Is the "new economy" benefiting rural places? A model of employment growth in high tech manufacturing industries

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Abstract

While the US experienced a remarkable economic expansion throughout the 1990s, not all regions and not all industries benefited. Over the decade, traditional sectors continued to decline, while growth in the service- and technology-based sectors that make up the “new economy” helped fuel the boom. For many, the transformation to a knowledge-based economy has heightened concerns that rural areas will fall further behind.

In this paper we investigate recent trends in high tech manufacturing industry employment and earnings growth, focusing on rural and urban differences. We first describe the growing earnings gap between rural and urban workers. We then introduce a spatial two-stage Heckman model that 1) identifies factors associated with the existence of an industry in a county, and 2) describes the factors that correlated with county-level employment growth in these industries in 6 states. The analysis examines the period 1990-2000. Our results indicate that rural, in and of itself, neither hinders nor fosters growth in high tech manufacturing industries. This suggests that place-based policies may not be necessary for these sectors. Given this, our results suggest the importance of agglomeration effects in driving both the existence and performance of high tech manufacturing industries.

Introduction

The US, experienced a remarkable economic expansion throughout the 1990s. Unfortunately, not all regions and not all industries benefited. Over the decade, traditional sectors continued to decline, while growth in the service- and technology-based sectors that make up the "new economy" helped fuel the boom. Regional growth patterns also vary, with the nation's rapid growth mostly in the south and west, while many Midwest and northeast states grew slowly.

Just like the US, rural and urban growth patterns have varied widely. While both types of areas have experienced overall growth in total employment, annual growth in urban areas has typically exceeded that in rural areas for at least 25 years (Figure 1).

[FIGURE 1 HERE]

Perhaps more striking, however, has been the increased disparity between rural and urban per capita incomes. For example, in 1969, rural per capita income was 82 percent of the urban average. By 2000, rural areas' share had declined to 77 percent. While differentials in aggregate job growth may have lead to some of this increased income difference, there are also likely other forces at work. In particular, much of this growing gap seems to have been driven by diverging earnings per worker. As an example of this growing gap, the Economic Research Service reports that rural per worker earnings as a share of metro declined from 73.8 percent in 1989 to 70 percent in 1997.

One explanation for the growing earnings gap is the reputed relatively slow transformation of rural areas to the "new economy." Because of increased competition, both at home and from abroad, businesses have embraced innovation, information and new technologies as a means to maintaining profitability. While this transformation has rewarded a large number of workers, not all have reaped the benefits, especially in rural communities (Johnson 2000; Isserman 2000). Summing up this argument, Gale and McGranahan (2001) argue that:

> Service- and technology- based industries that drove the expansion of recent years saw nearly all their growth occur in urban areas, largely leaving rural areas out of the "expanding new economy" (p 44).

As evidence of this, Gale and McGranahan note that metro earnings from producer services grew 9 percent annually between 1995 and 1998, whereas the annual growth rate was 6 percent in nonmetro areas. In response, Alan Greenspan (2000) has identified the adoption of new technologies as a great opportunity for rural growth, which can help close the earnings gap.

While previous studies have documented discrepancies between rural and urban places in the extent of participation in the “new economy,” there has been little research done in examining the “causes” of these disparities. One question of particular interest is to know whether or not rural areas are necessarily excluded from widely participating in “new economy” industries simply because they are rural; or, alternatively, are there certain resources or attributes that are not rooted in space that may be the driving factors of growth? If the former is the case, rural development policies may be a non-starter. However, if growth results from discrepancies in the endowment of (mobile) resources, then policy makers have an opening.

Starting from this perspective, we examine differentials in metro and rural participation in the high technology manufacturing industries of the “new economy.” We so by taking a closer look at recent economic performance in 6 states. In particular, we

- Describe rural growth trends in employment and earnings
- Examine factors influencing high-tech manufacturing employment growth at the county level.

At the heart of the project is a family of industry growth models. These models should help inform state-level rural development policy by improving our understanding of the correlates of high technology manufacturing growth. This information can then be used not only to refine current programs but also serve as the foundation for new initiatives.

While our work is based on well-accepted models of industry location and growth, we offer two important contributions. First, our model is fairly disaggregated. Whereas most county models focus on total or manufacturing employment growth, we examine growth at the 2-digit SIC level for counties in 6 northern states. Our second contribution arises from our first: because a number of counties have zero employment in various two digit manufacturing industries, the application of the econometric methods in similar studies—such as OLS—are inappropriate, due to selection bias (resulting when growth models are examine on counties where the industry does not exist). In this paper we correct for this problem—as well as spatial autocorrelation—by implementing a “two step” model (a la Heckman 1979) that allows for spatial spillovers.

Understanding Rural Growth Trends

When trying to understand rural economic development in the US, comparisons are important. In this section we provide a brief overview of recent trends in the rural places relative to metro places in 6 states.[1] Of particular interest is how rural areas fared in the high technology manufacturing sectors of the "New Economy" from 1990-2000. This analysis is based on definitions of "New Economy" industries forwarded by Gale and McGranahan. These definitions classify two groups of 2-digit SIC industries as key to the new economy, namely "high-technology manufacturing" and "producer services." The particular industries of interest are presented below.

Employment growth is one of the most important indicators of local economic performance. For the period 1990-2000, US employment increased 20.1 percent. In Figure 2, we compare metro and rural employment growth rates for the comparison states.

[FIGURE 2 HERE]

In this chart, we see fact that employment in rural counties grew at a slightly faster rate than it did in metro counties in 4 states (Michigan, Minnesota, Ohio and Pennsylvania. In 3 of these states (Minnesota, Michigan and Ohio), rural employment growth rates were faster than the US growth rate.

When looking at "high tech" manufacturing however, we see that the sector actually exhibited negative growth at the national level over the 1990s, declining by 7 percent (Table 1). Yet this loss was concentrated in metro areas, as aggregate "high tech" employment grew by 7 percent in the rural counties in the states of interest. Most of the rural employment growth was in "Transportation Equipment" with nearly 20,000 of the 24,000 new "high tech" manufacturing jobs accruing to this sector. Overall, this sector makes up 11 percent of all rural employment in the state's of interest.

[TABLE 1 HERE]

A second important economic indicator is earnings per worker. This is calculated as the total payroll divided by the number of workers, and is often thought of as a proxy for average employee wages.

In 2000, the average earnings per job in the United States were $35,304. This represents a 52 percent increase from 1990. In all comparison states, the average earnings per worker were greater in metro counties than they were in rural counties in 2000 (Figure 3). Rural Pennsylvania counties had lower average earnings per worker ($22,255) than any of the comparison states. The average

[1] In this study we examine performance in 6 states. These states were chosen by cluster analysis to identify the 5 states "most like" Pennsylvania. The clustering variables included: population, percent rural, per capita income and economic base. This method is detailed in the appendix.

earnings per worker in the state's metro counties ($32,649) was also less than the average for metro counties in each of the comparison states.

[FIGURE 3 HERE]

When looking at growth in average earnings per worker from 1990-2000, we see that rural counties tended to have slower per worker earnings growth than metro ones within the same states. For the states of interest, the average growth in earnings per worker was 38 percent for rural counties and 52 percent in metro counties. Looking at Pennsylvania, we see that earnings per worker in the state's rural counties grew slower than the state's metro counties: 36 percent versus 48 percent (Figure 4). Faster metro earnings growth is true for all of the comparison states as well. It is also noteworthy that growth in rural earnings per worker in Pennsylvania trailed all comparison states except Illinois (33 percent).

