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# The impact of industry clustering on Iowa manufacturing wages, 1986-1994 

Lee Edwin Hill<br>Iowa State University

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by

## Lee Edwin Hill

A thesis submitted to the graduate faculty in partial fulfillment of the requirements for the degree of MASTER OF SCIENCE

Major: Economics<br>Major Professor: Peter F. Orazem

Iowa State University
Ames, Iowa

# Graduate College 

Iowa State University

This is to certify that the Master's thesis of

## Lee Edwin Hill

has met the thesis requirements of Iowa State University

Signatures have been redacted for privacy

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#### Abstract

This thesis examines whether industry clustering results in higher manufacturing wages for Iowa counties. The industry for any given plant is defined to be the set of 3-digit SIC codes that use unusually large proportions of the same occupations as it's own 3-digit SIC code, as measured by key-occupation elasticities. Industry clustering is captured by measures of industry density (the number and relative size of plants in the industry) and industry size. A model is used which includes controls for workforce size (urbanization), plant size, mix of 4-digit industries, workforce education, and other relevant variables that predict county manufacturing earnings per worker. Weighted least squares regressions were performed for ten manufacturing sectors. The combined effect of industry size and industry density on manufacturing earnings is negative in half of the ten sectors. The four sectors where clustering has the largest negative effects on wages are sectors where a significant share of rural plants serve local markets. Increases in industry size raise earnings in metals, industrial equipment and transportation equipment by a modest amount. Workforce size has a substantial positive effect on earnings in most manufacturing sectors, as does plant size. Urbanization is estimated to have the strongest effect on earnings in printing \& publishing, electronics \& instruments, and chemicals. The only two sectors where it has virtually no positive effect on wages are textile \& leather products and meatpacking. The coefficients estimated by the model accurately predict differences between metro and nonmetro counties earnings in general, but are not able to fully account for wide differences in earnings among nonmetro county types.


## GENERAL INTRODUCTION

Nonmetro workers have lower earnings than metro workers, and the gap between them has widened over the past twenty years. Between 1979 and 1987, the share of nonmetro workers earning less than $\$ 5.58$ an hour (in 1987 dollars) grew from $31.9 \%$ to $42.1 \%$, compared with an increase for metro workers from 23.4 to $28.9 \%$. Among those with year-round full-time schedules, $25 \%$ of nonmetro workers earned less than $\$ 5.58$ an hour, compared to $14 \%$ in metro areas. (Gorham 1992, Gorham and Harrison 1990) While the 1990s brought renewed job growth to many nonmetro areas in the U.S., much of this growth continues to be in low-wage jobs.

Agriculture, forestry, mining and other extractive industries where rural areas traditionally had a comparative advantage have all shed large numbers of workers in recent decades, and will continue to do so. Future improvements in earnings for substantial numbers of rural workers will have to come through manufacturing and service jobs. Due to spatial division of labor in the production of goods and services, rural areas frequently gain the lower-skilled, lower-wage stages of production processes in both manufacturing and services. Although nationally the service sector is growing far more rapidly than manufacturing, so far much of the evidence also indicates that rural areas are at an even greater disadvantage in attracting and generating high-wage jobs in services (Coffey and Shearmur 1997).

The main purpose of this study is to examine a dataset on Iowa manufacturing plants to see whether industry clusters show significant potential to raise rural manufacturing earnings. We use a model of the determinants of county manufacturing wages to estimate the
effects of industry size, industry density, and overall workforce size, after controlling for workforce education, plant size, industry mix, and other area characteristics.

## Thesis Organization

This thesis begins with a general introduction that includes a literature review. The main body of the thesis is a manuscript prepared for submission to the journal Growth and Change, written according to their specifications and format. The third chapter contains a more detailed description of the data and methods of measurement, and a fourth chapter describes the procedure for estimating individual firm sizes. The appendix includes additional tables and maps. A list of references is at the end of the thesis.

## Literature Review

The economic literature on agglomeration dates back at least 100 years, when Alfred Marshall drew attention to external economies due to localization of industries in particular locales in his Principles of Economics (1920 [1890]) and other writings. Hoover first divided agglomeration externalities into localization and urbanization economies in his study of the shoe industry (1937), and this distinction found its way into regional science textbooks by the 1950s (Isard 1956). Regional scientists, urban economists, and regional economists have performed quantitative analyses of agglomeration for more than thirty years.

