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The effect of industrial diversity on state unemployment rate and per capita income

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Abstract. This paper examines the effect of industrial diversification on state unemployment and per capita income. Diversification may provide a form of employment insurance to states during cyclic downturns. Thus well diversified states should experience lower unemployment. To the extent that specialization confers economic benefit, however, more concentrated states should have higher per capita personal income. We use two sets of panel data for seventeen states spanning a thirty-eight year period to test these hypotheses. When state heterogeneity is controlled for properly, our results show that a strong link exists between industrial diversity and reduced unemployment. The evidence that per capita personal income is associated with industrial concentration is much weaker.

JEL classification: R23, J6

1. Introduction

The effect of industrial diversity in sub-national markets on unemployment rates has been the subject of numerous studies. In some studies[1] it is mentioned that the interest in the subject is mostly due to the potential (negative) spillover effect of the national business cycle (i.e., recession) on the sub-national economies. In other studies the tested hypothesis is that higher degrees of industrial diversity cause lower unemployment rates[2] or more stability[3]. The empirical analysis in many of these studies was performed on a cross-section sample of sub-national markets, mostly cities (or SMSAs).

The opportunity to lower unemployment through industrial diversity has also caught the attention of political leaders, especially during periods of recession. For example, in an article published in the *Detroit Free Press*

[1] See studies by Nourse (1968), Hackbart and Anderson (1975), St. Louis (1980).
[2] Simon (1988), Diamond and Simon (1990), Simon and Nardinelli (1992).
[3] Conroy (1975), Kort (1981), and Brewer (1985).

(June 18, 1988), James Blanchard, then the Governor of the State of Michigan, wrote that "... for the first time, we have the opportunity to begin breaking the boom-and-bust cycle that has marked Michigan. The simple reason is that our economy is more diversified and more competitive than at any other time in our lives."

Our paper addresses two aspects of the effect of industrial diversity – diversity's effect on unemployment rates and its effect on per-capita income. Using two sets of panel data for a sample of seventeen states, this paper first examines whether more industrially diverse states are less prone to spells of high unemployment. Then, because economic theory would suggest that some benefit to specialization should accrue, we also examine the associated question of whether or not states that are more industrially concentrated experience a benefit from such concentration in the form of higher income.[4]

The paper is organized as follows: Sect. 2 contains the theoretical background for the dual effect of industrial diversity and summarizes the hypotheses. Section 3 contains a short description of our sample, data, and statistical methods. In Sect. 4 we present the empirical results accompanied with interpretation of the results against the hypotheses presented in Sect. 2. The last section contains a summary of our main findings as well as some policy implications.

2. The model

The theory of comparative advantage shows very clearly the gain from specialization and trade. In the context of a nation, the geographic concentration of production benefits the sub-national units, i.e., regions.[5] This rationale explains why regions specialize in one or a few industries in which they enjoy a comparative advantage over their trade partners. The downside of the region specializing in one or a few industries, however, is that specialization makes the region's economy more sensitive to out-of-state economic developments.[6] Business cycles, the price of energy (or other materials), environmental policies, change in demand conditions for the specialized product(s), and competition from abroad are examples of out-of-state developments that either lead to severe decline in demand or to higher production costs, causing the production of the specialized product(s) to fall. The expected result is a decline in the demand for labor in the affected industry, higher unemployment through layoffs, and workers unable to find alternative employment in the region because there are no other industries in the region. Since labor is not very mobile in the short run, the region's unemployment rate rises because of its inability to absorb the newly unemployed workers.[7]

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[4] The dual effect of industrial diversity on economic stability and standard of living was researched also by Gilchrist and St. Louis (1990), Attanan (1986), and Cutler and Hansz (1971).

[5] Where region can be either a city (or SMSA) or a state as well as a group of states.

[6] Obviously, there are also in-state developments that may cause industry (or industries) to become less competitive. However, what happens out of state is beyond the control of an individual state whereas in-state developments are more likely to be, at least partially, under the control of the state.

[7] For a more detailed discussion on this point see Simon (1988).

