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The Growth of Texas Counties in the 1990s: The Roles of County Size and Industry Clusters

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Abstract

Blending regional studies with growth econometrics, we apply the seemingly unrelated regression (SUR) methodology to income, employment, and population growth over 1990-2000 for all 254 Texas counties organized in 24 geographic regions. Several results are discussed, along with the role of wages in the adjustment process. First, there is support for the convergence hypothesis on real income per capita, along with persistence in employment and population. Second, large metro areas and non-metro rural areas adjacent to metro areas grow much faster than purely rural areas. Third, we find strong links between economic growth and the more technologically advanced clusters.

Keywords: Convergence; Employment; Income; Persistence; Population

JEL classification: R11; O18

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1. INTRODUCTION

Across U.S. counties, population and employment growth depend positively on initial conditions. A question remains on how to reconcile the persistent population flows with varied income patterns. Among several empirical implications of his neoclassical local growth model, Rappaport (2004, p. 556) suggests that cross-sectional regressions of population growth on local characteristics can help “identify … types of possible shocks from which an observed pattern of local growth can arise.”

Local studies have addressed, in turn, several factors that affect regional growth. For the Texas economy in particular, Brown and Yucel (2004) provide evidence that the economy has become less sensitive to fluctuations in oil prices than in the 1970s and 1980s. Looking at county-level data, Gilmer, Gurch, and Wang (2001, p. 4) sustain a contrasting pattern: “Per capita personal income for Texas averaged 92.6 percent of the U.S. level in 1997…Texas and U.S. income levels converged rapidly in the 1970s, largely because of a major boom in oil and other natural resources. The 1980s bust virtually erased this gain, however. Since 1989, Texas has grown without interruption, gaining about 4.7 percentage points through 1997.” Analyzing the five major metropolitan areas in Texas over the boom of the 1990s and the recession that began in 2001, Petersen and Caputo (2004, p. 10) conclude that “Austin and Dallas/Fort Worth, the metros that benefited most from the national high-tech expansion, fell the hardest during the downturn. While San Antonio, Houston, and El Paso, with lower concentrations of high-tech employment, did not grow as rapidly in the 1990s, they performed better during the recession.”

It is illustrative to provide channels through which sectors of activity or metropolitan areas affect local economic growth. This paper explores the implication referred to above that cross-sectional regressions of growth on local characteristics can help identify types of shocks from which an observed pattern of local growth can arise. Adapting an empirical model from recent growth studies discussed by Durlauf, Johnson, and Temple (2004) and by Higgins, Levy, and Young (2003), we study how Texas counties’ income, employment, or population growth over the 1990-2000 decade can be explained by initial levels of the share of bachelor’s degrees or more to adult population, industry specialization, and dummy variables for urbanization, all measured as of 1990.

An important issue in this study is the policy focus on *industry clusters*. Based on classifications of industry clusters in the early 1990s such as TEDC (2005) and Perryman (2002), we attempt to answer the following question: do counties organize themselves as regions sharing economic and geographic features present employment, population, and income gains over the decade? Or, do they lose from industry specialization?

This research question has important policy implications. First, if specialization is the driving force, higher growth can be achieved with a high concentration of similar economic activities within a region. Government policies should then strengthen these links. Second, income and wages may respond less than proportionately when employment and population grow over the decade, which may lead to more room for higher investment in human capital. Third, the relationship between the size of counties and their growth may not be linear but rather asymmetric.[1]

Five sections form the remainder of this study. Section 2 contains the methodology, Section 3 introduces the data, and Section 4 presents the empirical models. The results are presented in Section 5, and Section 6 concludes the work.

2. METHODOLOGY

We test whether the specialization of economic activity within concentrated activities is more conducive to knowledge spillovers or if diversity is better suited to growth. Following Glaeser et al. (1992), Feldman and Audretsch (1999) find considerable support for the diversity thesis for U.S. city-industry observations. Testing manufacturing firms in the U.K., Baptista and Swann (1998) argue for mixed results; and Porter (2003) finds that the performance of regional economies is strongly influenced by local clusters and the plurality of innovation. More recently, Woodward, Figueiredo, and Guimarães (2006) estimate the impact of R&D expenditures at universities on the decision to locate high-tech facilities and find that localization economies have a positive effect on the number of high-technology plant openings in U.S. counties.

Our empirical model blends features of recent cross-country studies with local regional growth reports. The estimation procedure we put forward herein is the seemingly unrelated regression (SUR), which has been used in the cross-section country growth literature recently by, for example, Easterly and Levine (1997), Bluedorn (2001), Alesina et al. (2003), and Alesina and La Ferrara (2004). Following Carlino and Mills (1987) and contributions thereafter, we implement SUR systems consisting of two equations (one for employment and population, another for income per capita and income per worker) or three equations (employment, population, and income per capita) for the 1990-2000 decade. As argued by Glaeser, Scheinkman, and Schleifer (1995), there is difficulty in interpreting wage growth regressions, and we choose to discuss wage equations for robustness only.

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[1] Following Barro (1991), education or human capital (EDU) appears as an important variable in a large body of work. Simon (1998) shows that cities with higher average levels of human capital will grow faster, confirming this empirically for all U.S. metropolitan areas over 1940-1986. Entrepreneurship and innovation also contribute to growth, as Beugelsdijk and Noorderhaven (2004) show on European regional economic growth. Researching labor market areas, Acs and Armington (2004) explore the fact that differences in human capital levels lead to different formation rates of service firms, while Glaeser, Scheinkman, and Schleifer (1995), Glaeser and Saiz (2003), and Glaeser and Maré (2001) examine human capital as a major determinant of city growth in the post-World War II period. In a long-run study of U.S. city growth, Simon and Nardinelli (2002) find that human capital seems to have been economically more important in manufacturing cities than in non-manufacturing cities after the rise of the automobile, while Beeson, DeJong, and Troesken (2001) study the same issues for U.S. county growth.

Several reasons justify our approach. First, the literature so far has presented very few studies at the regional level that address simultaneously personal income and patterns of employment and population growth. Does Texas have the same correlation patterns of growth in income, employment, and population faced by the whole U.S.? It turns out that it does and that interesting policy implications can be derived. Second, the particular choice of Texas counties for empirical analysis follows from its diversity. Population growth rates in the decade ranged from -37.4 percent in Loving County to +86.2 percent in Collin County, and the share of college graduates as of 1990 stood at only 0.04 in Loving County against 0.391 in Collin County. Is this a coincidence, or is it the result of a general relationship? Third, Texas has by far the highest number of counties of all the U.S. (254), which certainly helps the asymptotic accuracy of the cross-section estimations. Fourth, in contrast to metropolitan areas, counties are fixed in size, as argued by Wheeler (2003), and represent a plausible way of setting the spatial dimension since counties are the primary legal divisions of most states and legal changes to county boundaries are infrequent.

We report several findings. First, there is support for the convergence hypothesis on real income, regardless of per worker or per capita measures. We find, however, persistence in employment and in population. One way to explain these findings is through the theoretical result in Rappaport (2004) that changes in productivity cause persistent population growth and non-monotonic wage adjustment. Second, we find that large metro areas have a positive effect on growth and that non-metro rural areas adjacent to metro areas have substantially higher growth than purely rural areas. This confirms the claim by Petersen and Caputto (2004) that urban areas present highly differing growth patterns. Third, employing a regional approach to the Texas 24 regions that share geographic and economic features put forward by TEDC (2005), counties with large concentrations of biotech and life sciences and petroleum and chemicals have lower rates of growth, all else constant. Overall, this suggests that specialization contributes to growth *only* in these technologically more intensive sectors: advanced technology and manufacturing, aerospace and defense, and information and computer technology.

3. DATA

The U.S. Censuses of 1980, 1990, and 2000 (www.census.gov) are the major sources of data in this paper, from which most variables (except real income and wages, location quotients, and the dummy variables) are obtained. Personal income data are from the Bureau of Economic Analysis (BEA) (www.bea.doc.gov), Regional State and Local Personal Income, Local Area Annual Estimates: Personal Income. In order to deflate income, the CPI all items for South Urban consumers is taken from the Bureau of Labor Statistics (www.bls.gov), for the base period 1982-84 = 100.[2] Average wages are also

[2] Personal income data by BEA are also employed by Higgins, Levy, and Young (2003) and converted to real dollars, while Monchuk et al. (2005) use nominal income. The South Urban CPI is slightly lower than the national Urban CPI: 127.9 of South against 130.7 of National in 1990;

from the BEA and are calculated by dividing salary disbursements by employment positions at the county level. We also deflate nominal wages by the South Urban CPI to obtain real average wages. Doing so, we get an average real wage per job of $13,505 in 1990 and of $14,402 in 2000, against the average nominal wage of $22,481 in 1990 provided in the BEA dataset.

Table 1 contains all the descriptive statistics, including nominal variations of employment and population over the decade that are not used in the estimations. The latter simply conveys more information than variables in logarithms. Table 1 also contains two sets of sample correlation coefficients. One can see the similarity between employment and population growth as long as they are both correlated with their own initial conditions (0.454 for employment and 0.505 for population); yet they appear to be uncorrelated with the rest, other than lnEMP90 and lnL90. For wage and income growth, however, each is (mildly) negatively correlated with its own initial values, ranging from -0.159 (income per capita) to -0.226 (real wages) and to -0.365 (income per worker). On the variables in levels as of 1990, employment and population are perfectly correlated (0.997) as well as income per capita and income per worker (0.843). Correlations are smaller in the other cases.