[FIGURE 4 HERE]

The difference in per worker earnings growth rates between rural and urban places was smallest in Ohio (43 percent versus 37 percent) and largest in New York (60 percent versus 40 percent).

The information in the two preceding charts translates into a growing per worker earnings gap between rural and urban places (Figure 5). For example, in 1990 the average rural earnings per worker in Pennsylvania were 74 percent of the metro average. In 2000, the rural average was only 68 percent of the metro average in the state. Of the comparison states, the 2000 gap between rural and metro average earnings per worker was smallest in Ohio (86 percent) and largest in New York (58 percent).

[FIGURE 5 HERE]

Understanding Industry Growth at the County Level

Researchers, policymakers and development professionals have a longstanding interest in identifying factors that foster local economic growth. In many instances, local economic growth is a matter of being in the right place at the right time. In these cases, a community may be home to one or several industries that produce goods and services that are seeing a substantial increase in demand. Such instances often reveal themselves as an "economic boom."

Given the serendipitous nature of many local economic booms, it may not be wise for a community to pin its hopes on happenstance. Thus, from a policy making perspective, the relevant question is "are there local factors that can positively influence the prospects for long-term economic growth?" If the answer is yes, then local development officials and various levels of government may be in a position to implement policies and strategies that strengthen rural economies.

In this section we estimate a series of econometric models that look at industry growth as a function of a number of potentially important local and state variables. In general, these models are based on an extensive review of previous studies that look at correlates of economic growth. While a detailed review of the literature is beyond the scope of this paper, our work draws mostly on the following studies: Carlino and Mills (1987); Kusmin (1994); Clark and Murphy (1986); Kusmin, Redman and Sears (1996); Aldrich and Kusmin (1997); Deller et al (2001).

An Empirical Model of Local Industry Growth

Overall, we looked at county employment growth from 1990-2000. This work uses data from the IMPLAN dataset (www.implan.com), allowing us to circumvent potential data disclosure problems. At the county level we look at the level of employment growth for (7) 2-digit SIC industries.

Explanatory Variables

Founded on the premise that businesses maximize profits and households maximize utility, regional growth theory and previous empirical work suggest that a number of factors influence local economic performance, including levels of taxation and public expenditure, local business conditions, local amenities, and government actions which vary by geographic location (e.g., Clark and Murphy, Carlino and Mills). The remainder of this section provides a conceptual basis for the influence of these factors on regional economic activity. In Table 2 we describe the specific measures used, as well as data sources.

[TABLE 2 HERE]

Local wages are hypothesized to affect regional employment growth. Economic theory suggests that firms making location and expansion decisions try to minimize production costs, including labor. This implies that firms will be drawn to counties with relatively low wage costs. In our models, we used the industry average earnings per worker as the measure of local wages.

Economic growth is also expected to depend on **local taxes**. Assuming that firms minimize costs, higher local taxes might discourage business location and slow economic growth. This may not be the case, however, if firms find that the benefits of higher taxes (i.e., more or higher quality public services) outweigh the costs. In our models we used data from the 1992 Census of Governments to arrive at a proxy for local taxes; namely, the total local tax revenue divided by the local population (i.e., per capita local tax revenues).

Locations providing higher quality **public services** are hypothesized to experience more rapid economic growth as they are thought to be more attractive to businesses. As noted above, firms may even be willing to pay higher taxes to finance higher quality services. The quality of a specific public service is typically proxied by the level of local expenditure on it, as greater expenditure is assumed to finance higher quality service. In our models we used data from the 1992 Census of Governments to arrive at a proxy for local government services; namely, the total local expenditures divided by the local population (i.e., per capita local expenditures).

Proximity to input and output markets can influence local economic growth. **Market access** refers to both the extent of the local transportation system and the location's proximity to input and output markets. Locations that provide easy access to suppliers and consumers likely offer firms both reduced transport costs and increased convenience. In our study, we used several measures: a metro/rural dummy variable, which takes on a value of one if the county is a rural county, as defined by the USDA Beale codes; a dummy variable that identifies rural counties that are not adjacent to metropolitan counties, once again from the Beale codes; the number of state and interstate highway miles in a county (from the Federal Highway Administration) and a dummy variable for the existence of a interstate highway interchange (from the Federal Highway Administration). Finally, we have a variable dummy for the existence of a commercial airport.

Labor market characteristics may also affect county growth. Firms are expected to prefer locations with an adequate labor supply, as these locations generally provide a more diverse and flexible work force and offer lower recruitment and retention costs (Henderson and McNamara). Here, we proxy this with local population from the 1990 Census.

Labor quality is also expected to spur growth. Educational attainment is considered a proxy for the quality of labor force (Duffy-Deno). As the level of skill and education in the labor market rise, areas with a greater supply of more educated labor are expected to experience more rapid growth (Teixeira and Swaim). However, demand for educated labor varies by industry, and some firms may find an area with lower educational attainment more attractive. Here we have several measure of labor quality: the percent of population with only a high school degree; the percent of population with at least a college degree; and the local poverty rate. These variables are all from the 1990 Census.

The extent of **industry agglomeration** is also suggested to have an influence on business location and economic growth. A new theory of growth suggests that "industry clusters" (groups of related industries) are the drivers of local growth. To capture this, we develop a measure of the local demand for industry products by other industries. This uses data from the 1990 US input-output model to determine the extent of linkages between industries in a county. It does this my multiplying the row coefficients of the industry direct requirements matrix (which capture the sales of one business to another) by the vector of local employment. This generates the number of local jobs supported by the industry of interest. According to this cluster hypothesis, growth will be stronger when local industries have greater linkages. In defining this variable, we use the Intermediate Demand Variable (IDV) forwarded by Moghadam and Ballard (1988), where the IDV serves as a proxy for the intermediate demand for deliveries from a given sector to all other sectors in the local economy. Specifically:

$$IDV_i = \sum_{j=1, j\neq i}^{n} a_{ij}^{US} EMP_i$$

Here, the IDV is the product of the *ith* row of the national IO coefficient table and the vector of employment in all the sectors of the regional economy.

The current **industry strength** is a related variable. Here, we look at the relationship between an industry's location quotient and growth. (The location quotient is the county industry's share of total employment divided by the US industry's share of total employment.) A location quotient great than one suggest that the industry has a competitive advantage in that industry, as it employs more workers in that sector relative to the US.

Natural amenities that enhance a location as a place to live or work are hypothesized to impact local economic growth. Natural amenities are thought to be of particular interest to individuals such as retirees and vacationers in search of pleasant places for recreation and residence. Thus, locations with warmer and/or milder climates, varied topography, and the presence of surface water are expected to experience more rapid economic growth (McGranahan). Businesses may also be drawn to these locations due to lower costs associated with them, such as reduced heating costs, or to accommodate a work force sensitive to quality-of-life concerns (Aldrich and Kusmin). Here, we use the natural amenities scale (NAS) developed Economic Research Service of USDA. This scale ranks counties according to the presence of a number of natural and climate amenities.

Local growth may also be closely related to **state policies**. Over time, states vary in their attractiveness to households and firms making location decisions. Counties located in states that are particularly attractive during a given period may be more likely to experience rapid economic growth themselves. State dummy variables serve as proxies for these differences in perceived attractiveness as they may capture statewide amenities, economic development policies, and infrastructures.