However, there is still vigorous debate about whether urbanization or localization economies are more important in the development of local and regional economies. Glaeser
et. al. (1992) studied long-term growth of large manufacturing, wholesale and service industries in 170 U.S. cities, and found that initially large industries (relative to the size of overall city employment) grew at a slower rate than initially small industries. Henderson (1995) found evidence of both urbanization and localization economies for new, high tech industries (electronic components, medical equipment, and computers), and evidence for localization but not urbanization economies in five mature capital goods industries. Other studies show a similarly wide range of results and conclusions.

In particular, there is considerable uncertainty and disagreement about the best ways to measure localization and estimate its impact. Consequently, a recent study by Harrison, Kelley, and Gant (1996) of the adoption of programmable machining tools among U.S. metalworking establishments reported results for seven models using seven alternative measures of localization (in otherwise identical specifications). When detailed individual plant characteristics were included neither urbanization or localization was significant to adoption, but both were significant after corrections were made for technical problems (urbanization was the more important of the two).

Unfortunately, estimates of the impact of localization economies are sometimes quite sensitive to production function specification. Greytak and Blackley (1985) found industry size to be statistically significant and positive using a Cobb-Douglas specification, but not when using a CES production function.

It may well be that urbanization economies are most significant in some industries and that localization economies make a greater difference in others, while in still other industries,
both are comparatively unimportant. Vernon Henderson (1988) argues that the largest megacities become centers for those industries where strong urbanization economies outweigh the higher rents and costs, while smaller cities specialize in one or more industries where localization economies are most important. Rural areas may do the same and specialize in industries where they can achieve localization economies. Or if we find industries where neither urbanization or localization economies are very important, this tells us that rural areas have stronger potential to engage in these industries and achieve comparable levels of productivity and wages.

Until quite recently, studies of agglomeration focused almost exclusively on large cities and metro areas. Henry and Drabenstott (1996) analyzed component economic areas (CEAs) with rural employment growth for 18 manufacturing, wholesale, and service industries, and reported that a critical mass of similar firms was a major factor in rapid rural job growth. The authors note that the strong results for overall manufacturing employment (clearly too broad to measure localization) suggest that their rural industry cluster variable may be capturing both rural county size (urbanization) and localization effects for the rural counties in question.

Gibbs and Bernat (1997) found that U.S. manufacturing workers in labor market areas with a cluster in their industry earned 7 percent more on average than otherwise identical workers in the same industry outside of clusters. The wage premium was twice as large (13 vs. 6 percent) for predominantly rural labor markets (less than $30 \%$ metro) as compared with labor markets that are over $70 \%$ metro. The reported effect was larger than the effect of
urbanization.
Saxenian (1994) asserts that it is differences in industrial systems and production organization, and not just industry size (or city size), that account for the long-term success or failure of regional industries. She attributes the strong economic growth of Silicon Valley to its large number of smaller firms linked by flexible subcontracting relationships, formal and informal networks, and institutions supportive of startups. Saxenian contrasts this with Route 128 , dominated by a handful of large vertically integrated firms, which failed to adapt to changes from mainframes to minicomputers to personal computers.

Florida (1990), Christopherson (1992), Harrison (1994) and others question the relevance of the Silicon Valley model to most regions and industries. Markusen (1996) argues that the vertically-disintegrated and highly entrepreneurial "Marshallian" industrial districts such as Silicon Valley, the Third Italy and southern German metalworking, which have received most of the recent attention, are comparatively rare and unusual. She asserts that "hub-and-spoke" clusters dominated by one or a few large, vertically-integrated firms are far more common, and far more important to sustained growth in today's economy.