Industrial diversity, it has been argued, is the solution to this problem. The diversification of employment is supposed to stabilize the regional economy. This is because the laid-off workers from one industry most likely will be able to find jobs with other industries in the area. The workers will find new jobs or stabilization will occur only to the extent that the cause for the falling demand in one industry has a different effect on the demand for the products of other industries.[8] For example, a national recession would cause a substantial decline in demand for highly income elastic goods but would only have a weak effect on demand for goods that are not sensitive to change in income.[9] The same change is likely to increase the demand for inferior goods.

In order to account for the link between industrial diversity and state unemployment and the link between diversity and state income, we propose the following model:

$$U_{it} = U(DIV_{it}, USU_t, RPIC_{it}, DEN_{it}, NWT_{it}, TEEN_{it}, OVER65_{it}, POP_{it}, POPCH_{it}) \tag{1}$$

$$RPIC_{it} = RPIC(DIV_{it}, RPICUS_t, DEN_{it}, NWT_{it}, TEEN_{it}, OVER65_{it}, POP_{it}, POPCH_{it}) \tag{2}$$

where: U – is state unemployment rate
DIV – is a measure of the degree of industrial diversity
USU – is the national unemployment rate
$RPIC$ – is state per capita income (in 1982 dollars)
DEN – is population density
NWT – is percent of working-age population that is non-white
$TEEN$ – is percent of working-age population that is 16–19 years of age
$OVER65$ – is the percent of the population 65 years and older
POP – is the state population
$POPCH$ – is the rate of population growth in a state
$RPICUS$ – is national per capita income (in 1982 dollars);
and i and t stand for state i and year t.

As noted above, the degree of state industrial diversity (DIV) is expected to have a negative effect on the state unemployment rate. States that are more diverse, will experience lower overall unemployment, while states that tend to specialize should be prone to higher levels of unemployment. This should

[8] If industries employ similarly skilled workers, this will accelerate the adjustment process and therefore maintain employment stability.

[9] We choose to abstract here from other possible influences such as movements in interest rates and the availability of bank loans. These factors change largely at the national level because of change in Fed policy. For example, the Fed moves to ease credit and reduce interest rates at the national level and thus all states benefit. However, such policy changes usually take considerable time to have significant effect. Our point here, however, is that an economically non-diverse state suffers in a recession to greater degree than other states because the lack of diversity subjects income to greater negative impact.

certainly be true during recessions. During boom times, on the other hand, we expect that the unemployment rate of a diverse state and a non-diverse state would not differ appreciably, as both unemployment rates would tend to gravitate toward the natural rate of unemployment. In other words, there is no upper bound on the unemployment rate for the non-diverse state in bad economic times, but there is a *lower bound* on the unemployment rate that such a state would enjoy during good economic times. Other things being equal, then, the average unemployment rate of a non-diverse state should be higher over time than that found for an industrially diverse state.

As is clear from Eq. (1), a variety of other variables also determine a state's unemployment rate. One important variable in this regard is the national economic condition. We use the national unemployment rate (USU) as a proxy of the condition of the national economy. It is expected that this variable has a positive effect on the state unemployment rate.

Population density (DEN) should have a negative effect on the unemployment level since higher (lower) density means lower (higher) production costs,[10] which helps a state's industries to become more competitive. State population (POP) may affect a state's unemployment rate in more than one way. It is possible that this variable serves as a proxy for economies of scale, which make a state more attractive to business. In that case, the population variable should have a negative coefficient. However, it is also possible that this variable indicates a higher cost of living and/or more generous welfare payments in more populated states. If this is the case, this variable probably has a positive coefficient. This ambiguity cannot be solved at the theoretical level and will be left for empirical test. The rate of population growth in a state (POPCH) is included to control for the impact that net migration has on a state's unemployment rate. We expect this variable to be inversely related to a state's unemployment rate, as an increase in in-migration to a state should alter the composition of the state's labor force toward individuals with a higher likelihood of employment.