We can now specify a basic county model, where growth is a function of the above factors.

Growth = f(wages, taxes, public services, market access, labor force, industry clustering, natural amenities, state policy)

Estimation Methods and Results

Before estimating this model, there are two important econometric issues that must be dealt with for the problem at hand. The first econometric problem is selection bias. As noted above, this model is being estimated at the county level for 2-digit SIC "high tech manufacturing" industries. Because this data is set is quite disaggregated--as these models go--there are a number of instances where a particular industry may not exist in a fair number of counties. A selection problem arises when trying to estimate a county-level model of industry growth when an industry does not exist: there can be no growth.

Sample selection arises in the model used in the analysis because location theory implies that an industry will exist only in those counties where expected profits are greater than zero. Conversely, the industry should not exist in a county where expected profits are negative. The omitted variables that explain location are not randomly chosen from the population of values for those variables, but from those values associated with the actual location of that industry. This potentially results in biased parameter estimates that could change the results implied by the growth model significantly. In this case the selection mechanism is the initial location of an industry.

The sample selection framework is actually a special case of a switching regression model. There exists an observed outcome and an unobserved outcome determined by a discrete choice model. The growth model is specified as:

(1) $y_i = x_i\beta + \varepsilon$

where y_i is employment growth, x_i is the set of regional characteristics, β is a corresponding parameter vector, and ε_i is an independently, identically, normally distributed error. The dependent variable is observed only when the industry location selection rule holds. This selection rule is given by:

(2) y_i is observed for $z_i^* > c$; where $z_i^* = \omega_i\gamma + \mu_i$

where z_i is the continuous location value, ω_i is the set of exogenous determinants of location, γ a corresponding parameter vector, and μ is an independently, identically, normally distributed error. In general one does not observe the variable z_i^* directly, but instead a discrete version is observed:

(3) $z_i = 1$ if $z_i^* > c$; *otherwise* $z_i = 0$

In our problem, we hesitate to assume independence between the errors, ε and μ. This is due to the likelihood that many of the omitted factors in equation (1) are important, but omitted, in equation (2). This has important implications in estimation, particularly, we now we have a jointly normal distribution with correlation coefficient ρ:

$$(4)\quad \begin{bmatrix} \mu_i \\ \varepsilon_i \end{bmatrix} \sim N\left(\begin{matrix} 0 \\ 0 \end{matrix} \middle| \begin{bmatrix} \sigma_\mu^2 & \sigma_{\mu\varepsilon} \\ \sigma_{\varepsilon\mu} & \sigma_\varepsilon^2 \end{bmatrix} \right) \quad \textit{where } \sigma_{\mu\varepsilon} = \sigma_{\varepsilon\mu} = \rho\sigma_\mu\sigma_\varepsilon$$

Now, taking conditional expectations, the observed *y* conditional on the selection rule is:

$$(5)\quad \begin{aligned} & E(y_i | z_i^* > c) = x_i\beta + M_i\left(\sigma_{\varepsilon\mu} / \sigma_\mu \right) + E(\eta_i | z_i^* > c) \quad \textit{where} \\ & M_i = \left[\phi\left(c - \omega_i\gamma / \sigma_\mu \right) \Big/ 1 - \Phi\left(c - \omega_i\gamma / \sigma_\mu \right) \right] \end{aligned}$$

M, which accounts for the PDF(φ) and CDF(Φ), is the inverse-Mills ratio. Spatial weights are represented by ω. By accounting for selection bias, the econometric model is alternatively written:

$$(6)\quad \begin{aligned} & y_i = x_i\beta + M_i\left(\sigma_{\varepsilon\mu} / \sigma_u \right) + \eta_i \quad \textit{for } y_i \textit{ such that } z_i^* > c, \\ & \eta \sim N(0, \sigma_\varepsilon^2\psi) \quad \textit{where } \psi_{ii} = (1 - \rho^2\delta_i) \end{aligned}$$

Here, Ψ is the matrix of heteroscedastic variances.

Heckman (1979) has developed a two-stage model that handles such problems. Given our framework, in the first stage we must estimate a model on the existence (i.e., location) of an industry and in the second stage we can estimate the growth of that industry in counties where it does exist. In Hekcman's model, the first step is to estimate a standard Probit model for the selection mechanism. From the first step results the bias correction variables are constructed (i.e., the inverse-Mills ratio). The second step is maximum-likelihood estimation of the growth value function corrected for selection bias and conditional on the first stage parameters.

Yet there is a second econometric problem that arises in such situations that is not accounted for in the Heckman procedure, namely spatial dependence. These spatial dependencies occur because omitted variables (unobserved) are themselves spatially correlated. This in turn leads to spatial error dependence, implying a non-spherical variance-covariance structure. While spatial error dependence does not bias OLS coefficients, it does reduce the efficiency of the parameter estimates and bias the standard error estimates.

A number of recent empirical papers in regional science note the importance of space in economic growth (CITE). Econometric results from these studies suggest that the empirical performance of standard growth models improves when spatial autocorrelation is accounted for. Thus, in order to properly address the problem at hand, we must have an estimator that allows for spatial dependence.

In an unpublished paper Mark Fleming (2000) forwards a model where sample selection and spatial dependence can be investigated simultaneously with the use of a two-step sample selection estimation method. This is a rather complicated problem, Fleming notes, as "sample selection alone causes inconsistency and parameter bias, while spatial error autocorrelation alone causes inefficiency. The combination of the two results in a more complex form of sample selection bias."

Fleming introduces spatial autocorrelation into (1) with:

$$(7)\quad \varepsilon = \lambda_\varepsilon W_\varepsilon \varepsilon + e,\ e \sim N(0, \sigma_e^2 I)$$

Here, λ_ε is unknown and needs to be estimated. The spatial weights matrix is **W**. (Below, we use queen contiguity for the weights matrix).

In effect, Fleming's model is a Heckman model with spatial autocorrelation. We do not delve into the particulars of the model here, as the derivation is lengthy. However, the basic premise of the model is to include a spatial weights matrix in both steps of the model. In particular, Fleming first derives a "spatial sample selection model," with the error term now incorporating a spatial weights matrix in the inverse-Mills ratio. He then uses this as a modified probit analysis for the first step of the Heckman procedure.

By doing so, Fleming derives bias corrected variables that allow for spatial autocorrelation. These results are then a variant of (5):

$$y_i = x_i\beta + M_i\left(\rho\sigma_\mu\sigma_\varepsilon \ {}_j a_{\varepsilon ij} \big/ \sigma_\mu \right) + \eta_i \quad \text{for } y_i^* \text{ observed when } z_i^* > c$$

$$(8)\quad M_i = \left[\phi\left(c - \omega_i\gamma \big/ \sigma_\mu \right) \Big/ 1 - \Phi\left(c - \omega_i\gamma \big/ \sigma_\mu \right) \right]$$

$$\eta \sim N(0,\Omega), \Omega = \sigma_e^2 (I - \lambda_\varepsilon W_\varepsilon)^{-1} \Psi (I - \lambda_\varepsilon W_\varepsilon)^{-1}, \Psi_{ii} = (1 - \rho^2\delta_i)$$

Here, the model is a function of the explanatory variables, the selection parameters in M, the variances, the correlation coefficient, the spatial parameter and the spatial weights structure.