Figure 1 contains the 254 observations of county *real income per capita growth* (vertical axis) against the level of income as of 1990. A negative relationship arises: the higher the county income in 1990, the lower the rate of growth of income over the 1990-2000 decade. Counties with higher income have had lower subsequent growth in Texas, in agreement with the convergence hypothesis set by Barro (1991) for countries of the world. *Real income per worker* has very similar graphic patterns. When employment and population are plotted in Figures 2 and 3, however, positive relationships stand out between initial values and their respective growth rates in the decade. Figure 4 displays the negative relationship between wage growth and initial wages as of 1990.

EDU90 is defined as the percentage of county population over 25 years old with a bachelor's degree or more divided by the total number of adults as of 1990. In our sample, EDU90 ranges from 0.040 in Loving County to 0.391 in Collin County, and EDU80 varies from 0.043 in Loving County to 0.319 in Brazos County. Omitted figures show that counties with a more educated workforce tend to grow faster than others.[3]

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and 167.2 of South against 172.2 of National in 2000. This CPI choice does not, however, substantially affect the calculation of real income.

[3] This human capital variable was used by Acs and Armington (2004, p. 256), while Zucker, Darby, and Brewer (1998) use the number of "top quality universities" in a region where top quality is defined by having one or more "biotech relevant" departments with scholarly quality reputational ratings. They also alternatively use "federal support" as the total number of faculty supported by federal grants to all universities in each region for biotech relevant research. Due to the level of aggregation employed in this study, our measure of education should capture appropriately the extent of knowledge across Texas counties.

All these relationships reported above for the 1990-2000 decade are also observed for the 1980-1990 decade.[4] In order to capture county size, we look at the distribution of population across counties. We expect that the more populated counties should have a different growth dynamic than the more sparsely populated areas. More rural and backward areas should be less integrated with main centers and are expected to grow slower. We classify the population of counties as of 1990 as dummy variables according to the county classification scheme by the Economic Research Service (ERS) of the U.S. Department of Agriculture (USDA) at http://www.ers.usda.gov/Data. Metro and non-metro areas are defined by the Office of Management and Budget (OMB). In 2003, OMB defined metro areas as: a) central counties with one or more urbanized areas, and b) outlying counties that are economically tied to the core counties as measured by work commuting. Non-metro counties are outside the boundaries of metro areas.

Figure 5 contains the distribution of Texas counties across the nine categories based on the ERS classification of the USDA as of 1990. We merged the central and fringe metro counties over 1 million people into one category of county size (dum90), as defined below. All others are exactly the same as in the ERS system. We list all size dummy variables (1 for the county that has population according to the figure specified as of 1990; 0 otherwise) as follows. (In parenthesis are the figures relative to 1980.)

The target competitive clusters are based on a project to build comparative advantage through industry clusters in the state of Texas, in particular, by Perryman (2002). Based on this study, the Texas Economic Development Council (TEDC, 2005) at www.texasedc.org/cluster_aug05.php defined six industry clusters as follows: "Industry cluster means a concentration of business and industries in a geographic region that are interconnected by markets they serve, the products they produce, their suppliers, the trade associations to which their employees belong, and the educational institutions from which their employees or prospective employees receive training." A similar industry classification (with five clusters, blending energy with chemicals into one single cluster) can be found in Acs, FitzRoy, and Smth (2002).

Each industry cluster is classified into three broad areas: core, support, and ancillary activities. We collect *location quotient data for the industry cluster core* areas as of 1990, except for the Middle Rio Grande Region where we take the support areas for two of the clusters due to the availability of data: advanced technology & manufacturing and

[4] The correlation coefficient between income growth rates (in logarithmic form) of all 254 counties between the 1980s and 1990s is negative: -0.351 with per worker values and -0.372 with per capita values. This is consistent with the convergence hypothesis. The same holds for average real wages: they are negatively correlated across decades by -0.248. On the other hand, correlation coefficients between employment or population growth rates (also in logarithmic form) over the same time periods are 0.704 and 0.720, respectively. These very high correlation coefficients are in line with the persistence in population flows (0.72) and convergence in income (-0.20) reported by Rappaport (2004) for the whole of U.S. counties over the 1980-1990 decade.

TABLE 1

Texas Counties: Descriptive Statistics and Correlation Coefficients in the 1990s

	Mean	**Median**	**Maximum**	**Minimum**	**Standard Deviation**	**Skewness**	**Kurtosis**
Dep. Vars.							
$\Delta \ln Y^{90\text{-}00}pc$	0.123	0.140	0.762	-0.388	0.132	-0.397	5.827
$\Delta \ln Y^{90\text{-}00}pw$	0.111	0.117	0.634	-0.388	0.131	-0.480	5.326
$\Delta \ln EMP^{90\text{-}00}$	0.114	0.109	0.612	-0.340	0.176	0.239	3.269
$\Delta \ln L^{90\text{-}00}$	0.101	0.092	0.622	-0.468	0.163	0.235	3.687
$\Delta \ln W^{90\text{-}00}$	0.062	0.063	0.795	-0.352	0.111	1.456	15.969
$\Delta Y^{90\text{-}00}pc$	1,591.92	1,494.54	22,194.35	-4,956.60	2,163.25	3.278	34.778
$\Delta Y^{90\text{-}00}pw$	3,395.65	3,417.85	31,165.10	-11,805.53	4,333.77	0.575	10.280
$\Delta EMP^{90\text{-}00}$	6,299.58	634.50	164,104	-1,305	20,802.21	5.124	30.874
$\Delta L^{90\text{-}00}$	15,217.76	1,646.00	582,379	-2,715	55,477.35	6.547	54.757
$\Delta W^{90\text{-}00}$	62.16	62.76	795.32	-352.90	111.27	1.456	15.969
Ind. Vars.							
LnY90pc	2.421	2.417	3.253	1.461	0.225	-0.292	5.342
LnY90pw	3.337	3.334	4.040	2.741	0.162	0.194	5.446
Y90pc	11,544.79	11,213.32	25,876.65	4,311.11	2,628.63	1.112	7.071
Y90pw	28,524.54	28,062.30	56,845.10	15,495.20	4,819.48	1.334	8.462
LnEMP90	30,056	5,810	1,381,829	59	118,638	8.532	85.220
LnL90	66,876	15,665	2,818,199	107	242,003	8.272	81.781
EDU90	0.129	0.113	0.391	0.040	0.053	2.077	8.294
MAN90	0.110	0.102	0.304	0.000	0.067	0.446	2.403
AMEN	1.273	1.020	5.930	-1.010	1.260	1.073	4.249
Sample Correlations	**ΔlnL90**	**ΔlnEMP90**	**ΔlnW90**	**ΔlnY90pw**	**ΔlnY90pc**		
lnEMP90	0.506	0.454	0.218	0.390	0.371		
lnL90	0.505	0.457	0.208	0.381	0.367		
lnRW90	-0.018	-0.021	-0.226	0.173	0.167		
lnY90pw	-0.093	-0.033	0.044	-0.365	-0.293		
lnY90pc	-0.025	-0.011	0.113	-0.176	-0.159		

	Mean	Median	Maximum	Minimum	Standard Deviation	Skewness	Kurtosis
Sample Correlations	**lnEMP90**	**lnL90**	**lnRW90**	**lnY90pw**	**lnY90pc**		
lnEMP90	1						
lnL90	0.997	1					
lnRW90	0.403	0.381	1				
lnY90pw	-0.001	-0.020	0.192	1			
lnY90pc	0.091	0.033	0.315	0.843	1		

Notes: The total number of observations is 254, the total of all Texas counties. Variables were defined in the text: pc stands for “per capita” and pw for “per worker” measures.

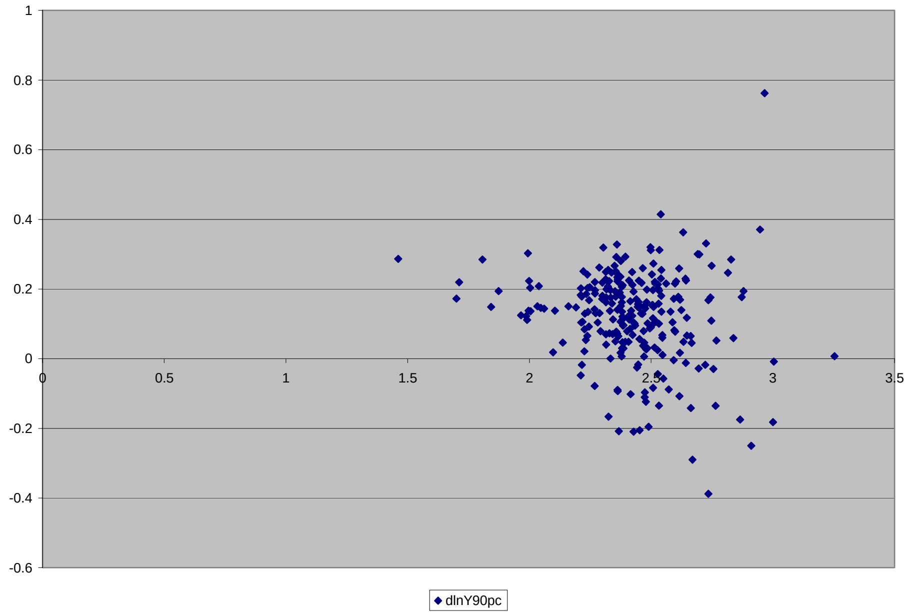

FIGURE 1. Logarithmic Growth of Texas Income Per Capita (dlnY90pc on the Vertical Axis) on Initial Income