The expected effect on unemployment of the proportion of teenagers (TEEN) and of people 65 years and older (OVER65) is ambiguous. On the one hand, the larger the proportion of population belonging to these two groups, the smaller is the labor force. A relatively small labor force supporting a relatively large population that is not in the labor force should lead to a lower unemployment rate. It may also be true, however, that the per capita income and thus the consumption level of these two groups is relatively low. These variables may, therefore, be positively related to unemployment due to weak demand for goods and services.

The proportion of the population that is non-white (NWT) is expected to have a positive effect on the unemployment rate because the incidence of unemployment is much higher for this group. A similar explanation can also be applied to the proportion of teenagers in the labor force variable.

The other aspect of more diversity (specialization) that we consider is the potential loss (gain) in standard of living. Equation (2) will test for this effect. The dependent variable in this case is state real per capita income, i.e., state per capita nominal income deflated by the national Consumer Price Index

[10] This is because higher density means shorter distance among economic agents, which lowers transportation as well as communication costs.

(CPI). Industrial diversity is the first explanatory variable. It is expected that more diversity has a negative effect on per capita income. A second explanatory variable is national per capita income. This variable is supposed to reflect national trends and therefore should be directly related to state real per capita income.

The other independent variables in the model are the same as in the unemployment equation. The expected effects of density of population and level of population are positive. That population density should be positively related to real per capita income follows because the cost of living index tends to be higher in states with high density. As a result, high density implies strong demand for land, leading to higher land rent. High density states therefore require higher nominal income, compared to other states, to be attractive.[11] We regard the population variable to be a proxy for disamenities such as congestion, pollution, crime, and so forth, and therefore real per capita income should be higher in more populated states. We include the measure of net migration (POPCH) because migration in response to amenities or disamenities should have a compositional effect on the level of real per capita income in a state. The proportion of the population that is non-white should have a negative effect on per capita income because this group has a higher incidence of unemployment, has lower educational attainment, and may suffer from discrimination with respect to labor market earnings. The two age-group variables – TEEN and OVER65 – should have a negative effect on per capita income because many people who belong to either one of these groups are not in the labor force yet or anymore. Thus income is probably below average for these two groups.[12]

3. Sample and data

Because most discussions of the perceived benefits of industrial diversity pertain to the state level, we use states as the geographic unit of study.[13] The variable of primary interest is the measure of industrial diversity. In order to gauge a state's degree of industrial diversity we use a standard Herfindahl Index. Calculation of this index in the work below is based on the following formula:

$$DIV_{it} = \sum_{j=1}^{n} (EMP_{ijt}/EMP_{it})^2 \tag{3}$$

[11] See Mills and Hamilton (1994) for a detailed discussion of the relationship between population density and land rent.

[12] To the extent that some of the demographic variables really proxy for something else (e.g., lack of labor market skill), one would prefer to use a more direct measure such as educational attainment of the state population. Unfortunately, good time series data for this variable do not exist, forcing us to use the demographic measures as proxy variables for the root cause of lower income.

[13] This is not to say, however, that the empirical model could not be run for other geographic units such as regions or MSAs. It is our belief, however, that regions represent a needlessly high level of aggregation. MSA data on the other hand have been shown to not be well suited to study of the industrial diversity issue. For example, Wasylenko and Erickson (1978) found that in some metropolitan areas the degree of specialization is very high and that the unemployment rate is relatively low. This happened in metropolitan areas specializing in public administration and education. In addition, metropolitan areas highly specialized in mining, primary metals, textiles, and electrical machinery showed large fluctuations in unemployment.

where DIV_{it} is the value of the Herfindahl index in state i and year t;
EMP_{ijt} is employment in state i in industry j in year t;
EMP_{it} is total state employment in year t; and
n is the number of industries in state i in year t.

Note that the higher is the value of this index, the less industrially diverse would a given state be. For example, DIV would equal 1 if there were a single industry in the state, while it would tend toward 0 if there were a large number of industries with equal employment shares.

