	−.4881**	−.0840	−.0417**			
		(−11.741)	(−7.686)	(−.545)	(−13.558)			
Los Angeles	OLS	.0104	−.0747	.4645**	−.0012	14.04**	.836	1.416
		(.645)	(−1.420)	(4.980)	(−.238)			
	SUR	−.0051	−.0628**	.7052**	−.0039**			
		(−1.570)	(−3.395)	(21.883)	(−3.985)			
Minneapolis	OLS	.0299**	−.0444	.6084**	.0000	18.11**	.868	1.590
		(2.419)	(−1.569)	(5.402)	(.006)			
	SUR	.0315**	−.0070	1.0324**	.0001			
		(6.580)	(−.974)	(25.598)	(.125)			
New York City	OLS	.0403	.0793	.4829**	.0026	16.79**	.859	2.174**
		(1.600)	(1.220)	(3.053)	(.661)			
	SUR	.0357**	.0939**	.6557**	.0038**			
		(−3.812)	(−8.371)	(11.0937)	(−10.248)			
Philadelphia	OLS	.0018	−.1977**	.5342**	−.0412	5.48**	.666	.982
		(.063)	(−2.068)	(2.773)	(−1.642)			
	SUR	−.0380**	−.2966**	1.0439**	−.0248**			
		(−3.812)	(−8.371)	(11.0937)	(−10.248)			
Pittsburgh	OLS	.0134	−.1179	.9677**	−.0040	9.62**	.778	1.945**
		(.638)	(−1.647)	(3.938)	(−1.003)			
	SUR	.0122**	.1424**	.4970**	.0054**			
		(2.429)	(5.348)	(3.608)	(4.872)			
San Francisco	OLS	−.0151	−.2115**	1.0867**	−.0132	14.01**	.836	1.166
		(−.455)	(−2.303)	(4.393)	(−2.024)			
	SUR	.0001	.0573**	.9368**	.0013**			
		(.030)	(2.697)	(12.723)	(3.365)			
Seattle	OLS	.0049	−.0260	.6637**	−.0016	6.47**	.702	1.941**
		(.356)	(−.421)	(4.881)	(−.693)			
	SUR	.0001	.0573**	.9368**	.0013**			
		(.030)	(2.697)	(12.723)	(3.365)			
St. Louis	OLS	.0073	−.0097	.6607**	.0040	13.81**	.834	1.130
		(.520)	(−.203)	(6.140)	(.649)			
	SUR	.0029	−.1073**	.8618**	.0055**			
		(1.407)	(−7.802)	(22.089)	(7.748)			

* significant at .05 level

** significant at .01 level

(T-ratios in parentheses)

Wage Equation Results

The results of the OLS and SUR estimations for the 17 regional labor markets are given in Table 1. The overall significance of the individual OLS equations are indicated by the F statistics. In every case (except for Atlanta), the equations appear to be significant. However in many cases, the significance is derived from coefficients which take signs different from those hypothesized. The coefficients for the change in unemployment rate (U) takes on the correct sign in only 6 of 17 cases using OLS. In only one case is it significant (Kansas City). The inverse of unemployment (UIN), predicted to be positive, is never significant with the correct sign when using OLS. The price variable (P) does however show up to be important in every case (except Atlanta), being significant at the .01 level. The dispersion of unemployment coefficient (DIS) is predicted with the correct sign and is important in only one city (Atlanta) for an OIS equation. In general then, the OLS estimates are hardly convincing evidence of the Phillips relationship. This is not unexpected as previous studies have obtained much the same results. For the most part, the price variable tends to predominate as an explanatory variable while unemployment rarely enters as significant. A number of reasons for this failure can be postulated, perhaps the most acceptable is that during the period for which data has been collected, a number of national wage and price policies by government and labor unions may have seriously affected the relationships between wages and unemployment.

The SUR estimation results are much more promising. In 11 of the 17 equations, U is predicted with the correct sign and in 7 of those cases it is significant at the .05 level or better. In 5 equations, UIN has the hypothesized signs and is significant in 4 cases. The price variable is again highly significant in every equation (except, interestingly, Kansas City). The dispersion of unemployment coefficients are greatly improved with the SUR estimation, with 9 equations having correct signs and 8 of them being significant. In general, the SUR results suggest that the technique does provide as good or better estimates than OLS. For every labor market, the SUR estimates are at least as significant (except the price variable for K.C.); in most cases they were much more significant.