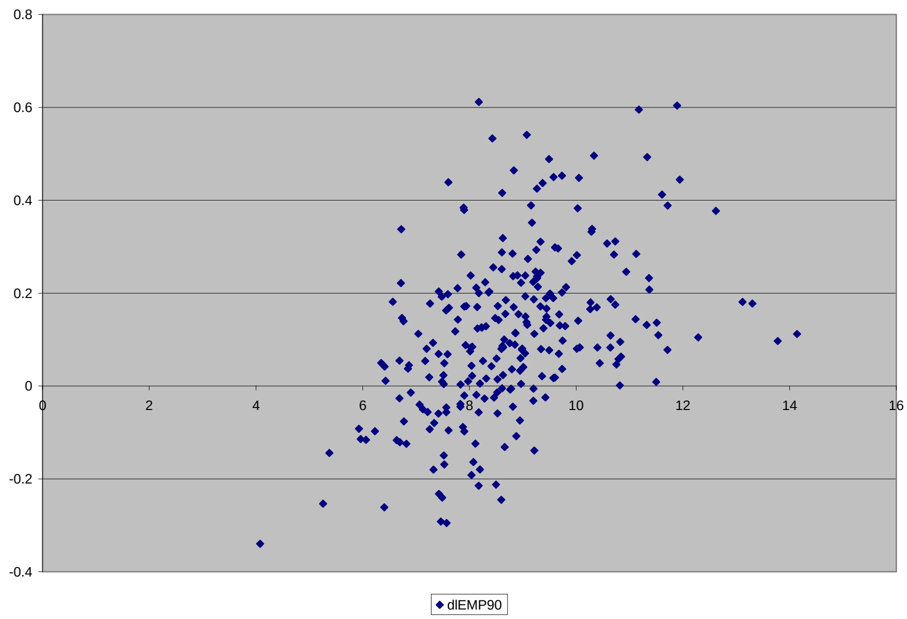

FIGURE 2. Texas Employment Growth between 1990 and 2000 (dlemp90 on Vertical Axis) on Initial Employment

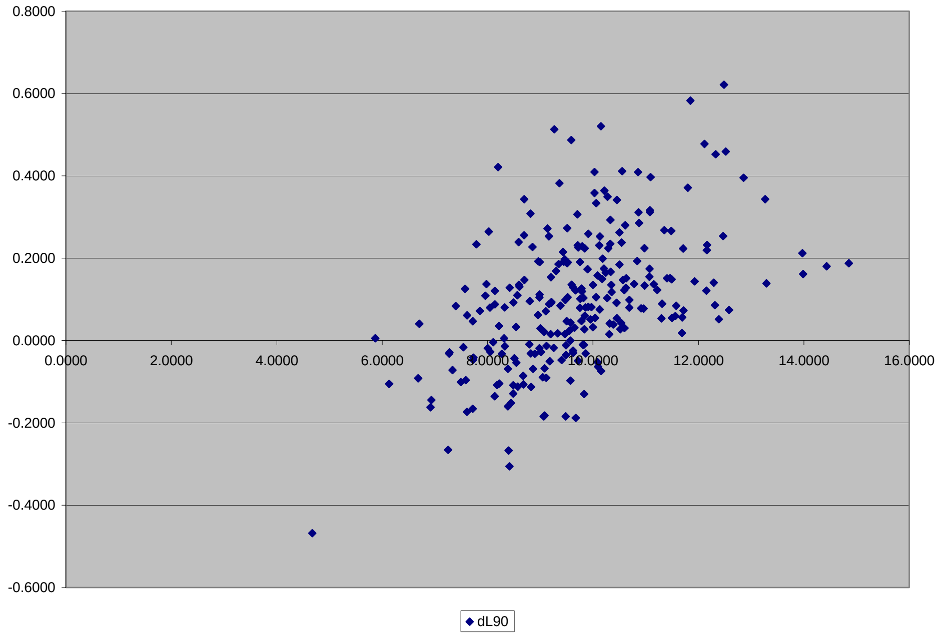

FIGURE 3. Texas Population Growth between 1990 and 2000 (logdl on Vertical Axis) on Initial Population

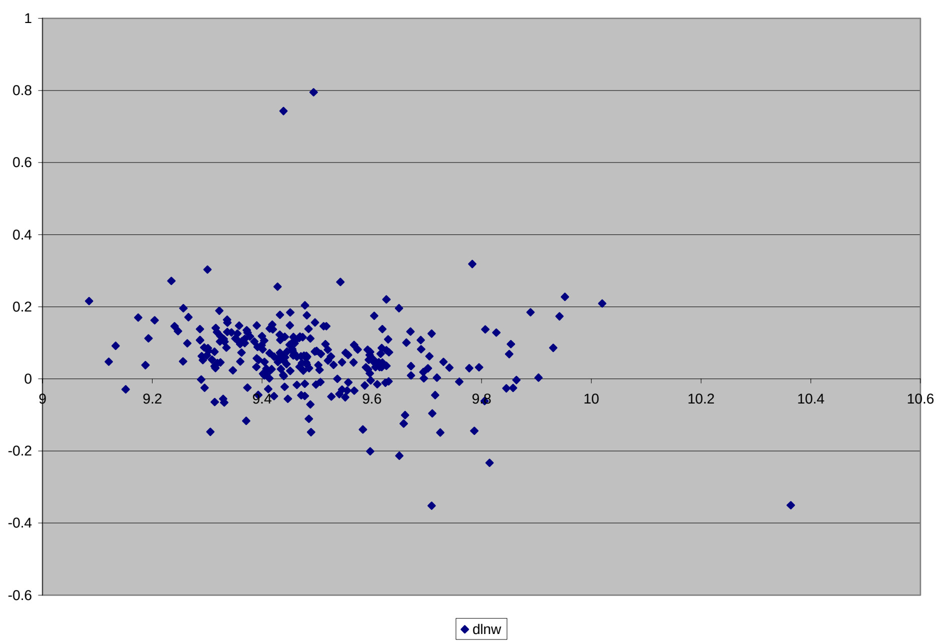

FIGURE 4. Texas Real Wage Growth between 1990 and 2000 (dlnw on Vertical Axis) on Initial Wages

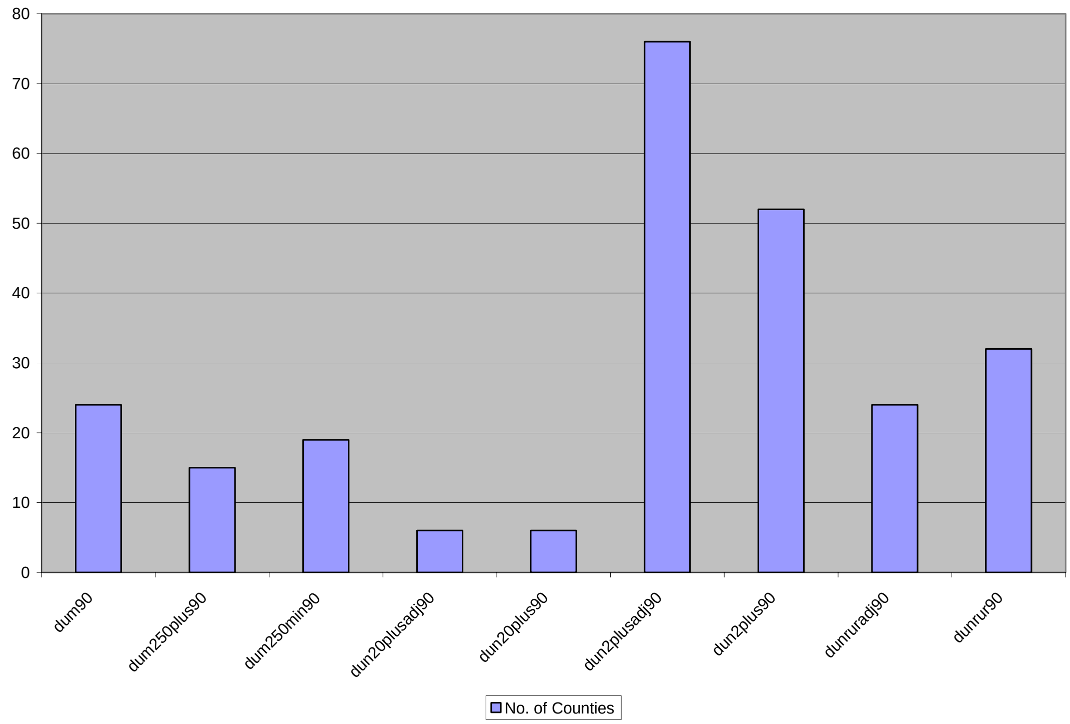

FIGURE 5. The Distribution of Texas Counties by Population Size as of ERS in 1990

dum90: 24 (up from 18 in 1980) metro counties over 1 million people;

dum250plus90: 15 (up from 10) metro counties with population over 250,000 people and less than 1 million people;

dum250min90: 19 (down from 21) metro counties with population over 20,000 people and less than 250,000 people;

dun20plusadj90: 6 (unchanged from 1980) nonmetro counties with population over 20,000 people and less than 250,000 people, adjacent to metro counties;

dun20plus90: 6 (down from 8) nonmetro counties with population over 20,000 people and less than 250,000 people;

dun2plusadj90: 76 (up from 68) nonmetro counties with population over 2,500 people and less than 20,000 people, adjacent to metro counties;

dun2plus90: 52 (down from 67) nonmetro counties with population over 2,500 people and less than 20,000 people;

dunruradj90: 24 (up from 22) nonmetro counties with population less than 2,500 people, adjacent to metro counties; and

dunrur90: 32 (down from 34) nonmetro counties with population less less than 2,500 people. In the estimations below **dunrur90** is the omitted (dummy) category.

information computer technology. The Texas Target Industry Clusters (TTICs) are described as follows.