# THE IMPACT OF INDUSTRY CLUSTERING ON IOWA MANUFACTURING WAGES 

A paper prepared for submission to Growth and Change<br>Lee Hill and Daniel Otto

## Introduction

Wages and earnings in nonmetro areas are considerably lower than in metro areas. Within U.S. manufacturing, rural earnings per job were around $74 \%$ of metro pay levels througout most of the 1970 s, peaked at $76 \%$ in 1979 , and have steadily declined since then to $70 \%$ of metro earnings in 1991. (Bernat 1994). In 1987, 28.9\% of nonmetro manufacturing workers earned less than $\$ 5.58$ an hour - the wage required for a full-time year-round job to earn an income equal to the poverty line for a household of four - compared to $16.7 \%$ of metro manufacturing workers (Gorham 1992). ${ }^{1}$

Nonmetro workers tend to have lower average levels of schooling and experience than metro workers, and we expect this to lead to lower wages. However, one study estimates that two-thirds of the metro-nonmetro earnings gap is because returns to education and work experience are lower for a nonmetro worker than for a metro worker with the same characteristics (McLaughlin and Perman 1991). Low wages in rural areas of the U.S. cannot be explained simply as a lack of human capital.

Studies that find industries have higher levels of pay in highly urbanized counties frequently assume that firms innovate, share information, and adopt new technologies more rapidly in metro areas and larger cities, and offer this as explanation for higher pay. But while

Kusmin found computer use in the overall work force was lower in nonmetro areas, most of this difference reflected differences in the composition of industries and occupations in nonmetro areas (Kusmin 1996). In a study focused on the metalworking, industrial and transportion equipment, electronics and instruments (SIC 33-38) industries, Gale (1998) found that nonmetro plants were slightly more likely to adopt advanced technologies than metro plants in these industries, even though metro counties had a higher proportion of new plants. In a study of machining firms, Harrison, Kelly and Gant (1996) found the highest levels of technology adoption in adjacent nonmetro counties and small metros, with the lowest in metro areas over 1 million and nonadjacent rural counties. $10.3 \%$ of nonmetro shipments were exported overseas in 1995 , little different from $11.3 \%$ of metro shipments. (Gale 1998b) As recently as 1989, new capital investment per manufacturing worker in nonmetro areas was $96 \%$ of metro levels, although rural investment per worker dropped rapidly to $86 \%$ of metro in 1991 and 1992, and was $73 \%$ of metro investment once paper and allied products are excluded (Bernat 1995).

In recent years, a growing number of economic development practitioners and researchers have turned to industrial districts, industry targeting, and sectoral clusters as a potential key to local and regional development (Piore and Sabel 1984, Pennsylvania Economic Development Partnership 1988, Rosenfeld et. al. 1989, New York State Department of Economic Development 1993, California Economic Strategy Panel 1994, Univ. of Minnesota, Metropolitan Council 1995, Aspen Institute 1995). Industrial and sectoral approaches to economic development are nothing new: growth pole strategies and
multiplier analyses were a centerpiece of development policy in the '50s and '60s (Isard 1956. 1960). The early emphasis was on sales linkages between firms and industries that increased the local or regional multiplier, in an era of broad growth across most sectors in the U.S. and many other industrialized nations. Foreign competition in steel and consumer products in the 1970s and 1980s and cutbacks in U.S. defense contracts during 1988-1992 taught us that strong multipliers that are a virtue during periods of growth can also exacerbate downturns resulting from sectoral contractions. This led to widespread calls for industrial diversification. What is distinctive about the new interest in industrial clusters is an added focus on their role in enhancing innovation, skill development, flexibility, and technology and information flows in order to maintain competitiveness in a rapidly changing global economy. In his analysis of photonics in Rochester NY and waste management services in Buffalo NY, Sternberg (1991) points out that the most important benefits of some sectoral clusters may have nothing to do with whether the firms buy from and sell to one another.

The literature on clusters generally treats industry size and density as necessary but not sufficient conditions for an industry cluster. Most of these writers also place a strong emphasis on interactions among firms, including sales-purchase linkages, direct communication and interaction with managers and employees in other firms, and transfer of skills and technology as workers and subcontractors move from one firm to another. Previous qualitative research by the author on plastics, foundries, and die-casters in eastern Iowa indicates that the nature and extent of such interactions can vary widely from one industry to another and among equally dense "potential clusters" in the same industry, and
that these interactions can be increased by policies such as fostering local industry consortia. But for purposes of this study, industry clustering is treated merely as synonymous with localization economies: effects of the density of plants and the size of a particular industry. I do not measure any flows of goods, services, information, or employees. Nevertheless, even if only a significant fraction of "potential clusters" actually have strong interactions of these types, it is reasonable to expect we can detect evidence of these effects in our regressions.