Wage Interdependence and Industry Structure

Table 2, which shows the residual correlations between cities, indicates why the estimates improve so greatly using SUR. By inspection, it can be seen that many regional markets are highly correlated. For example, Midwestern cities such as Detroit, Cleveland, Minneapolis, and St. Louis are highly correlated with most other markets. Other labor markets (such as Chicago and L.A.) are highly correlated with specific markets and uncorrelated with others. Pittsburgh and Houston, on the other hand, show weak correlations with almost all of the other cities. Kansas City is an anomaly, having weak negative correlations with all but six labor markets. In general however, the residual correlations are surprisingly strong and as a result the estimated OLS equations improve significantly.

Table 2. Residual Correlation Matrix

ATL	BALT	BOS	CHI	CINCI	CLEVE	DET	HOU	K.C.	L.A.	MINN	N.Y.C.	PHILA	PITT	S.F.	SEATTLE	ST. L.	
1.000	.558	.527	.475	.471	.441	.680	.203	.077	.509	.704	.662	.313	.398	.477	.571	.651	ATL
	1.000	.574	.788	.494	.799	.849	.174	.545	.651	.873	.428	.606	.474	.678	.658	.755	BALT
		1.000	.822	.531	.685	.784	.452	−.028	.777	.675	.400	.715	.177	.895	.323	.786	BOS
			1.000	.770	.884	.898	.522	−.122	.572	.709	.332	.810	.382	.877	.520	.805	CHI
				1.000	.708	.707	.623	−.106	.195	.465	.076	.534	.422	.598	.270	.644	CINCI
					1.000	.817	.280	−.015	.483	.674	.352	.672	.702	.678	.468	.669	CLEVE
						1.000	.347	−.104	.725	.886	.497	.716	.382	.846	.620	.859	DET
							1.000	−.531	.091	.176	−.185	.603	−.069	.562	.277	.313	HOU
								1.000	.021	−.101	.019	−.445	.027	−.187	−.381	.140	K.C.
									1.000	.828	.426	.550	.140	.730	.383	.760	L.A.
										1.000	.574	.632	.419	.703	.666	.782	MINN
											1.000	.308	.230	.204	.421	.359	N.Y.C.
												1.000	.231	.742	.578	.570	PHILA
													1.000	.131	.350	.273	PITT
														1.000	.469	.839	S.F.
															1.000	.310	SEATTLE
																1.000	ST.L.

Table 3. Industry Classifications Used In Study

SIC CODE	BRIEF DESCRIPTION
20	Food and Kindred
26	Paper
28	Chemicals
29	Petroleum and Coal
30	Rubber and Plastic
32	Stone Clay and Glass
33	Primary Metal
34	Fabricated Metal
35	Machinery, Except Electrical
36	Electrical
37	Transportation
38	Instruments

Table 4. Location Quotients For 2 Digit SIC Industries

SIC #	30	34	35	38	37	32	33	36	26	29	20	28
Atlanta	.434	.447	.259	.159	.582	1.055	.282	.237	1.137	.000	.814	.631
Baltimore	.434	.475	.351	.332	.578	.824	.467	.672	.778	.282	.709	.818
Boston	1.319	.715	1.128	3.290	.273	.383	.147	1.622	.985	.191	.767	.399
Chicago	1.111	1.696	1.328	1.881	.448	.739	1.173	1.800	1.152	.881	1.135	1.230
Cincinnati	.885	1.260	1.427	.781	1.794	.578	.545	.753	1.441	1.572	1.518	1.814
Cleveland	1.203	2.432	1.933	.883	1.618	.663	2.511	1.156	.709	.426	.485	1.385
Detroit	1.072	2.343	1.779	.181	4.513	.813	1.459	.195	.373	.367	.550	.698
Houston	.267	1.292	1.055	.323	.155	.855	.882	.324	.510	5.625	.622	1.929
Kansas City	.905	.627	.649	.447	.690	1.032	.668	1.010	.976	.979	.915	.994
Los Angeles	1.241	1.193	.928	1.380	1.804	.797	.522	1.100	.621	1.392	.742	.752
Minneapolis	.691	.868	2.155	2.041	.225	.641	.327	.769	1.027	.802	.907	.471
New York C.	.421	.505	.367	.918	.146	.255	.181	.451	.560	.151	.515	.628
Philadelphia	.986	1.195	1.066	1.509	.366	.947	1.045	1.102	1.269	2.499	1.098	1.526
Pittsburgh	.527	1.196	.993	.840	.269	1.914	6.228	.870	.502	.502	.656	.580
San Francisco	.345	.809	.471	.384	.464	.743	.527	.566	.581	1.912	.958	.731
Seattle	.189	.469	.482	.179	4.197	.702	.272	.426	.832	.291	.825	.204
St. Louis	.542	.733	.676	.661	3.532	1.414	2.063	.726	.100	2.817	.486	1.367