As Fleming notes, the correlated nature of the error terms within the selection mechanism and the growth function is the fundamental difference between the standard sample selection model and the spatial sample selection model. In the case of no spatial correlation, maximum likelihood procedures work well in estimating such a system. In our case, however, the correlated nature of the growth model function requires that the individual probabilities be simultaneously estimated. This is a difficult proposition. Fleming allows that:

> *In order to avoid these complexities, the spatial sample selection model can be estimated by a two step Maximum Likelihood method….Separating the spatial sample selection model allows one to estimate the first step selection mechanism independent of the second step, which is dependent on the first step through the estimated, but assumed non-random parameters.*

Overall, we applied this technique to the (7) 2-digit SIC “high tech” manufacturing industries using assorted econometric methods. The two-stage model is:

Stage 1: Spatial Probit

Location (= 1/0) = L(pct at least college, pct high school only, poverty rate 1990, airport dummy, major highway miles, interstate interchange dummy, 1990 population density, metro dummy, rural non-adjacent dummy, local taxes per capita, local govt fiscal leverage, 1-digit SIC wage, IDV, state dummies)

Stage 2: Spatial Selection Maximum Likelihood Model

Employment Growth = G(pct at least college, pct high school only, poverty rate 1990, airport dummy, major highway miles, interstate interchange dummy, 1990 population density, population growth rate 1990-2000, metro dummy, local govt expenditures per capita, local amenities, industry employment 1990, industry earnings per worker 1990, IDV, location quotient 1990, state dummies, Inverse Mills (from stage 1))

Descriptive Statistics for Select Independent Variables

Before examining the models in detail, it is useful to describe some of the basic characteristics of the counties in the study. Overall, 42 of Pennsylvania’s 67 counties are considered rural. For the comparison states, 315 of the 489 counties are rural. In Table 3 we provide the means of many independent variables used in our models.

[TABLE 3 HERE]

As we can see, both the *average* county level population change from 1990-2000 was a loss of about 1 percent; despite the fact that all states gained population over the decade. This suggests that population growth was concentrated in a few counties.

The percent of the population at least 25 years of age with only a high school degree in 1990 is also fairly similar across states and across rural and urban places. However, there is a much greater percentage of the population with at least a college degree in metropolitan counties than there is in rural counties. These two facts suggest that the percentage of population without a high school degree is greater in rural areas than it is in urban areas.

These statistics underscore two phenomena. First, it gives credence to the notion of a rural-to-urban migration of college educated people. Second, it reflects the fact that the rural population is, on average, older than the urban population, hence less likely to have a high school degree. Other trends of note include:

- The average poverty rate is higher in rural counties than it is in metro counties.

- Local governments tend to spend less and collect less revenue per person in rural areas than urban areas.

- Arterial road networks tend to be less developed in rural areas. Also, commercial airports are more prevalent in metro counties.

Results, Repercussions and Ruminations

[PRELIMINARY]

In Tables 4-9 we give empirical results. Each table provides the results of each stage of the estimation procedure. Overall, our results are quite disappointing in terms of rejecting the null hypotheses. We focus our comments on the variables that were statistically significant at the 10 percent level

[TABLES 4-9 HERE]

This investigation was sparked by an interest in examining whether or not rural areas are benefiting from the “new economy,” with our focus here on high-tech manufacturing. In the models we investigate, our evidence suggests that **rural** does not matter much; the only statistically significant “rural” indicator variable was “rural nonadjacent” in the Probit (i.e., location) analysis of SIC 29 (Petroleum Refining). Related, however, is population density, which is positive and significant in the location of that industry as well. In sum, we see that the fact that a county is a 'rural county' does not mean a predisposition to relatively slow employment growth, holding other things equal.

This suggests that market and spatial forces are not having a substantial and negative impact on rural counties, at least for these industries. Thus, if states seek to enhance the economies of rural places—that is, enact a place-based development strategy—then it must be realized that space and place in and of themselves may not be the problem. *Because of this, we are unwilling to conclude that rural areas are less able to participate in high-tech manufacturing simply because they are rural.* From a policy standpoint, this suggests no need for a unique rural development policy in these particular sectors.

So what local factors are correlated with industry location and growth? Overall, our results here provide limited insight, as most hypothesized factors seem to have little explanatory capability.

Still, we did learn a few things. First, **industry agglomeration** matters. In all six location models, a strong local presence of supporting industries (**IDV**) was important (of course, this is probably endogenous!). From a policy perspective, this notes the importance of local linkages when trying to attract new firms to a region: recruitment efforts, if the course chosen, should focus on businesses complementary to those currently located in the county. (NB: Future iterations of the model may well take this variable out).

While the results point to the positive effect of linkages on industry existence, evidence on the growth effects of these linkages is decidedly mixed. In two of our models (Chemicals and Allied Products (SIC 28) and Petroleum Refining (SIC 29)) the IDV variable was negatively related to industry growth. This may suggest that there are no real agglomeration effects in these industries (WHY?).

Yet agglomeration effects are positively related to growth in two other industries (Electronic and Electrical (SIC 36) and Measuring, Analyzing and Controlling Instruments (SIC 38)). WHY DIFFERENT THAN ABOVE?

Another noteworthy result is the typically negative effect that **initial employment** levels (EMP 1990) has on subsequent growth—the variable is negative and statistically significant in all but one model (Chemicals and Allied Products (SIC 28)). This suggests that industry employment growth is relatively slower in places with a relatively larger initial presence. There are a number of factors that could explain this, including industry maturity (potentially bad), or economies of scale (potentially good).

Other noteworthy findings are:

Average industry earnings per worker do not seem to drive employment growth. This suggests that employment growth in established industries is not all that sensitive to wages.

Neither per capita **government expenditures** nor **revenues** have particularly strong impacts on location or changes in employment. This suggests that local taxes are not necessarily a detriment to employment growth.

Contrary to both many previous studies and economic development policies, we find **education** has little effect on either location or growth. This could be due to the aggregate nature of our measure, however.

The number of state and interstate **highway miles** and existence of an **interstate interchange** have little effect in the models.

The **state dummy** variables are not significant, suggesting that state policies may either be 1) homogeneous, or 2) inconsequential.

Rumination

While these results are preliminary, they are also problematic. We recognize that no empirical model will explain everything; we also acknowledge that not every hypothesized relationship holds. Yet our results do not coincide well with most previous studies.

Why not? By investigating growth at the 2-digit level, we may be asking too much of the available data. For example, our data on education may not adequately reflect the high tech capabilities of the local workforce. Or, our aggregate data on local government expenditures and taxes may not capture the unique relationships between governments and particular industries or firms. For example, we are unable to get information on specific tax incentives offered to firms; rather we test for the general business climate. Or, our model could be grossly miss-specified.

Alternatively, the accepted models in regional science may just not do a very good job in explaining growth at the industry level. It may instead be that regional industry growth is indeed serendipitous, with industries in some places growing and in other places declining due primarily to chance. Alternatively, it may be that some businesses are just managed better than others, something our macro models simply cannot capture. If either of these alternatives dominates, then state and local policy will most likely have little impact.

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Appendix A: Defining Similar States

In order to better understand the role of state-level policies in economic development, it is essential to compare among states. In this study we identified (5) states that are "similar" to Pennsylvania: Illinois, Michigan, Minnesota, New York and Ohio.