In order to obtain the employment data necessary to calculate the Herfindahl Index we utilized two separate sources of data. The first source used is *Employment and Earnings, States and Areas* published by the Bureau of Labor Statistics. From this source we were able to obtain employment data at the 2-digit level for a variety of years for seventeen states dating as far back as 1960 in the case of California. These data run forward to 1987 in several cases. Table 1 gives descriptive statistics and makes clear that the *Employment and Earnings* data do not provide uniform coverage over time for the states in the sample. We also collected a second set of employment data for a later time period for the seventeen states in the original sample. These data are available electronically from the *County Business Patterns* web site – http://www.census.gov/epcd/cbp/view/cbpview.html. The CBP data have the advantage that observations are available for all seventeen states for each year from 1988–1997. Table 1 reports the sample mean Herfindahl for the two samples. One should note that the Herfindahl series from the two data sets differ because, while the *Employment and Earnings* data are at the 2-digit level, these data are nevertheless more aggregated than the *County Business Pattern* data, as some industrial categories are merged in the earlier data set. Because of this difference in measurement procedure, we estimated the unemployment rate and real per capita income models separately for the two series in the empirical work reported below.

The two dependent variables are annual state unemployment rate and annual state per capita personal income (in 1982 dollars). The source of data on unemployment rates and per capita personal income is the *U.S. Statistical Abstract* for various years.[14] Data for many of the other explanatory variables used in the regressions were also drawn from the *Statistical Abstract*. Data on the variables percent of the working age population that is 16–19 years of age (TEEN) and percent of the population that is 65 years and older (OVER65) come from the *Geographic Profile of Employment and Unemployment* and from state volumes of the *U.S. Census of Population* for various years.

[14] The annual state unemployment rates reported in the *Statistical Abstract* are calculated by the Bureau of Labor Statistics using the Current Population Survey. The CPS is a monthly survey administered to approximately 50,000 randomly selected households. Since it is a survey and not a census, the unemployment rate figures for all states are estimates of actual unemployment rates. The BLS seems confident that these estimates are accurate when aggregated to the annual level. Moreover, ten of the states in our sample fall into the category described by the BLS as "direct use" states, for which the unemployment rate estimates are extremely reliable. This is because these states have large populations and therefore large sample sizes in the CPS. See U.S. Bureau of Labor Statistics (2000: pp. 10–10 and 10–11).

Table 1. Descriptive statistics

Variable	Sample 1*	Sample 2**
State unemployment rate	6.54	5.60
	(2.44)	(1.54)
State per capita personal income (1982 dollars)	11755.44	15216.19
	(1512.17)	(1574.77)
Herfindahl index	636.89	354.03
	(257.70)	(34.29)
Population (in thousands)	8880.12	9508.76
	(6517.52)	(7388.02)
% Change in population	1.27	0.99
	(1.36)	(0.85)
Population density	161.4	188.09
	(1560.83)	(175.79)
% Non-white	10.18	12.98
	(6.52)	(7.48)
% Teen	9.35	7.19
	(1.15)	(0.70)
% 65 or older	11.41	12.84
	(2.23)	(2.18)
U.S. unemployment rate	6.90	5.96
	(1.65)	(0.80)
U.S. per capita personal income (1982 dollars)	11973.60	14904.78
	(1319.91)	(404.55)
Number of observations	224	170

Means with standard deviations in parentheses.

* Sample 1 ~ Time series length for individual state depends on availability of data in *Employment and Earnings, States and Areas*. Sample periods are as follows: California (1960–1986); Colorado (1972–1987); Florida (1972–1987); Georgia (1974–1987); Illinois (1966–1970, 1975–1976, 1978–1980, 1982–1987); Iowa (1964–1970, 1975–1976, 1978–1980, 1982–1987); Massachusetts (1966–1970, 1982–1987); Michigan (1976–1987); Nebraska (1975–1976, 1978–1980, 1983–1987); New Hampshire (1966–1970, 1975–1976, 1978–1980, 1982–1987); New York (1975–1976, 1978–1980, 1982–1987); North Carolina (1975–1976, 1978–1980, 1982–1985); Ohio (1975–1976, 1978–1980, 1982–1987); Oklahoma (1975–1976, 1978–1980, 1982–1986); Pennsylvania (1975–1976, 1978–1980, 1982–1986); Texas (1975–1976, 1978–1980, 1982–1987); Washington (1982–1987).