To better understand the role that industry structure plays in the process of wage interdependence, the results of the hierarchical grouping of SMSAs is reported in Table 5. Although no acceptable criteria has been established for determining the optimal grouping within a clustering analysis; by convention it is suggested that grouping should be stopped when the total sum of squared errors increases rapidly between successive groupings. For this data set, the cutoff occurred with 5 groups. Three of the groups are reported in Table 5 with Houston and Pittsburgh appearing as outliers, forming Groups 4 and 5.

Group 1, representing Atlanta, Baltimore, Boston, Minneapolis, and New York City, is dominated by labor markets with large location quotients in only a few of the 2-digit SIC industries. For this group, Boston has 4 industries with L.Q.s greater than 1.00, while Atlanta has only 2 and Baltimore and New York

City have none. As a result, this group exhibits an industry structure more service than manufacturing oriented.

Group 2, on the other hand, is mostly characterized by labor markets with large L.Q.s across the board. Chicago and Philadelphia lead with 9 industries with L.Q.s greater than 1.00, closely followed by Cincinnati, Cleveland, and Los Angeles. Only San Francisco fails to fit this general description of Group 2.

Detroit, Seattle, and St. Louis make up Group 3 as their industry structure seems to be dominated by one industry only, that being transportation. The extremely large values for the transportation industry across these labor markets seems to wash out any other structural characteristics.

The values appearing in each group's matrix in Table 5 are borrowed from the larger residual correlation matrix in Table 2. These smaller correlations matrices can be analyzed to see the extent to which similarity in industry structure may capture the residual covariation existing in the system. Overall, the groupings represented in Table 5 capture 5 of the 15 residual correlations

Table 5. Hierarchical Grouping Of SMSAs Based On Industry Structures

Group 1

	ATL	BAL	BOS	MIN	NYC
Atlanta	—	.558	.527	.704	.662
Baltimore		—	.574	.873	.428
Boston			—	.675	.400
Minneapolis				—	.574
New York City					—

Group 2

	CHI	CIN	CLE	KC	LA	PHI	SF
Chicago	—	.770	.898	−.122	.572	.810	.877
Cincinnati		—	.708	−.106	.195	.534	.598
Cleveland			—	−.015	.483	.672	.678
Kansas City				—	−.101	−.445	−.187
Los Angeles					—	.550	.730
Philadelphia						—	.742
San Francisco							—

Group 3

	DET	SEA	STL
Detroit	—	.620	.859
Seattle		—	.310
St. Louis			—

Outliers
Houston
Pittsburgh

greater than .80 in the larger matrix, as well as 10 of the 35 greater than .70 and 15 of the 54 greater than .60. Therefore, while industrial structure cannot be held solely accountable for regional wage interdependence it does provide some possible explanation as to the process generating wage transmissions over space.

Looking at the individual groupings, it is evident that the largest correlations are present in Group 2, where 3 of the 5 values greater than .80 and 7 or the 10 greater than .70 exist. This should not be surprising as this group is dominated by manufacturing oriented structures.

Finally, an analysis of the group outliers (Houston and Pittsburgh) is of interest. Because their industry structures are atypical of those found elsewhere in the system, it is hypothesized that their interactions with other labor markets would be minimal. Indeed, this is the case as shown in Table 2. Both Pittsburgh and Houston exhibit very little interdependence between other SMSA's, with only one value being greater than .70.

Conclusions

This research proposes a methodology in which wage leadership can be examined without the need to make a priori specifications regarding the identification of wage leaders. Although the analysis stops short of actually specifying wage leaders within the regional system, it does hopefully suggest ways in which the processes of wage interdependence can be modeled. While the processes are far more complex than the empirical work here can account for, the results suggest that industry structure may account for at least some of the interaction exhibited between labor markets.