To determine similar states, we examined all 50 states relative to Pennsylvania on several key economic and demographic indicators. These indicators are:

- percent of residents living in non-metropolitan counties in 1990
- 1990 state population
- state population growth from 1980-1990
- state per capita income in 1990
- percent of state employment in manufacturing in 1990
- percent of state employment in services in 1990

The exact process followed (3) steps:

(1) Standardize the value of the indicators (to a mean of zero and a standard deviation of one) to put them on a similar scale.

(2) Square the difference between the indicator value for each state and PAs indicator value.

(3) Add the squared differences, selecting the states with the smallest sum of squared differences.

Simply put, this process developed a similarity index, and the states with index values closest overall to Pennsylvania were chosen for comparison.

Figure 1. US metro and rural annual employment growth rates

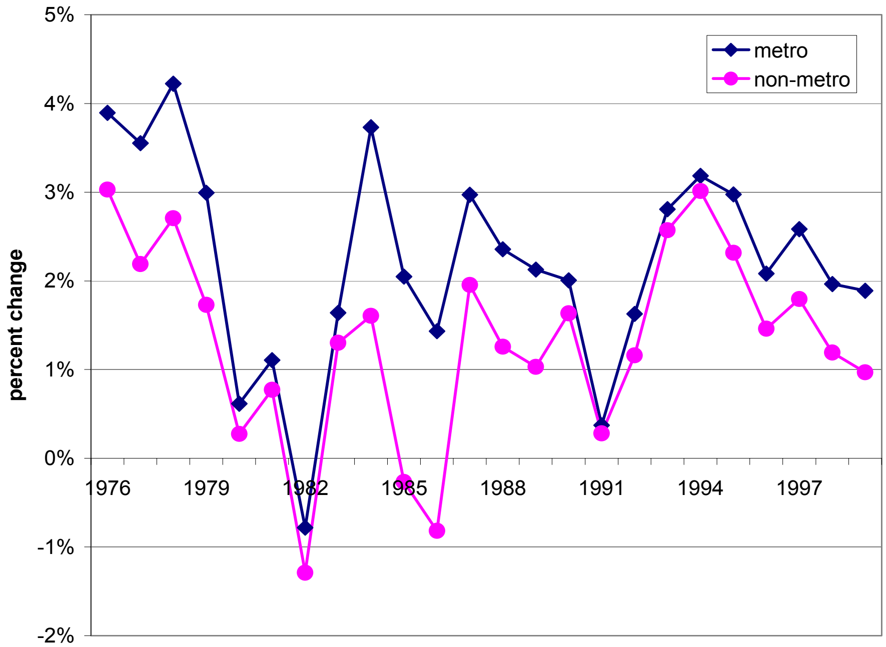


Figure 2. State rural and metro employment growth rates

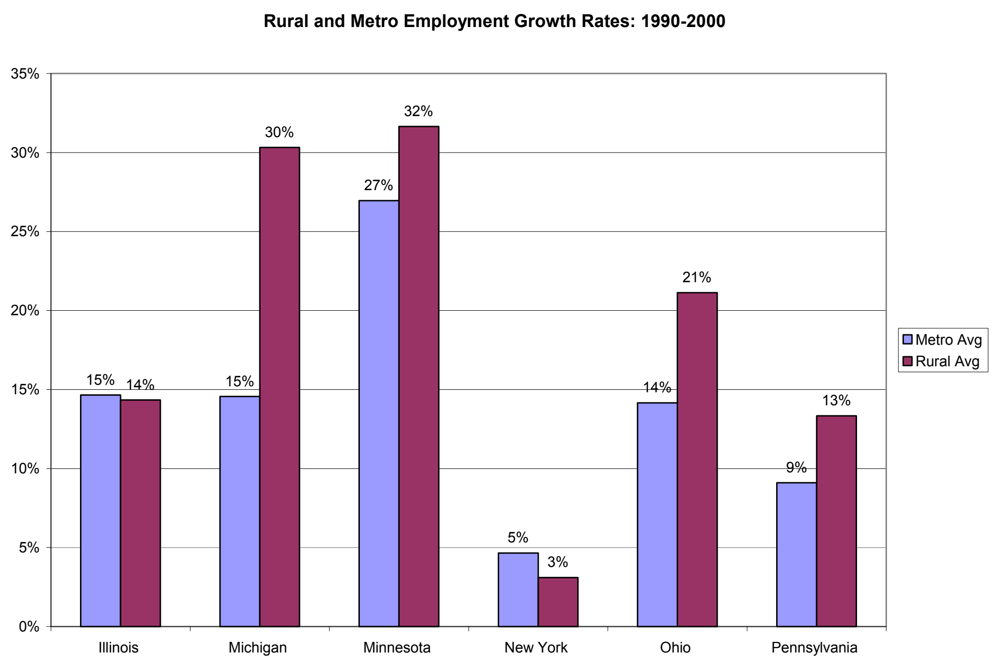


Figure 3.

Figure 4.