1. Advanced Technologies and Manufacturing (**adv tech & manuf**) with four sub-clusters: nanotechnology and materials, micro-electromechanical systems, semi-conductor manufacturing, and automotive manufacturing. Core areas (in terms of employment, named after the NAICS title, excluding federal and state government) include: architectural and engineering services, aerospace product & parts manufacturing, computer systems designs, semiconductor & electronic components.

2. Aerospace and Defense (**aerospace & defense**). Core areas include: aerospace product & parts manufacturing, scientific research & development services, support activities for air transport.

3. Biotechnology and Life Sciences (**biotech & life**) ranges from pharmaceuticals and medical devices to agriculture, oil spill & toxic waste remediation, marine & fisheries, and biohazard sensors to renewable energy sources. Direct patient health care delivery is not included, however, for the purpose of cluster grouping. Core areas include: architectural & engineering services, scientific research & development services, other professional & technical services, medical & diagnostic laboratories.

4. Energy (**energy**) with three sub-clusters: oil & gas production, power generation & transmission, and manufactured energy systems. Energy distribution and marketing industry are included here. Core areas include: scientific research & development services, utility system construction, other financial investment activities, management & technical consulting services.

5. Information and Computer Technology (**info & computer tech**) with three sub-clusters: communications equipment, computing equipment & semiconductors, and information technology. Core areas include: colleges & universities, electronics & appliance stores, data processing & related services, computer systems designs.

6. Petroleum Refining and Chemical Products (**petroleum & chemical**). Core areas include: plastics product manufacturing, other financial investment activities, pipeline transportation of natural gas.

TEDC has a dataset on the six TTICs based on the location quotient, which gauges the relative concentration or specialization of industry clusters. The location quotient is calculated as a ratio of an area's employment in a specific cluster compared to a larger, presumably self-sufficient geography (the U.S.) in the same cluster. The LQ (also referred to as coefficient of specialization) is calculated as: LQ = (Total Employment in the Texas Cluster/Total Employment in Texas) / (Total Employment in the Cluster in the

U.S. /Total Employment in the U.S). Any figure at or below 1.00 implies that the region is either producing at self-sufficient levels or that it must import that product or service to meet regional demand. An LQ > 1.2, for example, indicates a very large regional concentration of an industry (such as oil & gas field services in the Permian Basin).

Due to the concept of clusters above, there is overlap between clusters 1 and 2 with respect to the aerospace product & parts manufacturing activities. On the "biotechnology & life sciences" sector, inspection reveals that the cluster captures traditional fields in areas such as "support activities for crop production" as a NAICS title. The latter includes aerial dusting or spraying, cotton ginning, planting crops, and vineyard cultivation services. This subsector tends to be large in the more remote areas of Texas. As a share of regional employment, for example, it represents only 0.009 percent of the positions in the industry core in the Alamo region (where the San Antonio MSA is located), 0.130 percent in the Panhandle, and can be as high as 69.58 percent in the Lower Rio Grande Valley.

Both TEDC (2005) and Perryman (2002) employ the regional grouping of Texas counties along geographic areas, as described in Table 2. Since specialization data are available for TEDC (2005) but not for the classification system by Perryman (2002) with 16 industry clusters, we focus on the former. For each county, we assign the respective LQ as of 1990, depending on its geographical area.

Earlier versions of this paper considered the employment shares of sectors (manufacturing & government, for example) as control variables.[5] Since the TTICs classification encompasses all sectors, we abstract from employment shares in this paper.[6] We use the natural amenity (AMEN) scale by the USDA in order to control for natural characteristics of counties such as temperature, sunshine, humidity, topographic variation, and water area. (See McGranahan (1999) for details.)

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[5] Studies have found mixed results on the manufacturing share. Glaeser, Scheinkman, and Schleifer (1995) find that income growth grew slower in cities with higher share of manufacturing employment than that of cities less involved in manufacturing (203 cities over 1960-1990). With employment or population as dependent variables, results have been mixed. Looking at 45 U.S. states over 1969-1985, Garcia-Milá and McGuire (1993) argue that states with concentrations of manufacturing or transportation & public utilities experience low employment growth. In Wheeler (2003), however, total U.S. county population and employment growth over 1990-2000 is positively affected by the percentage of employment in manufacturing. Glaeser, Scheinkman, and Schleifer (1995) find that population and employment growth involved in manufacturing grew slower than those of cities less involved in manufacturing.

[6] Manufacturing (MAN) measured as share of total employment in Texas gradually decreased over the decade. The mean and median values of MAN90 are 0.110 and 0.102 and of MAN80 are 0.130 and 0.117. Recent research in Dinlersoz (2004) presents the average share of manufacturing employment across metropolitan statistical areas (MSAs) as of 1990 at 0.200 with standard deviation of 0.09. It may be the case that Texas, having a smaller manufacturing base than the rest of the U.S., is subject to Marshallian positive externalities in that particular sector of production. After those initial stages in which externalities are operative, it is natural that MAN decreases and other sectors take up the slack.

TABLE 2

Geographical Regions Across Texas Counties

Region	**Number of Counties**	**Counties**	**Major MSA in the Region**
Alamo	12	Atascosa, Bandera, Bexar, Comal, Frio, Gillespie, Guadalupe, Karnes, Kendall, Kerr, Medina and Wilson	San Antonio
Brazos	7	Brazos, Burleson, Grimes, Leon, Madison, Robertson, and Washington	Bryan-College Station
Capital	10	Bastrop, Blanco, Burnet, Caldwell, Fayette, Hays, Lee, Llano, Travis, and Williamson	Austin-San Marcos
Central	7	Bell, Coryell, Hamilton, Lampasas, Milam, Mills, and San Saba	Killeen-Temple
Coastal Bend	12	Aransas, Bee, Brooks, Duval, Jim Wells, Kenedy, Kleberg, Live Oak, McMullen, Nueces, Refugio, and San Patricio	Corpus Christi
Concho Valley	13	Coke, Concho, Crockett, Irion, Kimble, Mason, McCulloch, Menard, Reagan, Schleicher, Sterling, Sutton, and Tom Green	San Angelo
Deep East	12	Angelina, Houston, Jasper, Nacogdoches, Newton, Polk, Sabine, San Augustine, San Jacinto, Shelby, Trinity, and Tyler	
East	14	Anderson, Camp, Cherokee, Gregg, Harrison, Henderson, Marion, Panola, Rains, Rusk, Smith, Upshur, Van Zandt, and Wood	Longview-Marshall and Tyler
Golden Crescent	7	Calhoun, DeWitt, Goliad, Gonzales, Jackson, Lavaca, and Victoria	Victoria
Gulf Coast	13	Austin, Brazoria, Chambers, Colorado, Fort Bend, Galveston, Harris, Liberty, Matagorda, Montgomery, Walker, Waller, and Wharton	Houston, Galveston-Texas City, and Brazoria
Heart of Texas	6	Bosque, Falls, Freestone, Hill, Limestone, and McLennan	Waco
Lower Rio Grande	3	Cameron, Hidalgo, and Willacy	Brownsville-Harlingen-San Benito and McAllen-Edinburg-Mission
Middle Rio Grande	9	Dimmit, Edwards, Kinney, La Salle, Maverick, Real, Uvalde, Val Verde, and	

Region	Number of Counties	Counties	Major MSA in the Region
		Zavala	
North	11	Archer, Baylor, Clay, Cottle, Foard, Hardeman, Jack, Montague, Wichita, Wilberger, and Young	Wichita-Falls
North Central	16	Collin, Dallas, Denton, Ellis, Erath, Hood, Hunt, Johnson, Kaufman, Navarro, Palo Pinto, Parker, Rockwall, Somervell, Tarrant, and Wise	Dallas and Fort Worth-Arlington
Northeast	9	Bowie, Cass, Delta, Franklin, Hopkins, Lamar, Morris, Red River, and Titus	Texarkana
Panhandle	26	Armstrong, Briscoe, Carson, Castro, Childress, Collingsworth, Dallam, Deaf Smith, Donley, Gray, Hall, Hansford, Hartley, Hemphill, Hutchison, Lipscomb, Moore, Ochiltree, Oldham, Parmer, Potter, Randall, Roberts, Sherman, Swisher, and Wheeler	Amarillo
Permian Basin	17	Andrews, Borden, Crane, Dawson, Ector, Gaines, Glasscock, Howard, Loving, Martin, Midland, Pecos, Reeves, Terrell, Upton, Ward, and Winkler	Odessa-Midland
South Plains	15	Bailey, Cochran, Crosby, Dickens, Floyd, Garza, Hale, Hockley, King, Lamb, Lubbock, Lynn, Motley, Terry, and Yoakum	Lubbock
South	4	Jim Hogg, Starr, Webb, and Zapata	
Southeast	3	Hardin, Jefferson, and Orange	Beaumont-Port Arthur
Texoma	3	Cooke, Grayson, and Fannin	Texarkana
Upper Rio Grande	6	Brewster, Culberson, El Paso, Hudspeth, Jeff Davis, and Presidio	El Paso
West Central	19	Brown, Callahan, Coleman, Comanche, Eastland, Fisher, Haskell, Jones, Kent, Knox, Mitchell, Nolan, Runnels, Scurry, Shackelford, Stephens, Stonewall, Taylor and Throckmorton	Abilene

Sources: TEDC (2005) and Perryman Group (2002).