This study analyzes a dataset on Iowa manufacturing plants to look for evidence of whether clustering among plants that hire large proportions of the same specialized occupations leads to higher manufacturing wages. We estimate a model of the determinants of county manufacturing earnings that also includes controls for differences in industry mix, workforce education, plant size, and other relevant variables in order to distinguish the effects of industry scale and density from the effects of general size of the local economy. If a firm has higher productivity when located in a dense concentration of establishments in the same industry than it would when isolated from firms in its own industry, then localization economies are said to be at work. When a firm located in a large city has higher productivity than an otherwise identical firm operating in a smaller local economy, urbanization economies exist. If manufacturing plants located randomly according to population, the larger counties would naturally tend to have larger and denser concentrations of plants within specific industries, as well. So if agglomeration economies account for much of wage/productivity gap, it is not immediately obvious whether it is localization or urbanization economies that are responsible. Urbanization and localization economies (and diseconomies) may exist for a
number of reasons. These include greater scope for specialized occupations, skills. infrastructure, and producer services, economies of scale in upstream (input) and downstream markets, potentially increased technology transfer and exchange of information, more possibilities for contracting arrangements, the development of institutions that cater to the needs of the industry, or improved access to markets.

There is wide disagreement in the literature about whether urbanization or localization economies are more important in the development of local and regional economies. Glaeser found that urbanization economies but not localization economies contributed to the growth of industries in cities. Henderson reports that only localization economies were important to local employment growth in a set of mature manufacturing industries, while both industrial diversity and own industry size contributed to growth in newly emerging industries. In particular, there is considerable debate and uncertainty about the best ways to measure localization and estimate its impact. For this reason, one recent study of technology adoption by metalworking firms (Harrison, Kelley, and Gant 1996) reported results for seven alternative measures of localization (in otherwise identical models).

Early work on urbanization and localization economies defined urbanization as city scale, and defined localization as industry scale. (Isard 1960) More recent discussions of agglomeration economies emphasize the importance of industrial diversity to urbanization economies (Jacobs 1969) and the importance of production organization to localization economies (Piore and Sabel 1984; Saxenian 1994). Most recent quantitative studies attribute urbanization and localization to benefits from the presence of other local firms. But when
they perform their analyses, most of these studies use only measures of industry scale for localization economies (either absolute size of the local industry, or size of the industry as a share of the local economy). These measures do not distinguish whether other sizeable plants are present, or whether nearly all of the industry employment is concentrated in a single large plant. If both plant size and industry size are measured in a similar fashion, then industry size may implicitly capture differences in the relative size of plants, but few studies do so. By contrast, many studies have included variables that measure industrial diversity for urbanization economies. (Glaeser 1992; Henderson 1996) It is far more difficult to measure structure within specific industries, for the simple reason that individual firm data usually cannot be obtained from publicly-available sources of data.

Nondisclosure of detailed establishment and industry data is also related to a second criticism about the definition of industries in quantitative studies: either industrial data is too aggregated, or existing SIC codes often do not categorize relevant firms together well at any given level of detail. Some SIC codes are grouped more by final source of demand than by similar skills, production methods and materials. While useful and appropriate for some applications such as input-output analysis, these categories frequently do not group together plants using similar production technologies. Washers, dryers, refrigerators, and food and beverage equipment are classified under SIC 35 when sold for commercial use, while potentially almost identical appliances sold to households are classified in SIC 36. If three plants in a local economy all produce transmissions - one for motor vehicles (SIC 37), one for household laundry equipment (SIC 36), and one for industrial tractors (SIC 35) - most
analyses of localization using 2-digit SIC codes treat these three plants as if they were no more related to one another than a canning plant, a steel mill, and a semiconductor plant.

This study is able to use finer levels of industry detail than most previous analyses because it utilizes ES 202 data with complete disclosure of earnings and employment (even where there is only a single establishment in the industry). Because this data was only available for 99 counties in a single state, this increased precision comes at the cost of fewer cross-section observations. This study also defines which plants are in the same "industry" in a different fashion. Rather than classify 3-digit industries into mutually exclusive categories, for any given plant I include in the same "industry" the plants in those other 3digit industries that also use unusually large proportions of the same occupations. While my emphasis is on specialized worker skills, this method will naturally also tend to group industries which rely on similar technologies, since specific occupations will often be closely related to particular production processes and types of capital equipment.