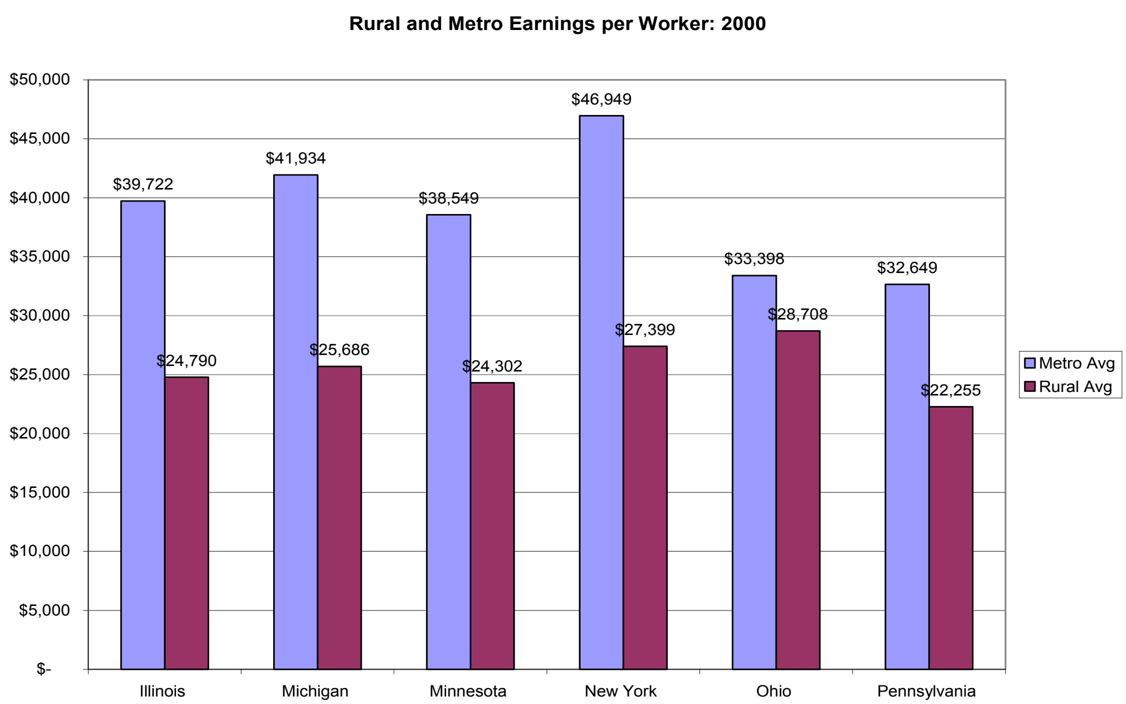
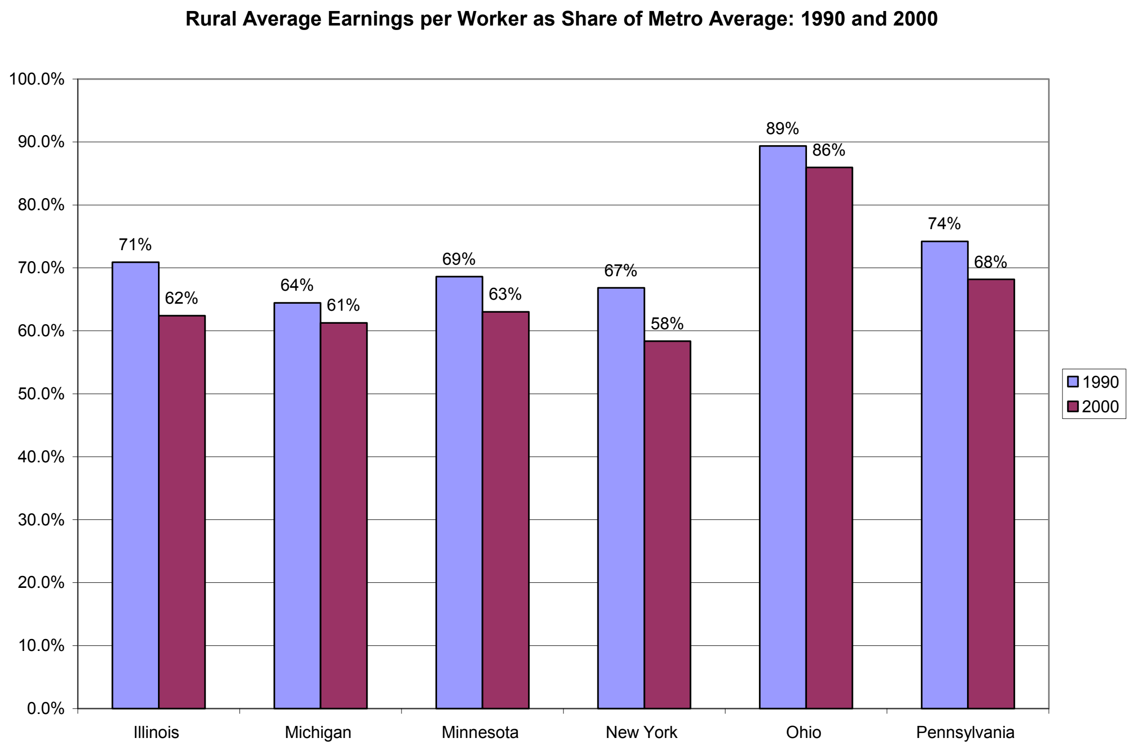


Figure 5.



Rural Average Earnings per Worker as Share of Metro Average: 1990 and 2000
100.0%
90.0%
80.0%
70.0%
60.0%
50.0%
40.0%
30.0%
20.0%
10.0%
0.0%
71%
62%
64%
61%
69%
63%
67%
58%
89%
86%
74%
68%
Illinois
Michigan
Minnesota
New York
Ohio
Pennsylvania
1990
2000

Table 1. Growth in high technology manufacturing

SIC	Industry	2000 Employment (rural)	Change since 1990	pct change rural	pct change metro	pct change US
27	Printing Publishing and Allied Industries	59,608	543	1%	-8%	-2%
28	Chemicals and Allied Products	24,046	(1,172)	-5%	1%	-6%
29	Petroleum Refining and Related Industries	4,567	(831)	-15%	-23%	-20%
35	Industrial and Commercial Machinery and Computer Equipment	122,826	5,301	5%	-8%	1%
36	Electronic and Other Electrical Equipment and Components	74,300	41	0%	-7%	2%
37	Transportation Equipment	85,642	19,730	30%	-11%	-29%
38	Measuring Analyzing and Controlling Instruments	14,814	585	4%	-22%	-16%
Total High Tech Manufacturing		385,803	24,197	7%	-9%	-7%
Share of Overall Total		11%		4%		

Table 2. Variables Used in the Model and their Data Sources

Variable Name	How measured	Data Source
1990 Employment	Number of industry jobs in 1990	IMPLAN
Airport	Dummy variable that takes on value of 1 if there is a commercial airport in the county; else 0	Bureau of Transportation Statistics, U.S. DOT
High School Degree	Percent of population more than 25 years old with at *only* a high school degree in 1989	US Census, Census of Population
College Degree	Percent of population more than 25 years old with at least a College degree in 1989	US Census, Census of Population
Employment change	Level of change in the number of industry employment	IMPLAN
Earnings per worker: 2-digit in 2nd stage, 1-digit in1st stage	Total industry earnings divide by total employment	IMPLAN
Tax per capita	Per capita local tax revenue, fiscal year 1992	US Census Census of government
Expenditures per capita	Per capita public expenditures, fiscal year 1992	US Census Census of government
Leverage	Ability to leverage local funds (local expenditures/local revenues)	US Census Census of government
Poverty rate 1990	Percentage of population below poverty level, 1989. Among whom poverty status is determined.	US Census, Census of Population
Natural amenities index	It is including measures of (1) average Jan temp, (2) avg. Jan days of sun, (3) low winter – summer temp gap, (4) low avg July humidity, (5) variation in topography, and (6) water area as share of total county area	USDA
Metro	1 if county is metropolitan, else 0	USDA Economic Research Service, Beale Codes
Rural County not Adjacent	1 if rural county is not adjacent to metro county	USDA Economic Research Service, Beale Codes
Location quotient 1990	A calculated ratio between the local economy and the economy of US.	Own calculation
Highways	Miles (or kilometers) of interstates, freeways, expressways, principal arterials, and rural minor arterials.	USA Federal Highway Administration, Special Request
Interstate	Dummy variable takes value of one if county ahs an interstate interchange	
Agglomeration (IDV)	Based on 1990 IO data, measures extent of local industry linkages	Own calculation
Population density	Population per square mile	Census
Population growth rate	(pop 2000 – pop 1990)/pop 1990	Census

Table 3. Means of select independent variables

Variable	Rural	Metro
Pop Growth Rate	5.3%	7.9%
High School Only	61%	60%
At Least College	11%	18%
Poverty Rate 1990	11%	9%
Local Government Expenditures per Capita	$2,203	$2,343
Local Government Revenues per Capita	$628	$895
Highway Miles	164	297
Interstate Interchange?	0.37	0.86
Airport?	0.1	0.4
Amenities Scale	-1.7	-1.4
Number of Counties	315	174