4. THE EMPIRICAL MODELS

Our estimation strategy is based on observations of all 254 counties in Texas across two different time periods: 1990 and 2000. Data for the 1980s are used as additional controls for robustness purposes. We adopt fairly standard specifications from the cross-country growth literature, initiated by Barro (1991), and modified by the hypothesis on the size of counties and on the formation of industry clusters.[7] Specifically, we postulate models that link logarithmic county income per capita between 1990 and 2000 ($\Delta \text{lnYpc}^{90\text{–}00}$) to initial conditions of income and to the set of X-variables below.

$$(1) \qquad \Delta \text{lnYpc}^{90\text{-}00}{}_i = \alpha + \beta_1 \text{lnYpc90}_i + \gamma_1 \text{EDU90}_i + \sum_{i=1}^{p} \rho_i \, \text{SIZE90}_i + \sum_{i=1}^{q} \phi_i \, \text{CLUSTER90}_i +$$

$$\varphi_1 \text{AMEN}_i + \lambda_1 \text{lnL90}_i + \lambda_2 \Delta \text{lnYpc}^{80\text{-}90}{}_i + \varepsilon_i$$

where subscript "*i*" denotes county; and lnYpc90 stands for the 1990 county personal real income per capita, upon which quadratic or cubic terms are allowed as in Wheeler (2003). A similar equation holds for lnYpw90, the per worker values. Our set of *X*-variables contains the following variables: the percentage of college graduates (EDU90); dummy variables to capture the size of county growth as of the beginning of the 1990s according to the ERS classification (SIZE90); the location quotients as of 1990 (CLUSTER90) associated with each geographic region according to TEDC (2005); the ERS amenity variable (AMEN) capturing water and climate considerations along the lines of Rappaport and Sachs (2003) and Monchuk et al. (2005); lnL90 stands for initial population conditions following Glaeser, Scheinkman, and Schleifer (1995); and $\Delta \text{lnYpc}^{80\text{-}90}$ controls for the previous decade growth in per capita income at the county, also following Glaeser, Scheinkman, and Schleifer (1995).[8]

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[7] Durlauf, Johnson, and Temple (2004) provide comprehensive coverage of these models, and Higgins, Levy, and Young (2003) apply the methodology to U.S. counties. Growth regressions are obtained by fitting to cross-sectional data the equation: $g_i = \alpha + \beta y_{i0} + \gamma' x_i + \eta_i$ where g_i is the average growth rate of per capita income for the county *i* between years 0 and *T* $[(1/T)\ (y(\text{i}) - y(0))]$, α is a constant representing the exogenous rate of technological progress, $\beta = (1\text{-}e^{-BT}/T)$, x_i is a vector of control variables to take into account cross-economy heterogeneity in determinants of the steady-state, γ is a vector of coefficients of those variables, and η_i is the error term with zero mean and finite variance. *B* captures the responsiveness of the average growth rate to the gap between the steady-state log of income per effective unit of labor and the initial value. Durlauf, Johnson, and Temple (2004, pp. 34-35) refer to the choice of growth determinants that lie outside Solow's original theory as "varying greatly." Sala-I-Martin (1997) reports the "three fixed variables" as the ones that systematically seem to matter in all regressions run in the previous literature: the income level, life expectancy, and primary school enrollment, all measured at their initial levels. Having a total of 62 variables for each variable tested for robustness, he combines the remaining 58 variables in sets of three, estimating almost 31,000 regressions per variable. When justifying his estimation strategy, Sala-I-Martin (1997, p. 180) mentions that the "typical growth regression in the literature has (at least) seven right-hand side variables." See Fernández, Ley, and Steel (2001) for a Bayesian approach to variable selection.

[8] Previous versions of this paper for the two decades restricted the SUR system such that the coefficients on the independent variables, other than the constant term, were the same across equations. Herein the unrestricted SUR is adopted since only one decade is taken into account due to data availability on CLUSTER90. Information on growth in the previous decade is now used as an additional λ-control variable.

For examples of extending the cross-country growth model based on income to the measurement of employment and population, see Glaeser, Scheinkman, and Schleifer (1995) and Wheeler (2003), with Simon (1998) providing a theoretical approach based on localized knowledge spillovers. Empirical works by Simon and Nardinelli (2002), Glaeser and Saiz (2003), and Wheeler (2003) stress the role of human capital in a variety of contexts. The higher the college share, the higher the rate of growth of a given region since a more educated labor force contributes to productivity and to innovation. The expected sign on EDU90 in (1) is positive.

Casual observation from Section 2 suggests the most largely populated counties tended to grow faster between 1980-1990 and 1990-2000. The expected signs of SIZE90 coefficients are positive since the dummy variables are measured with respect to non-metro rural and non-adjacent counties. Along the lines of Glaeser et al. (1992), Feldman and Audretsch (1999), and Woodward, Figueiredo, and Guimarães (2006), the coefficients of CLUSTER90 should be positive if specialization is the driving force.[9] A negative coefficient, on the other hand, is consistent with diversity being more conducive to growth. Natural amenities should have a positive effect on real income as well as initial population, all else constant.

In addition to the estimation of (1) or bivariate versions with $\Delta \ln Ypw^{90\text{-}00}$, we estimate bivariate systems using variation in employment (ΔlnEMP) and variation in population (ΔlnL) over the decade as dependent variables. Carlino and Mills (1987) offer perhaps a benchmark study on the joint behavior of these variables at the county level. Others, such as Goetz and Hu (1996), have dealt with the influence of income on employment and population. Therefore, depending on the equation, we modify the variables associated as additional controls λs. For instance, when estimating (1) for ΔlnYpw, lnEMP in 1990 is used as (RHS) variable; when estimating ΔlnEMP, lnYpw in 1990 is used; and when estimating ΔlnL, lnYpc in 1990 is used. In all cases, the λ_1-coefficient is expected to be positive, capturing the extent of the market. The λ_2-coefficient on the previous decade's growth, however, could have different expected signs, depending on the degree of convergence: it should be negative for income growth equations.

Further modifications of (1) are discussed below. In SUR estimations, the efficiency gain relative to OLS increases with the correlation of the errors of the equations, as shown by Zellner (1962), Binkley (1982), Bartels and Fiebig (1991), and Binkley and

[9] An omission in the employment equation is the growth of national employment of the industry groups as regressors to account for demand shifts as in Glaeser et al. (1992). Since changes in national industry employment would be particularly important for traditional U.S. manufacturing industries, the targeted industry group LQ may also be picking up national trends. Therefore, in the current specification, the coefficients on CLUSTERS cannot be interpreted as solely reflecting localization externalities. Since the introduction of national employment growth as regressors would violate the assumption of exogenous regressors, they are omitted in the estimations. See more on this below.

Nelson (1988). Since the errors of the population and employment equations turn out to be highly correlated in practice, this motivates the SUR approach.

Estimations of the two equations in each of the systems by OLS yield consistent estimators if all RHS are exogenous variables. This is a reasonable assumption as long as only initial conditions are considered as regressors in (1). While endogeneity is an interesting issue and has been the topic of research efforts lately, our results are robust to this critique as long as all regressors are exogenous due to their initial conditions.[10]

We implement SUR systems consisting of two or three equations, each equation fitted for a dependent variable: ΔlnEMP, ΔlnL, and ΔlnY. The use of decennial data implies long-lasting sectoral shocks are taken into account across equations, as noted by Persson (1997) on Swedish counties. In order to check robustness, we adopt a "general to specific" approach, removing explanatory variables or groups of them at a time.

5. RESULTS

5.1 Preliminaries and OLS Estimations

Using OLS, we estimate simple AR (1) regressions to capture the degree of persistence in the series across decades. For employment, the estimated coefficient is 0.628 (standard error of 0.040) of past decade growth affecting growth in the 1990s (adjusted R^2 of 0.493); for population it is 0.669 (standard error of 0.041) of past decade growth affecting growth in the 1990s (adjusted R^2 of 0.517); for income per worker it is -0.257 (standard error of 0.043) of past decade growth affecting growth in the 1990s (adjusted R^2 of 0.12); for income per capita it is -0.275 (standard error of 0.043) of past decade growth affecting growth in the 1990s (adjusted R^2 of 0.135); and for wages it is -0.252 (standard error of 0.062) of past decade growth affecting growth in the 1990s (adjusted R^2 of 0.058). These suggest that employment and population move together across decades, while income and wages diverge.

We next estimate (1) and its variations for alternative dependent variables by OLS. Examining these first-pass results, Wald and t-tests on the β_2 or higher order coefficients do not suggest nonlinearities for the income growth equation. The β_1 coefficient turns out to be invariably negative when income per capita is the dependent variable. This supports the convergence hypothesis by Barro (1991) as poorer counties tend to grow

[10] In addition to national sector employment growth, the growth of LQ over the decade is not included in the regression since it would violate the exogeneity of the regressors. Another possibility is that economic growth may lead to higher education levels. There are theoretical reasons to suspect that with higher growth, density increases and human capital accumulation eventually increases in the region. In addition to initial human capital stock, Goetz and Hu (1996) add the growth in human capital as an important contributor and estimate income growth by TSLS for southern U.S. counties. Mollick (2006) studies the effects of higher education and estimates population growth by GMM for Texas counties over the 1980-2000 decade and quantifies the extent of deviation between instrumental variable methods and OLS.

faster. For employment growth, Wald and t-tests on the β_2 or higher order coefficients do suggest nonlinearities for the 1990s but not for the 1980s. This sort of result is in agreement with Wheeler (2003) for U.S. counties over the 1990s. Similar results are found for population growth. Persistence is found for employment and population in the 1990s. In all, the case for higher-order terms in population is weak.