** Sample 2 ~ Time series span the period 1988–1997 for all seventeen states.

4. Empirical analysis

4.1. Econometric issues

Estimation of Eqs. (1) and (2) requires that two econometric problems be addressed. The first problem is that of possible omitted variable bias. While the list of regressors is reasonably long in both equations, the omitted variable problem nevertheless arises because of one's inability to specify or find data for all of the factors that might determine a state's unemployment rate or its level of real per capita income. Hence Eqs. (1) and (2) may be thought of in more general terms as being described by:

$$y_{it} = X_{it}\beta + \delta_i + \varepsilon_{it} \tag{4}$$

where y_{it} is the dependent variable (state unemployment rate or state real per capita income);
X_{it} is the row vector of regressors and β is the corresponding column vector of regression coefficients;
δ_i is an unobserved fixed effect specific to state i; and
ε_{it} is a random error term.

The fixed effect term, δ_i, captures idiosyncratic factors specific to a state that are unobservable to the econometrician. With respect to unemployment these factors would include unobservable differences in state labor market structure, differences in institutions such as unemployment insurance and local minimum wages, unobservable differences in types of general and specific human capital, differences in the degree to which firms pay efficiency wages, and so on. If one had only a single cross-section of data, then estimation of (4) would be confounded by an inability to take account of the δ_i terms as they would be relegated to the error term. This would not necessarily be a problem if the δ_i were orthogonal to the included regressors. But certainly it seems much more likely that there will be correlation between the fixed effects and at least some of the regressors and, as a consequence, estimates of β are likely to be biased. Fortunately, in the case at hand, both data sets are longitudinal in nature and we are able to use panel data techniques in the estimation of (1) and (2). Such techniques permit removal of the δ_i and therefore allow unbiased estimation of the parameters of interest.

The second econometric problem that we are able to address (to some degree) in the empirical work is that of spatial correlation among the states. Specifically, it seems likely that unemployment (or per capita income) in one state is likely affected by shocks to economies of neighboring states. For example, to the extent that two states such as New York and Pennsylvania or Michigan and Ohio are significant trading partners, then a demand shock in one state would have repercussions for unemployment and/or per capita income in a nearby state.

In order to deal with these two problems in the econometric work, we utilize a two-step procedure. In the first step we estimate the regression model using the standard fixed effects approach.[15] This step removes the heterogeneity term from (4) and allows unbiased estimation of the parameter vector. From the first stage estimation, we save the resulting residuals and use these to generate the contemporaneous covariance matrix for the model. In the second stage, we then re-run the fixed effects regression using feasible generalized least squares.[16] In using the feasible generalized least squares approach, we improve the efficiency of the parameter estimates.

[15] Specifically, we transform the dependent and independent variables by subtracting out a given state's mean values for these variables. This yields the regression model:

$$y_{it} - \bar{y}_i = (X_{it} - \bar{X}_i)\beta + (\varepsilon_{it} - \bar{\varepsilon}_i).$$

Note that de-meaning the data also sweeps the heterogeneity term, δ_i, from the error term, permitting unbiased estimation of the parameter vector β.

[16] Specifically, letting $\hat{\Sigma}$ symbolize the contemporaneous cross-correlation matrix determined by the first-stage residuals, we generated the feasible generalized least squares estimate of the parameter vector using $\hat{\beta} = (\tilde{X}'(\hat{\Sigma}^{-1} \otimes I)\tilde{X})^{-1} * \tilde{X}'(\hat{\Sigma}^{-1} \otimes I)\tilde{y}$, where the $\{\tilde{X}, \tilde{y}\}$ are the demeaned values of the independent and dependent variables respectively.