A more promising methodological approach towards analyzing the structural characteristics of regional economies is offered by White and Hewings [20] in modeling general space-time systems. Although the methodology requires both industry and region specific data (which was unavailable for this study), it allows for the incorporation of explicit input-output relationships into a model of wage interdependence. The addition of such information should allow for a more exact accounting of industry structure than can be given in the present context.

REFERENCES

1. Archibald, G. C. (1969) "The Phillips Curve and the Distribution of Unemployment," *American Economic Review* (59) pp. 124-34.

2. Arora, S. and M. Brown. (1977) "Alternative Approaches to Spatial Autocorrelations: An Improvement Over Current Practice," *International Regional Science Review* (2) pp. 67-78.

3. Bennett, R. J. *Spatial Time-Series* (London: Pion).

4. Casetti, E., L. King, and D. Jeffrey. (1971) "Structural Imbalance in the U.S. Urban-Economic System, 1960-1965," *Geographical Analysis* (3) pp. 239-55.

5. Clark, G. L. (1978) "The Relationship Between Canadian National and Regional Unemployment: Implications For a Full Employment Policy." Discussion Paper D78-12, Harvard Dept. of Regional Planning.

6. Cowling, K. and D. Metcalf. (1967) "Wage-Unemployment Relationships: A Regional Analysis for the United Kingdom 1960-65," *Oxford University Bulletin* (29) pp. 31-39.

7. Eckstein, O. and T. A. Wilson. (1962) "The Determination of Money Wages in American Industry," *Quarterly Journal of Economics* (76) pp. 379-414.

8. Hordijk, L. (1979) "Problems in Estimating Econometric Relations in Space," *Papers of the Regional Science Association* (42) pp. 99-115.

9. King, L., E. Casetti, and D. Jeffrey. (1969) "Economic Impulses in a System of Cities: A Study of Spatial Interaction," *Regional Studies* (3) pp. 213-18.

10. Kmenta, J. (1971) *Elements of Econometrics* (New York: MacMillan).

11. McGuire, T. W. and L. A. Rapping, "The Role of Market Variables and Key Bargains in Manufacturing Wage Determination," *Journal of Political Economy* (76) pp. 1015-36.

12. Marcis, R. G. and J. D. Reed. (1974) "Joint Estimation of the Determinants of Wages in Subregional Labor Markets in the United States: 1961-1972," *Journal of Regional Science* (14) pp. 259-67.

13. Martin, R. L. (1981) "Wage Change Interdependence Amongst Regional Labor Markets," in Martin, R. L. ed. *Regional Wage Inflation and Unemployment* (London: Pion) pp. 96-135.

14. Martin, R. L. and J. E. Oeppen. (1975) "The Identification of Regional Forecasting Models Using Space-Time Correlation Functions" *Transaction of Institute of British Geographers.* (66) pp. 95-118.

15. Mehra, Y. P. (1976) "Spillovers in Wage Determination in U.S. Manufacturing Industries," *Review of Economics and Statistics* (67) pp. 300-12.

16. Reed, J. D. and P. M. Hutchinson. (1976) "An Empirical Test of a Regional Phillips Curve and Wage Rate Transmission Mechanism in an Urban Hierarchy," *Annals of Regional Science,* (10) pp. 19-30.

17. Thirlwall, A. P. (1970) "Regional Phillips Curves," *Bulletin of the Oxford University Institute of Economics and Statistics* (32) pp. 19-32.

18. Thomas, R. L. and P. J. M. Stoney (1971) "Unemployment Dispersion As a Determinant of Wage Inflation in the U.K.: 1925-66." *The Manchester School* (39) pp. 83-116.

19. Weissbrod, R. S. (1976) "Diffusion of Relative Wage Inflation in Southeast Pennsylvania," *Studies in Geography 23,* Northwestern University.

20. White, E. N. and G. J. D. Hewings. (1982) "Space-Time Employment Modeling: Some Results Using Seemingly Unrelated Regression Estimators," *Journal of Regional Science,* (22) pp. 283-302.

21. Zellner, A. (1982) "An Efficient Method of Estimating Seemingly Unrelated Regressions and Tests for Aggregation Bias," *Journal of the American Statistical Association* (57) pp. 348-368.