5.2 SUR Estimations of Two-Equation Systems

We implement the two-equation SUR system for a particular decade,1990-2000, with two sets of dependent variables, employment and population growth, on the one hand and income per worker and income per capita on the other. As demonstrated by Zellner (1962) and Blinkley and Nelson (1988) more recently, the efficiency gain in the SUR procedure increases with the correlation in the residuals of the equations. Therefore, the tables below report the correlation coefficients for the residuals between the two equations. As correlation (ε_1, ε_2) is very high for each pair of equations, there are efficiency gains in the SUR procedure with respect to OLS. The two equations of each system are estimated several times, each using a smaller set of independent variables. The determinant residual covariance is invariably very low across the specifications.

Consider first the bivariate systems of equations: ΔlnEMP and ΔlnL. Table 3 presents the results for the employment equation of the SUR system of employment and population growth equations. We find the β_1-coefficient to be consistently positive, which is in agreement with the persistence hypothesis in Rappaport (2004): counties with higher initial employment tend to grow faster. The magnitude of the β_1 coefficient varies from 0.022 in column (2) to 0.045 in column (6) and to 0.050 in column (7), all statistically significant. A large initial employment base helps EMP to grow over time. These numbers are in agreement with those reported by Wheeler (2003) on all U.S. counties under OLS methods.

The γ_1-coefficient on the percentage of college degrees is positive, albeit not statistically significant in all cases. Whenever significant, higher levels of college graduates contribute to employment growth, *ceteris paribus*. The coefficient values vary from 0.395 to 0.418 in columns (5) and (6), respectively. Relative to non-metro rural (non-adjacent) counties that form the omitted category, counties with over 1 million residents contribute to higher employment growth over the decade, with ρ_1-coefficients ranging from 0.131 to a higher 0.207 in column (5). Similarly, non-metro rural counties adjacent to metro areas have higher growth than non-adjacent counties: the estimated effect varies from 0.087 in column (1) to 0.154 in column (5) for ρ_8.

Table 3 provides a mixed picture for the effect of industry clusters on employment growth across the 1990s. Throughout the specifications in columns (1) to (4), positive and strong effects of the advanced technology and manufacturing clusters are found on growth: ϕ_1 from 0.081 in column (1) to 0.140 in column (4). Similar positive effects are seen in the aerospace & defense clusters, with ϕ_2 ranging from 0.073 in column (1) to

0.111 in column (2). The impact of the information & technology cluster is also positive but smaller in magnitude, at around $\phi_5 = 0.030$. There is, however, a strong negative effect of the biotech & life sciences cluster on employment growth: ϕ_3 varying from -0.061 to -0.105. The petroleum & chemical cluster is also found to be negatively related with 1990 employment growth, with ϕ_6 ranging from -0.069 in column (1) to -0.162 in column (4).

Keeping in mind the caveat for the ϕ-coefficients discussed in footnote 9, the negative signs associated with these two clusters suggest that specialization adds little to the employment creation of these already concentrated regions. Positive employment effects are found for the more advanced manufacturing sectors comprising three clusters.

For the models with only county size dummies and simpler specifications, natural amenities have positive and statistically significant effects (φ_1) on employment growth between 0.017 and 0.019. This suggests that amenities may capture some of the omitted variables problem caused when clusters (ϕs) or other initial conditions (λs) are not taken into account. Also, Carlino and Mills (1987) demonstrated that family income has a powerful effect in stimulating both employment and population in U.S. counties. We confirm this result, as initial county income helps explain the growth of employment in the decade, with the λ_1-coefficient varying from 0.168 in column (1) to 0.144 in column (2). Consistent with employment persistence, past employment growth leads to employment creation in the decade: 0.314, statistically significant at 1 percent in column (1).

The (RHS) variables explain between 31 percent in column (5) to 55 percent in column (1) of employment fluctuations as measured by the adjusted R^2 statistics. The explanatory power is a little over 20 percent for the specifications without the county size and industry clusters. The county size and industry clusters therefore seem to help explain the variance of employment across counties, with an added contribution by the additional controls (λs).

These results are qualitatively the same when population is the dependent variable, as shown in Table 4. The results on the persistence population coefficient are about the same as before, varying between 0.020 in column (1) to 0.052 in column (7). In contrast, college degree education has a positive effect on population growth in all but the specifications in columns (1) and (2). All other coefficients for the ρs and ϕs are as before with similar magnitudes, which make about the same inference on county size growth as well as on the impact of cluster effects. The explanatory power varies from 37 percent in column (5) to 54 percent in column (1) of the variance of population growth as measured by the adjusted R^2 statistics. Omitting the size and clusters, RHS variables yield lower explanatory power than before, though close to 30 percent. We confirm that initial county income helps explain the growth of population in the decade in column (1) with a

TABLE 3

Employment Growth across Texas Counties: Two-Equation SUR Estimations

	ΔlnEMP	ΔlnEMP	ΔlnEMP	ΔlnEMP	ΔlnEMP	ΔlnEMP	ΔlnEMP
β_1	0.023**	0.022**	0.023**	0.029***	0.027**	0.045***	0.050***
	(0.009)	(0.011)	(0.011)	(0.006)	(0.012)	(0.007)	(0.006)
γ_1	-0.114	0.136	0.226	0.289	0.395*	0.418***	
	(0.174)	(0.188)	(0.188)	(0.180)	(0.208)	(0.206)	
ρ_1 (> 1 mil. metro)	0.064	0.133**	0.131**		0.207***		
	(0.050)	(0.055)	(0.055)		(0.060)		
ρ_2 (> 250k metro)	0.034	0.102*	0.086		0.152**		
	(0.054)	(0.059)	(0.059)		(0.064)		
ρ_3 (> 20k metro)	0.012	0.037	0.022		0.034		
	(0.047)	(0.053)	(0.053)		(0.059)		
ρ_4 (> 20k non-metro adj.)	0.004	-0.002	-0.015		0.028		
	(0.056)	(0.063)	(0.063)		(0.071)		
ρ_5 (> 20k non-metro)	0.033	0.054	0.041		0.058		
	(0.058)	(0.064)	(0.065)		(0.072)		
ρ_6 (>2.5k non-metro adj.)	0.025	0.043	0.035		0.090**		
	(0.031)	(0.035)	(0.035)		(0.038)		
ρ_7 (> 2.5 non-metro)	0.007	0.008	0.005		0.022		
	(0.029)	(0.032)	(0.033)		(0.037)		
ρ_8 (non-metro rural adj.)	0.087***	0.121***	0.111***		0.154***		
	(0.032)	(0.035)	(0.036)		(0.039)		
ϕ_1 (adv tech & manuf)	0.081***	0.127***	0.116***	0.140***			
	(0.021)	(0.022)	(0.022)	(0.022)			
ϕ_2 (aerospace & defense)	0.073***	0.111***	0.092***	0.108***			
	(0.018)	(0.019)	(0.018)	(0.018)			
ϕ_3 (biotech & life sciences)	-0.061***	-0.095***	-0.097***	-0.105***			
	(0.022)	(0.024)	(0.024)	(0.024)			

	ΔlnEMP	ΔlnEMP	ΔlnEMP	ΔlnEMP	ΔlnEMP	ΔlnEMP	ΔlnEMP
ϕ_4 (energy)	-0.045 (0.031)	-0.029 (0.034)	-0.021 (0.034)	-0.036 (0.035)			
ϕ_5 (info & computer tech)	0.022*** (0.008)	0.031*** (0.008)	0.030*** (0.009)	0.030*** (0.009)			
ϕ_6 (petroleum & chemical)	-0.069* (0.039)	-0.154*** (0.041)	-0.128*** (0.040)	-0.162*** (0.039)			
φ_1	0.004 (0.006)	0.008 (0.007)	0.008 (0.007)	0.007 (0.007)	0.017** (0.007)	0.017** (0.008)	0.019** (0.008)
λ_1 (lnYpw in 1990)	0.168*** (0.043)	0.144*** (0.044)					
λ_2 (ΔlnEMP in 1980s)	0.314*** (0.052)						
Correlation (ε_1, ε_2)	0.791	0.844	0.837	0.847	0.863	0.879	0.879
Adj. R^2	0.550	0.454	0.445	0.414	0.311	0.227	0.218
DW	2.154	2.108	2.127	2.104	2.087	2.047	2.102

Notes: The constant terms are not reported. The system of two equations is estimated by the unrestricted SUR method. We start with the most general specification (8 county size dummies, 6 industry clusters and initial controls) and then move on to smaller sets of independent variables. Correlation (ε_1, ε_2) measures the correlation coefficient between the residuals of the employment and population equations. The dependent variable is the change in logarithmic employment (ΔlnEMP) between 1990 and 2000. The number of observations is N = 254, the total of Texas counties, and the total number of system observations is 508.

λ_1-coefficient of 0.080. Past population county growth reinforces population creation in the decade: 0.295, statistically significant at 1 percent in column (1).

Tables 5 and 6 present the results for the SUR system between variations in income per worker and variations in income per capita equations. Wishing to exploit the inferences on income usually present in the cross-country growth literature, several observations are worth mentioning. First, the β_1-coefficient is invariably negative, lending support to the convergence hypothesis by Barro (1991): counties with higher real income tend to grow slower. The magnitude of the β_1-coefficient in column (1) changes only slightly as we go from the more general specification in column (1) (β_1 = -0.215) to the one in which only amenities in column (7) appear together with the initial level of income (β_1 = -0.213).