Table 4. Chemicals and Allied Products

SIC 28			
Variable	Estimate	Std Error	t-statistic
AIRPORT	9.14055044	112.612	0.081169
COLLLT	-3.37628933	1418.295	-0.00238
EAWORK90	-4.28E-03	0.00346	-1.23737
EMP90	0.02067696	0.013001	1.590416
EXPPERC	-2.57340168	149.4499	-0.01722
HIGHONLY	-2.1898521	2081.711	-0.00105
HWY	0.07152527	292.9462	0.000244
HWYDUM	3.26890899	211.2921	0.015471
IOMA90	-0.25889749	0.018047	-14.346
LQ90	0.4588788	11.92738	0.038473
METRO	1.2856972	165.4703	0.00777
NAS	0.85639196	46.82932	0.018288
ONE	-3.06967665	1696.439	-0.00181
POPGR	-15.0148724	574.6347	-0.02613
PORVER90	-1.46466369	2188.086	-0.00067
STATEIL	0.85665643	175.8881	0.00487
STATEMI	5.09166648	167.2464	0.030444
STATEMN	2.03812297	334.9905	0.006084
STATENY	-3.88511016	201.3348	-0.0193
STATEOH	3.44105915	158.9892	0.021643
TAXPERC	1.10625556	328.2844	0.00337
Lambdae	-2.13603501	2.50E+01	-0.0853
Sigmae	467.459734	13.31651	35.10377
rho	1.36E-03	9.43E-03	0.144219

Probit			
Variable	Estimate	Std Error	t-statistic
AIRPORT	0.073422	0.263541	0.278598
COLLLT	0.288472	2.703006	0.106723
HIGHONLY	-0.04213	2.631793	-0.01601
HWY	0.101867	1.115602	0.091311
HWYDUM	0.370815	0.170835	2.170605
IOMA90	0.001766	0.00084	2.102189
LEVER	0.028177	0.047152	0.597583
METRO	0.046351	0.269662	0.171887
one_wg90	2.35E-05	1.54E-05	1.521067
ONE	-1.11235	1.944341	-0.57209
POPSQM90	0.00477	0.003465	1.376604
PORVER90	0.254092	2.364605	0.107456
RUNOADJ	-0.21925	0.183621	-1.19405
STATEIL	-0.1564	0.401299	-0.38973
STATEMI	0.027957	0.433793	0.064447
STATEMN	0.415546	0.481082	0.863774
STATENY	0.188121	0.588422	0.319704
STATEOH	0.029425	0.430396	0.068368
TAXPERC	-0.08418	0.447861	-0.18797

Table 5. Petroleum Refining and Related Industries

SIC 29			
Variable	Estimate	Std Error	t-statistic
AIRPORT	4.18060002	51.53395	0.081123
COLLLT	6.78469361	673.2593	0.010077
EAWORK90	7.73E-04	0.002506	0.308443
EMP90	-0.27460731	0.026113	-10.516
EXPPERC	-6.53454545	84.20262	-0.07761
HIGHONLY	2.43678226	1060.914	0.002297
HWY	-2.35081006	136.5186	-0.01722
HWYDUM	-3.88442411	69.15152	-0.05617
IOMA90	-0.04493315	0.012448	-3.60954
LQ90	2.70482794	3.971027	0.681141
METRO	-9.5363274	78.50384	-0.12148
NAS	-3.94249843	27.4328	-0.14371
ONE	0.69073443	786.2992	0.000878
POPGR	-1.9420034	183.0096	-0.01061
PORVER90	1.93417959	1079.741	0.001791
STATEIL	3.25189489	95.50635	0.034049
STATEMI	1.94655772	106.6124	0.018258
STATEMN	-1.5442643	160.548	-0.00962
STATENY	4.78243171	103.4793	0.046216
STATEOH	0.72901011	87.3976	0.008341
TAXPERC	1.74861089	235.7483	0.007417
Lambdae	-1.88340529	13.2966	-0.14165
Sigmae	149.770376	9.224024	16.23699
rho	0.00182086	0.005173	0.351964

Probit			
Variable	Estimate	Std Error	t-statistic
AIRPORT	0.183942	0.236225	0.778676
COLLLT	1.758317	2.156017	0.815539
HIGHONLY	-0.00327	2.901812	-0.00113
HWY	0.161497	0.863254	0.187079
HWYDUM	-0.12832	0.177535	-0.72279
IOMA90	0.002256	0.001029	2.192117
LEVER	-0.15927	0.074695	-2.1323
METRO	0.009091	0.232873	0.03904
one_wg90	1.39E-05	1.75E-05	0.793988
ONE	-0.86893	2.096546	-0.41446
POPSQM90	0.002673	0.001187	2.251996
PORVER90	0.858561	2.451633	0.3502
RUNOADJ	0.29848	0.197356	1.512397
STATEIL	-0.61693	0.44167	-1.39682
STATEMI	-0.22737	0.482311	-0.47142
STATEMN	-0.28809	0.557513	-0.51674
STATENY	0.63769	0.566611	1.125446
STATEOH	-0.06038	0.459023	-0.13153
TAXPERC	-0.25271	0.532815	-0.4743

Table 6. Machinery and Computer Equipment

SIC 35			
Variable	Estimate	Std Error	t-statistic
AIRPORT	2.02001564	135.2628	0.014934
COLLLT	-0.95667252	1604.294	-0.0006
EAWORK90	-0.00164293	0.010477	-0.15681
EMP90	-0.16546183	0.02283	-7.24743
EXPPERC	1.34574535	190.3884	0.007068
HIGHONLY	4.01288901	2037.795	0.001969
HWY	-5.1897404	281.5285	-0.01843
HWYDUM	1.70210697	203.3196	0.008372
IOMA90	0.1217032	0.089882	1.354026
LQ90	-1.03328165	31.30498	-0.03301
METRO	-7.44716871	161.6367	-0.04607
NAS	-1.17895123	56.41996	-0.0209
ONE	1.53657877	1580.215	0.000972
POPGR	-14.2150187	559.8215	-0.02539
PORVER90	-1.08291239	1960.224	-0.00055
STATEIL	13.026717	311.0102	0.041885
STATEMI	0.20899122	344.5316	0.000607
STATEMN	-3.05911947	555.1964	-0.00551
STATENY	-2.79961554	335.5904	-0.00834
STATEOH	5.05382181	269.8974	0.018725
TAXPERC	3.78115599	493.4141	0.007663
Lambdae	0.59257877	0.292242	2.027697
Sigmae	696.9236	17.24852	40.40483
rho	3.04E-05	5.64E-05	0.538771

Probit			
Variable	Estimate	Std Error	t-statistic
AIRPORT	-0.10976	1.419219	-0.07734
COLLLT	0.876005	6.844774	0.127982
HIGHONLY	0.702937	7.315335	0.096091
HWY	-0.99947	3.101678	-0.32223
HWYDUM	-0.02087	0.40517	-0.05152
IOMA90	0.017873	0.010695	1.671195
LEVER	0.006141	0.058065	0.105762
METRO	-3.86323	26369.36	-0.00015
one_wg90	5.07E-05	3.57E-05	1.41954
ONE	2.605199	26369.36	9.88E-05
POPSQM90	0.012415	0.018627	0.666506
PORVER90	0.56326	5.46096	0.103143
RUNOADJ	-0.2889	0.455046	-0.63489
STATEIL	-0.52969	0.734306	-0.72135
STATEMI	-0.21872	0.892691	-0.24501
STATEMN	0.107365	1.118711	0.095972
STATENY	-0.99341	1.741831	-0.57032
STATEOH	-1.13794	0.975858	-1.16609
TAXPERC	0.922701	1.239552	0.744383