The question we wish to answer is whether manufacturing earnings are higher for plants located in a cluster of plants that use unusually large proportions of the same specialized occupations than for plants that are not. If increases in industry size and industry density raise earnings holding workforce size and other factors constant, then rural areas can potentially increase manufacturing earnings by specializing in one or more industry clusters, where we define an industry cluster to be a set of industries that share a reliance on a particular set of specialized occupations and worker skills.

## Model

In order to look for evidence of the relative importance of urbanization and localization economies in determining manufacturing wages, we estimate a model of the determinants of county manufacturing earnings for ten manufacturing sectors. This is derived from aggregating the production functions of individual plants to the county level based on previous work by Henderson $(1988,1996)$ and Glaeser et. al. (1992). Factors that increase the productivity of labor will raise the marginal product of labor and the value of marginal product. Under conditions of competitive market equilibrium, this increases demand for labor which, depending on the elasticities for supply and demand for labor, will lead to increases in either the equilibrium wage, the equilibirum level of employment, or some combination of both effects.

In the neoclassical theory of the firm, individual firms are assumed to make decisions about their own output based entirely on their individual marginal costs/marginal productivity of their inputs. Where external economies exist, the collective outcome of these individual production decisions may change the costs or productivity of inputs in all the individual firms, and initially may result in a temporary disequilibrium. However, as firms respond to their new individual cost and production functions in each subsequent period through changes in output and entry/exit, the firms in the industry will move toward equilibrium.

We begin with the production function of an individual firm. In a basic model of the individual firm, total firm output is assumed to be a function only of the firm's own technology and input levels. By assuming that individual firms use production technology
with constant returns to scale in own output, we can aggregate individual firms and write a production function for a specific sector $s$ in a particular county $c$ at a particular time $t$.

$$
\begin{equation*}
\mathrm{Q}_{c s t}=\mathrm{Q}_{c s t}\left(\mathrm{x}_{c s t 1}, x_{c s t 2}, \ldots x_{c s t n}\right)=\mathrm{Yx}_{1} x_{2} \ldots x_{n} \tag{1}
\end{equation*}
$$

where $\mathrm{x}_{c s t 1}, \mathrm{x}_{\text {cst } 2} \ldots x_{c s t n}$ are inputs.

Measures of capital utilization in manufacturing are not available at the countyindustry level, due to nondisclosure in Census of Manufacturing and similar data. We assume a Leontief production function, where capital is assumed to vary proportionally to labor. While this specification does not allow for the possibility of substitution between capital and labor inputs based on changes in their relative prices, the advantage of this county-level approach is that we can measure characteristics specific to the local labor market area. Studies which use state-level data can derive a model with two inputs, but must necessarily include plants in the same unit of observation that may in fact be several hundred miles apart, in completely different labor markets. Since I am looking specifically for external effects through labor skills within a labor market area, which may vary widely within a state, I believe the use of sub-state data is important.

If external economies exist with regards to industry scale or overall size of the local economy and we assume capital to vary proportionately to labor, this can be rewritten as:

$$
\text { (1') } \mathrm{Q}_{c s t}=\mathrm{A}_{c s t}(\bullet) \mathrm{Q}_{c s t}\left(\left(\mathrm{x}_{c s t I}, x_{c s t 2}, \ldots x_{c s t n}\right)=\mathrm{AY} \mathrm{x}_{1} x_{2} \ldots x_{n}\right.
$$

where, following Glaeser et. al. (1992) and Henderson (1996), a term for industry technology
$\mathrm{A}_{c s t}(\bullet)$ represents the external effects of agglomeration.