As noted above, we were only partially successful in implementing the second step of this approach. With respect to the earlier sample of data, we found that use of feasible generalized least squares was precluded due to the non-uniformity of the sample periods among the states. With respect to the second set of data pertaining to the 1988–1997 period, we were able to utilize a restricted version of feasible generalized least squares. Specifically, because the later sample consists of 17 cross-sectional units but only 10 time periods, it is impossible to generate a non-singular contemporaneous correlation matrix, taking possible correlation among all of the states into account. Accordingly, some restrictions must be imposed on the correlation matrix. We imposed these restrictions by grouping the states into the four major census regions. So, for example, correlation between the error terms of Michigan and Ohio is accounted for, but correlation between the error terms of Michigan and Washington state is assumed to be zero. This solution seems reasonable in that one would expect cross-state correlation in disturbances to be strongest among neighboring states. These geographically determined restrictions yielded an invertible covariance matrix.

4.2. Unemployment and industrial diversity

Tables 2 and 3 report regression results for state unemployment rates and for state per capita personal income respectively. Beginning with discussion of Table 2, we report estimates for both pooled OLS and fixed effects versions of Eq. (1) for the two sample periods. We think it useful to show both sets of results in order to get a sense of how correcting for heterogeneity affects the parameter estimates. The reader should note, furthermore, that our preferred specifications are the fixed effects column for the 1960–1987 time period and fixed effects II (which corrects for correlation among neighboring states) for the 1988–1997 time period.

The Herfindahl Index possesses the hypothesized sign and is of approximately the same magnitude in the fixed effects specifications reported in Table 2. Thus a 10-point increase in the Herfindahl Index is associated with almost a tenth of a percentage point increase in a state's unemployment rate. Given the measurement differences in the Index across the two periods, it is also useful to evaluate the influence of the Herfindahl in elasticity terms using the means reported in Table 1. Accordingly, during the earlier period the elasticity is 0.74, while in the later period the elasticity is somewhat smaller at 0.52. Thus some difference exists in the degree by which state unemployment rates respond to changes in industrial concentration across the two periods.

Though the fixed effects versions are the preferred specifications, it is nevertheless interesting to compare the pooled OLS with the fixed effects results in Table 2. Without accounting for heterogeneity (as in the pooled results), the Herfindahl Index appears to have no significant impact in either time period. Comparing this finding with the fixed effects coefficients (columns (2) and (5)) then implies that higher unemployment rate states tend to have lower Herfindahl values. In other words, the coefficient on the diversity variable is biased toward zero when heterogeneity is not controlled for. Removal of the heterogeneity term via fixed effects estimation then clearly reveals the impact of higher industrial concentration (less diversity) on state unemployment.

Table 2. Regression results: Dependent variable is state unemployment rate

Variable	1960–1987		1988–1997		
	Pooled OLS	Fixed effects	Pooled OLS	Fixed effects I	Fixed effects II*
Herfindahl index	−0.00043	0.0076	−0.0026	0.0070	0.0082
	(−0.88)	(3.68)	(−0.93)	(1.63)	(3.04)
U.S. unemployment rate	0.871	0.7004	0.825	0.936	0.923
	(7.75)	(9.54)	(6.90)	(10.22)	(20.32)
State per capita income	−0.0003	−0.00076	−0.0014	−0.00025	−0.00029
(1982 dollars)	(−2.49)	(−5.41)	(−1.59)	(−1.67)	(−3.49)
Population density	0.00012	−0.0559	0.0012	−0.0492	−0.0433
	(0.13)	(−4.75)	(1.57)	(−2.38)	(−4.22)
% Non-white	0.0316	0.169	0.0141	0.0682	0.0168
	(1.46)	(2.65)	(1.10)	(0.99)	(0.58)
% Teen	−0.273	−0.399	−0.516	−0.113	−0.0709
	(−1.62)	(−3.35)	(−3.12)	(−0.73)	(−0.98)
% 65 or older	−0.0846	0.0056	−0.137	−0.402	−0.5264
	(−1.38)	(0.04)	(−2.73)	(−1.30)	(−3.90)
Population (in thousands)	0.00012	0.00038	0.000103	0.000237	0.000239
	(5.58)	(3.65)	(8.12)	(1.19)	(4.11)
% Change in population	−0.409	−0.333	−0.425	−1.011	−0.9414
	(−4.47)	(−4.06)	(−3.72)	(−8.52)	(−16.59)
1970s	0.881	1.377	–	–	–
	(1.48)	(3.34)			
1980s	0.822	1.668	–	–	–
	(1.13)	(3.27)			
Intercept	6.451	–	8.279	–	–
	(2.93)		(2.79)		
R^2	0.63	–	0.60	–	–

Note: Parentheses contain *t*-statistics.
* Adjusts for spatial autocorrelation.