Second, the γ_1-coefficient on college degree is statistically significant for the model with clusters in column (4) and also with clusters in column (6), with estimated values of 0.381 and 0.520, respectively. This supports, to a certain extent, the idea that the share of college degree is conducive to income growth. Third, in columns (3) and (5) the dummy variables of more populated counties have some role in explaining variations in income per worker across Texas counties. Three industry clusters' variables are statistically significant in column (4). Columns (3) and (4) suggest positive effects of localization economies for the advanced technology & manufacturing cluster on growth: 0.033 significant at 10 percent in column (3) and 0.062 significant at 1 percent in column (4). There are, however, some negative effects of the petroleum & chemical cluster on income growth in column (4): -0.064, statistically significant at 10 percent.

In Table 5 natural amenities are important since the φ_1-coefficients usually have a positive and statistically significant effect on income growth from 0.011 to 0.013. Contrary to the employment and population regressions, the φ_1-coefficients are now almost always positive and statistically significant. The magnitudes of the φ_1-coefficients themselves are fairly stable in the income equations. Related research by Monchuk et al. (2005) reports estimated coefficients for the amenity index of 0.002 or 0.005, depending on their specifications. Employing amenity measures on employment, population, and income growth for reduced forms of decade growth in U.S. rural counties, Deller et al. (2001) find that all statistically significant amenity attributes are positively related to growth, with varying coefficients.

On diagnostics, the RHS variables chosen explain about 20.5 percent of income per worker variations as measured by the adjusted R^2 statistics in the model with industry clusters only and 29.4 percent in the model with city size only. The adjusted R^2 figures for the unconditional model are relatively smaller.

The results in Table 6 are for the growth of income per capita as the dependent variable and are similar to those in Table 5, except for two findings. First, the speed of convergence is slower for income per capita, varying from -0.075 in column (1) to -0.153

TABLE 4

Population Growth across Texas Counties: Two-Equation SUR Estimations

	ΔlnL	ΔlnL	ΔlnL	ΔlnL	ΔlnL	ΔlnL	ΔlnL
β_1	0.020**	0.024**	0.022**	0.032***	0.025**	0.045***	0.052***
	(0.009)	(0.009)	(0.009)	(0.006)	(0.010)	(0.006)	(0.006)
γ_1	0.066	0.251	0.371**	0.403**	0.515***	0.547***	
	(0.173)	(0.184)	(0.168)	(0.160)	(0.181)	(0.178)	
ρ_1 (> 1 mil. metro)	0.076	0.141***	0.150***		0.217***		
	(0.047)	(0.050)	(0.050)		(0.053)		
ρ_2 (> 250k metro)	0.055	0.104*	0.103**		0.143**		
	(0.049)	(0.053)	(0.053)		(0.056)		
ρ_3 (> 20k metro)	0.002	0.031	0.032		0.038		
	(0.044)	(0.048)	(0.048)		(0.052)		
ρ_4 (> 20k non-metro adj.)	-0.005	-0.002	-0.005		0.033		
	(0.052)	(0.058)	(0.058)		(0.063)		
ρ_5 (> 20k non-metro)	0.040	0.058	0.055		0.069		
	(0.054)	(0.059)	(0.059)		(0.064)		
ρ_6 (>2.5k non-metro adj.)	0.035	0.055*	0.054*		0.097***		
	(0.029)	(0.032)	(0.032)		(0.034)		
ρ_7 (> 2.5 non-metro)	0.016	0.024	0.023		0.037		
	(0.027)	(0.030)	(0.030)		(0.033)		
ρ_8 (non-metro rural adj.)	0.060**	0.096***	0.091***		0.126***		
	(0.030)	(0.033)	(0.033)		(0.035)		
ϕ_1 (adv tech & manuf)	0.060**	0.096***	0.093***	0.116***			
	(0.020)	(0.020)	(0.020)	(0.020)			
ϕ_2 (aerospace & defense)	0.070***	0.096***	0.087***	0.103***			
	(0.017)	(0.018)	(0.016)	(0.016)			
ϕ_3 (biotech & life sciences)	-0.034*	-0.060***	-0.062***	-0.070***			
	(0.020)	(0.022)	(0.022)	(0.022)			

	ΔlnL	ΔlnL	ΔlnL	ΔlnL	ΔlnL	ΔlnL	ΔlnL
ϕ_4 (energy)	-0.061**	-0.039	-0.035	-0.049			
	(0.029)	(0.031)	(0.031)	(0.032)			
ϕ_5 (info & computer tech)	0.018**	0.023***	0.022***	0.023***			
	(0.007)	(0.008)	(0.008)	(0.008)			
ϕ_6 (petroleum & chemical)	-0.069*	-0.138***	-0.127***	-0.160***			
	(0.036)	(0.037)	(0.036)	(0.035)			
φ_1	0.006	0.009	0.009	0.007	0.017**	0.016**	0.019**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
λ_1 (lnYpc in 1990)	0.080**	0.056					
	(0.035)	(0.035)					
λ_2 (ΔlnL in 1980s)	0.295**						
	(0.056)						
Correlation (ε_1, ε_2)	0.791	0.844	0.837	0.847	0.863	0.879	0.879
Adj. R^2	0.539	0.458	0.465	0.438	0.371	0.291	0.270
DW	2.036	1.972	1.986	1.989	1.896	1.888	1.993

Notes: The constant terms are not reported. The system of two equations is estimated by the unrestricted SUR method. We start with the most general specification (8 county size dummies, 6 industry clusters and initial controls) and then move on to smaller sets of independent variables. Correlation (ε_1, ε_2) measures the correlation coefficient between the residuals of the employment and population equations. The dependent variable is the change in logarithmic population (ΔlnL) between 1990 and 2000. The number of observations is N = 254, the total of Texas counties, and the total number of system observations is 508.

in column (6). Second, there is robustness to the positive findings of the advanced technologies and aerospace & defense clusters to economic growth: from 0.059 to 0.093 and from 0.031 to 0.052, respectively, across columns. On the other hand, there are clearly negative effects for the biotech & life science clusters on economic growth (from -0.046 to -0.057), as well as for the petroleum & chemical cluster (-0.080).

The role of past decade growth is negative for both income equations. Lagged income per worker growth has an estimated coefficient of -0.080, and lagged income per capita growth has an estimated coefficient of -0.152 in their respective equations. This confirms the degree of persistence in income across decades.

The persistence of initial employment and population levels to their subsequent growth is thus widespread, together with income convergence. A possible explanation is through the role of wages.[11] A related issue is that there may also be convergence in wages such that counties with higher initial wages are associated with lower wage growth. Simulations elsewhere show that changes in productivity cause persistent population growth and non-monotonic wage adjustment.[12]

5.3 Robustness Issues

We estimate further a system composed by income per worker and wage growth, despite the well-known difficulty in interpreting wage growth regressions since they reflect population composition changes as well as compensation changes. The correlation coefficients between the residuals of the two equations are not as high as in the foregoing systems but are not negligible either, ranging from 0.457 to 0.541, which helps the efficiency gains of SUR versus OLS. In both income and wage equations, the β_1 coefficient is invariably negative, ranging from -0.294 to -0.349 (income) to values from -0.226

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[11] The net effect on wages is difficult to ascertain. Suppose we have a simple production function with output depending on labor (EMP). In the labor market, real wages and employment are determined by the intersection between demand and supply of labor. If labor supply increases during the decade (due, e.g., to net migration to Texas), real wages can remain constant if demand for labor increases as well. In this case, there will be an expansion in EMP as well as in real income. If the supply shift is higher than the demand shift, however, real wages will fall with EMP creation. In the latter, smaller rates of growth of real wages lead to lower income growth. Employment and population rise; yet income and wages do not rise as much.

[12] The theory by Rappaport (2004) assumes two open regional economies, one large and one small, and explores the small economy's transition to its new steady-state following *small* one-time changes to its productivity and to its quality of life. Calibration exercises associated with a 5 percent increase of the steady-state small economy wages leads to an initial jump in labor wealth, which induces a population inflow. There is also a jump in the shadow value of capital, thereby inducing a capital inflow. The jump in labor wealth causes a jump in the price of housing, which dampens the population inflow. Immediately following the increase in productivity, population flows at an annual rate of 1.1 percent and at gradually decreasing rates thereafter. Wages, however, respond non-monotonically to the increase in productivity.

to -0.305 (wages). For the income equation, the coefficients on amenities were positive; for the wage equation, they were zero.[13]

Glaeser, Scheinkman, and Schleifer (1995) discuss two reasons why initial wages might be negatively correlated with wage growth: 1) technology improves more slowly in advanced cities; and 2) the net migration of labor to high-wage regions causes the wages in those regions to decline. If lagged growth rates of population are omitted from wage growth regressions and there is some parameter linking negatively quality of life to county population, then the coefficients on initial conditions will be biased. Including lagged population growth rates into a wage growth regression is a test of such bias. As long as the coefficient on the lagged population growth rate is zero, there is no theoretical link. Otherwise, wages are being driven down by net migration. Applying this idea to a system of employment and wage growth, we find that population growth in the 1980s has a statistically different from zero effect on wage growth in the 1990s.

One three-equation system is estimated for employment, population, and income per capita growth (income per worker yield very similar results). There are higher correlations between the residuals of employment and population (over 80 percent) than between each of these and income per capita. None of the qualitative results reported earlier for two-equation systems change. In particular, the findings on the dummy variables for county size are all maintained; and counties with large concentrations of biotech & life sciences and petroleum & chemicals have lower rates of growth, all else constant.