In equilibrium, the wage rate for sector $s$ in county $c$ at time $t$ will equal the value of marginal product.
(2) $\quad \mathrm{W}_{c s t}=\mathrm{VMP}=\mathrm{P}_{c s t} * \mathrm{Q}_{c s t}\left(\mathrm{X}_{c s t}, \ldots\right)$

So with the presence of agglomeration economies, (2) becomes:
(2') $\quad \mathrm{W}_{c s t}=\mathrm{VMP}=\mathrm{P}_{c s t} * \mathrm{~A}_{c s t}(\bullet)^{*} \mathrm{Q}_{c s t}\left(\mathrm{x}_{c s t}, \ldots\right)$
Here $\mathrm{P}_{s}$ is the price of sector output. Differences in the price of sector output are assumed to be captured by dummy variables for sectors. In this model, $\mathrm{A}_{c s t}$ is represented by measures of urbanization (workforce size and urban/metro dummies) and localization (industry size and industry density).

We estimate models for manufacturing sector $s$ in county $c$ separately in each of ten manufacturing sectors:
$\log \left(\mathrm{EARN}_{c s t}\right)=\mathrm{b} 0+\mathrm{b} 1 * \log \left(\mathrm{US}_{-}\right.$PR_EARN $\left.{ }_{c s t}\right)+\mathrm{b} 2 * \log \left(\mathrm{PLANT}_{-} \mathrm{SZ}_{c s t}\right)+$ $\mathrm{b} 3^{*} \log \left(\mathrm{WKFC}_{-} \mathrm{SZ}_{c}\right)+\mathrm{b} 4^{*} \log \left(\mathrm{IND}_{-} \mathrm{SZ}_{c s t}\right)+\mathrm{b} 5^{*} \log \left(\right.$ CLUSTR-M $\left._{c s t}\right)+$ $\mathrm{b} 6^{*}\left(\mathrm{HS}_{-} \mathrm{ED}_{c}\right)+\mathrm{b} 7^{*}\left(\mathrm{C}_{-} \mathrm{ED}_{c}\right)+\mathrm{b} 8^{*}(\mathrm{D} 86)+\mathrm{b} 9^{*}(\mathrm{D} 87)+\mathrm{b} 10^{*}(\mathrm{D} 88)+\mathrm{b} 11^{*}(\mathrm{D} 89)+$ b12* $(\mathrm{D} 90)+\mathrm{b} 13^{*}(\mathrm{D} 91)+\mathrm{b} 14^{*}(\mathrm{D} 92)+\mathrm{b} 15^{*}(\mathrm{D} 93)$
and a second model with dummies for additional county characteristics:
$\log \left(\mathrm{EARN}_{c s t}\right)=\mathrm{b} 0+\mathrm{b} 1 * \log \left(\mathrm{US}_{-}\right.$PR_EARN $\left.{ }_{c s t}\right)+\mathrm{b} 2 * \log \left(\mathrm{PLANT}_{-} \mathrm{SZ}_{c s t}\right)+$
$\mathrm{b} 3^{*} \log \left(\mathrm{WKFC}_{-} \mathrm{SZ}{ }_{c}\right)+\mathrm{b} 4^{*} \log \left(\mathrm{IND}_{-} \mathrm{SZ}_{c s t}\right)+\mathrm{b} 5^{*} \log \left(\mathrm{CLUSTR}_{c s t}\right)+$
$\mathrm{b} 6^{*}\left(\mathrm{HS}_{-} \mathrm{ED}_{c}\right)+\mathrm{b} 7 *\left(\mathrm{C}_{-} \mathrm{ED}_{c}\right)+\mathrm{b} 8^{*} \log \left(\mathrm{MET}_{c}\right)+\mathrm{b} 9 * \log \left(\mathrm{URB} 20_{c}\right)+\mathrm{b} 10 * \log \left(\mathrm{ADJ}_{c}\right)+$
$\mathrm{b} 11^{*} \log \left(\mathrm{HWY}_{c}\right)+\mathrm{b} 12^{*} \log \left(\mathrm{COL}_{c}\right)+\mathrm{b} 13^{*}(\mathrm{D} 86)+\mathrm{b} 14^{*}(\mathrm{D} 87)+\mathrm{b} 15^{*}(\mathrm{D} 88)+\mathrm{b} 16^{*}(\mathrm{D} 89)+$ $\mathrm{b} 17^{*}(\mathrm{D} 90)+\mathrm{b} 18^{*}(\mathrm{D} 91)+\mathrm{b} 19 *(\mathrm{D} 92)+\mathrm{b} 20^{*}(\mathrm{D} 93)$

A combined model with all ten sectors combines also includes nine dummy variables for all but one of the manufacturing sectors, to allow for different intercepts by sector. The slope parameters for explanatory variables are assumed to be the same across sectors.