Before proceeding to discussion of other results, it is also interesting to compare the *t*-statistics for the Herfindahl coefficients reported in columns (4) and (5) of Table 2. As noted above, given the uniformity of the time series for all seventeen states during the later time period (1987–1997), we were able to take into account spatial autocorrelation across the states within broad census regions using feasible generalized least squares estimation. The results in column (4) ignore the impact of such spatial spillover effects from neighboring states, while the results in column (5) account for the possibility of spatial correlation among the states. Without taking correlation among neighboring states into account, the Herfindahl coefficient is only of borderline statistical significance during the years 1987–1997. Taking spatial autocorrelation into account, however, further reveals the effect of the industrial diversity variable to be highly significant.

Though our interest is mainly on the effect of the industrial diversity measure on state unemployment, it is nevertheless worthwhile to briefly comment on results obtained for some of the other explanatory variables. Generally speaking, many of the variables do have a statistically significant effect and most seem to have the expected sign. The coefficients on the variables measuring the impact of national (U.S. unemployment rate) and local (State per

Table 3. Regression results: Dependent variable is state real per capita income

Variable	1960–1987		1988–1997		
	Pooled OLS	Fixed effects	Pooled OLS	Fixed effects I	Fixed effects II*
Herfindahl index	0.105	3.329	−1.897	−1.413	0.233
	(0.47)	(4.11)	(−0.67)	(−0.90)	(0.26)
U.S. per capita income	1.142	1.054	1.355	1.335	1.274
(1982 dollars)	(12.61)	(13.94)	(6.67)	(16.86)	(24.25)
Population density	3.116	32.262	6.011	16.882	19.306
	(8.36)	(6.76)	(12.84)	(2.29)	(4.37)
% Non-white	−84.726	73.622	−58.509	−19.486	−24.413
	(−8.91)	(2.758)	(−5.50)	(−0.77)	(−1.74)
% Teen	−160.947	−56.684	−441.177	−18.502	0.588
	(−2.03)	(−1.08)	(−3.72)	(−0.36)	(0.019)
% 65 or older	−131.458	−216.252	−183.018	−334.70	−292.151
	(−4.77)	(−2.81)	(−4.69)	(−2.96)	(−3.80)
Population (in thousands)	0.0951	−0.153	0.0465	−0.201	−0.249
	(9.97)	(−3.25)	(4.57)	(−2.83)	(−6.41)
% Change in population	124.784	131.917	148.913	337.496	321.747
	(2.82)	(3.70)	(1.53)	(9.21)	(11.87)
1970s	−679.40	−932.62	–	–	–
	(−2.25)	(−5.07)			
1980s	−902.38	−1243.03	–	–	–
	(−2.73)	(−6.30)			
Intercept	1111.85	–	250.92	–	–
	(0.73)		(0.09)		
R^2	0.81	–	0.72	–	–

Note: Parentheses contain t-statistics.
* Adjusts for spatial autocorrelation.

capita income) economic conditions, for example, have the expected signs and are highly significant. Moreover, comparison of the two fixed effects columns for the later time period makes clear the usefulness of correcting for possible spatial autocorrelation, as t-statistics double in both instances when neighboring state effects are taken into account.