6. CONCLUDING REMARKS

Blending the Texas experience with growth econometrics, the SUR methodology yields several findings. First, controlling for several initial conditions, there is support for the convergence hypothesis on real income per worker (from β_1 = -0.213 to -0.249) and on real income per capita (from β_1 = -0.115 to -0.153). We find, however, persistence in employment growth (from β_1 = 0.022 to 0.050), as well as in population growth (β_1 = 0.022 to 0.052). We explain these findings by the theoretical result that changes in productivity cause persistent population growth and non-monotonic wage adjustment, as shown by Rappaport (2004). Natural amenities have a positive effect on income but a negligible role in employment and population regressions.

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[13] Rappaport (2004) shows an extremely long transition for an increase in the small-economy quality of life. There is a population inflow, which causes a capital inflow. The path of house rental prices also rises, thereby dampening the incentive to migrate. Wages respond non-monotonically to the increase in quality of life. Immediately following the change, wages decline at a 0.3 percent annual rate. Wage growth turns positive but remains quite small, never exceeding 0.03 percent per year. If land is allowed to enter as a factor of production, an increase in quality of life decreases steady-state wages.

TABLE 5

Income Per Worker Growth across Texas Counties: Two-Equation SUR Estimations

	ΔlnYpw	ΔlnYpw	ΔlnYpw	ΔlnYpw	ΔlnYpw	ΔlnYpw	ΔlnYpw
β_1	-0.215***	-0.234***	-0.231***	-0.220***	-0.243***	-0.249***	-0.213***
	(0.044)	(0.039)	(0.039)	(0.040)	(0.037)	(0.038)	(0.037)
γ_1	-0.008	-0.004	0.074	0.381***	0.109	0.520***	
	(0.159)	(0.160)	(0.156)	(0.145)	(0.153)	(0.143)	
ρ_1 (> 1 mil. metro)	0.085*	0.098**	0.163***		0.185***		
	(0.047)	(0.047)	(0.034)		(0.031)		
ρ_2 (> 250k metro)	0.004	0.016	0.085**		0.105***		
	(0.050)	(0.050)	(0.037)		(0.034)		
ρ_3 (> 20k metro)	0.006	0.016	0.079**		0.084***		
	(0.045)	(0.045)	(0.033)		(0.032)		
ρ_4 (> 20k non-metro adj.)	-0.036	-0.028	0.018		0.030		
	(0.053)	(0.053)	(0.049)		(0.048)		
ρ_5 (> 20k non-metro)	-0.032	-0.025	0.028		0.035		
	(0.054)	(0.055)	(0.048)		(0.048)		
ρ_6 (>2.5k non-metro adj.)	0.005	0.010	0.045		0.058**		
	(0.029)	(0.029)	(0.024)		(0.023)		
ρ_7 (> 2.5 non-metro)	-0.012	-0.012	0.015		0.019		
	(0.027)	(0.028)	(0.024)		(0.024)		
ρ_8 (non-metro rural adj.)	-0.034	-0.033	-0.022		-0.013		
	(0.030)	(0.030)	(0.030)		(0.029)		
ϕ_1 (adv tech & manuf)	0.025	0.029	0.033*	0.062***			
	(0.019)	(0.019)	(0.019)	(0.019)			
ϕ_2 (aerospace & defense)	0.016	0.018	0.019	0.041**			
	(0.016)	(0.016)	(0.016)	(0.016)			
ϕ_3 (biotech & life sciences)	0.001	-0.010	-0.010	-0.021			
	(0.021)	(0.020)	(0.020)	(0.021)			

	ΔlnYpw	ΔlnYpw	ΔlnYpw	ΔlnYpw	ΔlnYpw	ΔlnYpw	ΔlnYpw
ϕ_4 (energy)	-0.008 (0.029)	-0.006 (0.029)	-0.010 (0.029)	-0.037 (0.030)			
ϕ_5 (info & computer tech)	0.002 (0.007)	0.003 (0.007)	0.002 (0.007)	0.003 (0.008)			
ϕ_6 (petroleum & chemical)	-0.023 (0.034)	-0.026 (0.034)	-0.030 (0.035)	-0.064* (0.034)			
φ_1	0.009 (0.006)	0.011** (0.006)	0.012** (0.006)	0.006 (0.006)	0.013** (0.006)	0.008 (0.006)	0.012** (0.006)
λ_1 (lnEMP in 1990)	0.020** (0.009)	0.018** (0.009)					
λ_2 (ΔlnYpw in 1980s)	-0.080** (0.042)						
Correlation (ε_1, ε_2)	0.804	0.805	0.807	0.824	0.802	0.829	0.839
Adj. R^2	0.303	0.297	0.287	0.205	0.294	0.174	0.128
DW	2.133	2.112	2.106	2.012	2.101	2.018	2.024

Notes: The constant terms are not reported. The system of two equations is estimated by the unrestricted SUR method. We start with the most general specification (8 county size dummies, 6 industry clusters and initial controls) and then move on to smaller sets of independent variables. Correlation (ε_1, ε_2) measures the correlation coefficient between the residuals of the income per worker and income per capita equations. The dependent variable is the change in logarithmic income per worker (ΔlnYpw) between 1990 and 2000. The number of observations is N = 254, the total of Texas counties, and the total number of system observations is 508.

TABLE 6

Income Per Capita Growth across Texas Counties: Two-Equation SUR Estimations

	ΔlnYpc	ΔlnYpc	ΔlnYpc	ΔlnYpc	ΔlnYpc	ΔlnYpc	ΔlnYpc
β_1	-0.075** (0.037)	-0.128*** (0.035)	-0.129*** (0.034)	-0.120*** (0.034)	-0.145*** (0.032)	-0.153*** (0.032)	-0.115*** (0.028)
γ_1	-0.005 (0.172)	0.036 (0.176)	0.078 (0.172)	0.392** (0.161)	0.174 (0.172)	0.632*** (0.163)	
ρ_1 (> 1 mil. metro)	0.079* (0.047)	0.104** (0.048)	0.150*** (0.035)		0.189*** (0.033)		
ρ_2 (> 250k metro)	0.009 (0.050)	0.019 (0.051)	0.068* (0.038)		0.115*** (0.037)		
ρ_3 (> 20k metro)	0.011 (0.045)	0.031 (0.046)	0.076** (0.034)		0.089*** (0.034)		
ρ_4 (> 20k non-metro adj.)	-0.045 (0.054)	-0.030 (0.055)	0.004 (0.050)		0.024 (0.051)		
ρ_5 (> 20k non-metro)	-0.035 (0.055)	-0.028 (0.056)	0.010 (0.050)		0.021 (0.052)		
ρ_6 (>2.5k non-metro adj.)	-0.009 (0.030)	0.001 (0.030)	0.026 (0.025)		0.054** (0.025)		
ρ_7 (> 2.5 non-metro)	-0.029 (0.028)	-0.029 (0.028)	-0.009 (0.025)		0.000 (0.026)		
ρ_8 (non-metro rural adj.)	-0.012 (0.030)	-0.010 (0.031)	-0.002 (0.031)		0.017 (0.031)		
ϕ_1 (adv tech & manuf)	0.059*** (0.019)	0.063*** (0.019)	0.065*** (0.019)	0.093*** (0.019)			
ϕ_2 (aerospace & defense)	0.036** (0.016)	0.031* (0.017)	0.032* (0.017)	0.052*** (0.016)			
ϕ_3 (biotech & life sciences)	-0.028 (0.021)	-0.046** (0.021)	-0.046** (0.021)	-0.057*** (0.021)			

	ΔlnYpc	ΔlnYpc	ΔlnYpc	ΔlnYpc	ΔlnYpc	ΔlnYpc	ΔlnYpc
ϕ_4 (energy)	0.005	0.004	0.002	-0.023			
	(0.029)	(0.030)	(0.030)	(0.031)			
ϕ_5 (info & computer tech)	0.010	0.009	0.009	0.009			
	(0.007)	(0.007)	(0.007)	(0.008)			
ϕ_6 (petroleum & chemical)	-0.049	-0.044	-0.046	-0.080**			
	(0.035)	(0.035)	(0.036)	(0.035)			
φ_1	0.006	0.010*	0.010*	0.005	0.013**	0.007	0.012**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
λ_1 (lnL in 1990)	0.014	0.013					
	(0.009)	(0.009)					
λ_2 (ΔlnYpc in 1980s)	-0.152***						
	(0.041)						
Correlation (ε_1, ε_2)	0.802	0.805	0.807	0.824	0.802	0.829	0.839
Adj. R^2	0.287	0.253	0.251	0.188	0.206	0.079	0.029
DW	2.007	1.997	2.003	1.942	2.046	2.003	2.002

Notes: The constant terms are not reported. The system of two equations is estimated by the unrestricted SUR method. We start with the most general specification (8 county size dummies, 6 industry clusters and initial controls) and then move on to smaller sets of independent variables. Correlation (ε_1, ε_2) measures the correlation coefficient between the residuals of the income per worker and income per capita equations. The dependent variable is the change in logarithmic income per capita (ΔlnYpc) between 1990 and 2000. The number of observations is N = 254, the total of Texas counties, and the total number of system observations is 508.

Second, we find that large metro areas have a positive effect on growth and that non-metro rural areas adjacent to metro areas have substantially higher growth than purely rural areas. This confirms the claim in Petersen and Caputto (2004) that urban areas present highly differing growth patterns in Texas. Third, employing a regional approach to the 24 Texas regions that share geographic and economic features by TEDC (2005), counties with large concentrations of biotech & life sciences and petroleum & chemicals have lower rates of growth, all else constant. Employment and population growth in the 1990s have been associated with the following clusters: advanced technology & manufacturing, aerospace & defense, and information & computer technology. The effect is weaker for real income equations, but it is still there. Overall, this suggests that specialization contributes to the growth of Texas counties *only* in these technologically more intensive sectors.

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