Table 7. Electronic and Other Electrical Equipment and Components

SIC 36			
Variable	Estimate	Std Error	t-statistic
AIRPORT	-0.63778941	151.6128	-0.00421
COLLLT	-0.88396173	1567.129	-0.00056
EAWORK90	-0.00168056	0.009755	-0.17228
EMP90	-0.38178117	0.02616	-14.594
EXPPERC	0.26196293	240.0348	0.001091
HIGHONLY	0.5734194	2360.492	0.000243
HWY	2.68895544	333.9109	0.008053
HWYDUM	1.6705906	258.7566	0.006456
IOMA90	0.48446261	0.069184	7.002498
LQ90	-0.83214096	39.71513	-0.02095
METRO	0.57151579	247.4629	0.00231
NAS	-0.30940893	71.52011	-0.00433
ONE	-3.1444289	1718.464	-0.00183
POPGR	0.16865424	643.4786	0.000262
PORVER90	-1.05584571	2857.762	-0.00037
STATEIL	-0.80670077	302.3476	-0.00267
STATEMI	0.83774497	349.3461	0.002398
STATEMN	-0.70757493	491.9965	-0.00144
STATENY	-0.64272173	333.6595	-0.00193
STATEOH	1.27743226	284.4036	0.004492
TAXPERC	0.06578591	604.8043	0.000109
Lambdae	-0.65171077	1.30E+01	-0.05007
Sigmae	728.187111	18.16143	40.09525
rho	0.00014188	0.001047	0.135498

Probit			
Variable	Estimate	Std Error	t-statistic
AIRPORT	0.031984	0.347609	0.092013
COLLLT	0.427546	2.953289	0.144769
HIGHONLY	0.040478	3.08676	0.013113
HWY	0.042613	1.272163	0.033497
HWYDUM	0.199218	0.217537	0.915789
IOMA90	0.0278	0.00447	6.219758
LEVER	-0.08935	0.096299	-0.92788
METRO	-0.3896	0.359981	-1.08229
one_wg90	-6.66E-06	2.19E-05	-0.30429
ONE	0.059214	2.264818	0.026145
POPSQM90	-0.00311	0.003149	-0.98788
PORVER90	-0.34671	2.85859	-0.12129
RUNOADJ	-0.2006	0.223818	-0.89626
STATEIL	0.275653	0.538141	0.512232
STATEMI	-0.14272	0.56511	-0.25254
STATEMN	0.06252	0.679771	0.091972
STATENY	-0.00258	0.829142	-0.00311
STATEOH	0.010516	0.545581	0.019274
TAXPERC	-0.19555	0.685665	-0.2852

Table 8. Transportation Equipment

SIC 37			
Variable	Estimate	Std Error	t-statistic
AIRPORT	-15.3678774	175.3223	-0.08766
COLLLT	1.43622074	2161.014	0.000665
EAWORK90	-0.0044671	0.011452	-0.39007
EMP90	-0.4378275	0.02387	-18.3423
EXPPERC	19.4444736	141.8023	0.137124
HIGHONLY	9.75950535	2873.584	0.003396
HWY	-24.7701514	329.3149	-0.07522
HWYDUM	-10.7306572	272.2684	-0.03941
IOMA90	-0.0132862	0.075908	-0.17503
LQ90	23.0354177	22.12787	1.041014
METRO	-13.3535007	275.1771	-0.04853
NAS	-52.4082546	75.11872	-0.69767
ONE	40.7707257	2235.28	0.01824
POPGR	12.0811707	895.64	0.013489
PORVER90	35.4669798	2676.397	0.013252
STATEIL	-15.1013799	426.3604	-0.03542
STATEMI	-4.72281777	408.161	-0.01157
STATEMN	-14.7305069	576.0701	-0.02557
STATENY	-7.66412207	460.0198	-0.01666
STATEOH	21.6109997	390.4446	0.05535
TAXPERC	25.6700534	373.0353	0.068814
Lambdae	-0.85911787	1.04E+01	-0.08278
Sigmae	847.928857	26.51129	31.98369
rho	3.11E-04	1.61E-03	0.193455

Probit			
Variable	Estimate	Std Error	t-statistic
AIRPORT	0.200398	0.356475	0.562166
COLLLT	-0.33051	2.198608	-0.15033
HIGHONLY	-0.20225	2.820474	-0.07171
HWY	-0.11171	1.290296	-0.08658
HWYDUM	0.291664	0.186439	1.564396
IOMA90	0.014028	0.003442	4.075571
LEVER	-0.15739	0.078463	-2.00589
METRO	0.113256	0.278268	0.407002
one_wg90	1.60E-06	1.78E-05	0.089769
ONE	0.455145	2.080252	0.218793
POPSQM90	-5.26E-05	0.00287	-0.01833
PORVER90	0.13479	2.683289	0.050233
RUNOADJ	-0.07021	0.209055	-0.33582
STATEIL	-0.41377	0.420488	-0.98403
STATEMI	0.076428	0.498625	0.153278
STATEMN	0.409142	0.537189	0.761635
STATENY	-0.01448	0.546131	-0.0265
STATEOH	0.051519	0.546852	0.094209
TAXPERC	-0.38053	0.290763	-1.30871

Table 9. Measuring, Analyzing and Controlling Instruments

SIC 38			
Variable	Estimate	Std Error	t-statistic
AIRPORT	-11.1041566	99.94559	-0.1111
COLLLT	-6.72383487	1277.951	-0.00526
EAWORK90	0.00191409	0.009831	0.194693
EMP90	-0.13298788	0.015861	-8.38473
EXPPERC	-31.6679421	126.9146	-0.24952
HIGHONLY	-57.884277	1379.965	-0.04195
HWY	-10.4377874	272.7785	-0.03826
HWYDUM	51.1876301	191.6686	0.267063
IOMA90	0.12971891	0.063489	2.043157
LQ90	-18.7636813	17.35584	-1.08112
METRO	6.40877975	205.4021	0.031201
NAS	-18.3017474	45.88357	-0.39887
ONE	14.9062189	1040.716	0.014323
POPGR	-17.4427348	469.9235	-0.03712
PORVER90	30.9238079	1881.479	0.016436
STATEIL	3.54904547	277.6233	0.012784
STATEMI	-40.1290009	325.5037	-0.12328
STATEMN	75.5894203	355.5242	0.212614
STATENY	13.0486831	328.7794	0.039688
STATEOH	-38.2656318	267.4756	-0.14306
TAXPERC	2.42177964	336.1648	0.007204
Lambdae	0.59724383	0.286761	2.082727
Sigmae	402.073697	14.21389	28.28738
rho	-3.40E-05	8.62E-05	-0.39403

Probit			
Variable	Estimate	Std Error	t-statistic
AIRPORT	0.295847	0.269436	1.098023
COLLLT	-1.09203	2.244215	-0.4866
HIGHONLY	-0.37475	2.850681	-0.13146
HWY	-0.80928	1.000785	-0.80865
HWYDUM	0.107023	0.157684	0.678717
IOMA90	0.012769	0.003197	3.994198
LEVER	-0.07819	0.064537	-1.21151
METRO	-0.33533	0.241604	-1.38794
one_wg90	4.32E-06	1.79E-05	0.241645
ONE	-0.17449	2.102264	-0.083
POPSQM90	0.002276	0.003194	0.712622
PORVER90	0.311946	2.437347	0.127986
RUNOADJ	-0.00131	0.183731	-0.00712
STATEIL	0.172268	0.447737	0.384752
STATEMI	-0.05033	0.46549	-0.10813
STATEMN	0.576795	0.557151	1.035259
STATENY	0.529918	0.558271	0.949214
STATEOH	0.139128	0.500618	0.277912
TAXPERC	0.110747	0.391709	0.282727