Time period analyzed matters most for the demographic variables. For example, percent of a state's population that is non-white is significantly associated with higher state unemployment in the earlier period, but does not appear to matter for the same set of states when looked at more recently. Similarly, the fraction of a state's working-age population that is 16–19 years of age is negatively related to state unemployment rate during the 1960–1987 period but the coefficient on the variable is small in magnitude and insignificant in the later period. With respect to the coefficient on this variable in the later period, it is also useful to compare the pooled versus fixed effects results. The pooled OLS coefficient would suggest that as in the earlier period a higher teen population is associated with lower unemployment. Removal of heterogeneity via the fixed effects approach suggests that this apparent relationship is an illusion and results from generally lower unemployment states having higher teen population and vice versa. Other things equal, an increase in teen population has no measurable impact on state unemployment in the later period, however. The importance of percent 65 or older moves opposite to what is found for the non-white and teen variables. Specifically, the fraction of the adult population 65 or older is not significant in the earlier period, but has a significant negative impact in the later period. In addition, controlling for heterogeneity more than triples the absolute magnitude of the coefficient on this variable (column (3) versus column (5)).

Looking at the effect of the various population measures on state unemployment rate, we note first that population density seems clearly to be associated with lower unemployment as hypothesized. Moreover, this relationship would not be evident in either period had heterogeneity gone uncontrolled. The coefficient on the population size variable suggests that larger states tend to have higher unemployment rates regardless of period. Finally, Table 2 indicates that migration to a state is associated with lower unemployment. This is particularly evident in the later period when heterogeneity is controlled for.

4.3. Personal income and industrial diversity

Table 3 contains regression results for state real per capita personal income. As was true in Table 2, our preferred specifications are reported in columns (2) and (5) of the table, where we are able to control for heterogeneity in the earlier period and are able to account for both heterogeneity and state spill-over effects in the later period. As for the variable of chief interest to this study, the Herfindahl Index, we obtain somewhat mixed results concerning its impact on state real per capita income. Column (2) of the table reveals, as hypothesized, a positive and statistically significant relationship between industrial concentration and income. In absolute terms, the coefficient estimate predicts a more than \$30 increase in real per capita income per 10 point increase in the Herfindahl Index. Evaluated at means, the elasticity for the variable is 0.18; so, though the coefficient seems large in absolute terms, its relative impact on per capita personal income is relatively small. Using data from the later period, however, evidence of any relationship between the Herfindahl and per capita income disappears. We are able to conclude at best, then, that the hypothesis that an industrially diverse state trades off employment security for lower overall income may have been weakly true at one time but does not seem to be the case more recently.

The table indicates that economic conditions at the national level, as proxied by U.S. per capita income, drive variation in per capita income at the local level regardless of time period. We find also that, as hypothesized, population density and per capita income are positively associated. This relationship becomes particularly apparent when heterogeneity is controlled for.[17] Of the demographic variables, percent 65 or older is significantly negative in both time periods, which is consistent with the notion that a more elderly population generates a compositional effect reducing income.[18] Table 3 also

[17] An anonymous referee notes, however, that it is possible income causes density by attracting in-migrants and deterring out-migration. If this is the case, then this coefficient by definition suffers some degree of simultaneity bias.

[18] Although we do acknowledge, as in the preceding footnote, that it may be the case that low income encourages out-migration and inhibits in-migration of working-age people thereby causing the demography.

shows that state population size is associated with lower per capita income in both time periods. This relationship only becomes clear once the fixed effects are eliminated. Finally, net migration, as measured by percent change in population, has a statistically significant and positive impact on real per capita income, particularly in the 1988–1997 period. The table also shows that failing to account for heterogeneity, biases this coefficient toward zero in the later time period.

5. Summary and conclusions

This paper has examined the question of whether industrial diversity is associated with lower unemployment in states. The empirical evidence that diversity does reduce unemployment is compelling. Our results also suggest, however, that the link between diversity and unemployment is not clear unless state heterogeneity is controlled for properly. Mixed evidence is found, on the other hand, to support the notion that industrial concentration (i.e., lack of diversity) can raise state per capita income. The coefficient on the diversity variable in this case is only of the right sign and statistically significant in the earlier period studied.

On the basis of the evidence presented here, we believe the conclusion that state policies aimed at diversifying industrial base are well motivated, particularly in terms of the ability of such policies to provide some degree of employment security for workers during bad economic times. Moreover, the results suggest that states engaging in industrial diversification policies do not face much in the way of downside with respect to possible personal income tradeoffs. This is particularly true in the later period studied where state per capita income is not falling (rising) with more (less) diversity.

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