## Variables:

$\mathrm{EARN}_{c s t}=$ Average Annual Earnings per Job in county $c$ in manufacturing sector $s$ at time $t$.

## Plant Characteristics

US_WT_EARN ${ }_{c s t}=$ U.S. weighted average earnings: earnings if local industry mix in the sector earned the U.S. average annual wage for that year in each 4-digit SIC Code, to control for industry mix. U.S. weighted average earnings for sector s in county c at time t is:

$$
\text { US_WT_EARN }_{\text {cst }}=\frac{\mathrm{N}_{-} \text {it }^{*} \text { Wuit }}{\sum \mathrm{N} c i t} \text { for } \mathrm{i}=1 \text { to } \mathrm{n}
$$

where $\mathrm{N}_{c i t}=$ employment in 4-digit SIC $i$ in county $c$ at time $t, \mathrm{~W}_{u i t}=$ U.S. average annual earnings in 4-digit SIC $i$ at time $t$, and $\sum \mathrm{Ncit}=$ total sector $s$ employment in county $c$ at time $t$. Changes in national earnings for 4-digit SICs are assumed to capture changes in the price of final output, parallel to Glaeser et. al (1992).

$$
\begin{aligned}
& \text { PLANT_S }_{c s t}=\text { Weighted average employment size of plants in County } c \text { in Sector } s \\
& \text { PLANT_SZ }_{\text {cst }} \quad=\frac{N p t^{*} N p t}{\sum N p t} \text { for } \mathrm{p}=1 \text { to } \mathrm{n}
\end{aligned}
$$

where $\mathrm{N} p t=$ employment in plant $p$ at time $t$, and $\sum \mathrm{N} p t$ is total employment in sector $s$ in
county $c$. Plant size may be interpreted as a proxy for differences in product mix within 4 digit SICs. In those SICs where large plants do have significantly higher earnings, large plants generally produce quite different products from small plants. ${ }^{2}$

## Agglomeration/Clustering (A)

WKFC_SZ $=$ Size of overall workforce in the labor market area about county $c$

$$
\text { WKFC_SZ }=\sum \mathrm{L} c^{*} \mathrm{f}(\text { miles })
$$

for $\mathrm{c}=1$ to 244
where $\mathrm{L} c=$ number of workers in county $c$ in 1990 Census of Population and $f($ miles $)$ is a weight between 0 and 1 , which is a function of the distance between the center of population in the county A and the center of population in county B (the distance function is shown below - I use a piecewise linear function to approximate values derived at 5-mile increments from Census commuting data. This function reaches zero at a distance of 80 miles).

IND_SZ ${ }_{c s t}=$ Own industry employment in sector $s$ within the labor market area about County $c$ at time $t$

Industry size for Plant $o$ at time $t$ is:

$$
\mathrm{IND}_{-} \mathrm{SZ}_{c o t}=\sum \mathrm{N}_{p t} * \mathrm{f}(\text { miles }) * \mathrm{E}(\mathrm{~S} p, \mathrm{R} o), \text { for } p=1 \text { to } \mathrm{n}
$$

where $\mathrm{N}_{p t}=$ employment in plant $p$ that lies within the labor market area of plant $o, \mathrm{n}=$ the number of plants within the Labor Market Area about plant $o$ that employ unusually large numbers of the same occupations as plant $o, \mathrm{f}$ (miles) is a function of the distance between plant $o$ and plant $p$, and $\mathrm{E}(S p, R o)$ is a weight based on the occupational similarity of 3-digit SIC $S$ (the 3-digit SIC of plant $p$ ) to 3-digit SIC $R$ (that of plant $o$ ).

Industry size for sector $s$ in county $c$ at time $t$ is the weighted average of all plants in sector $s$ in county $c$ :

$$
\mathrm{IND}_{-} \mathrm{SZ}_{c s t}=\frac{\sum\left(\mathrm{N} o^{*}(\mathrm{IND} \mathrm{SZ} p t)\right)}{\sum \mathrm{N} o} \text {, for } o=1 \text { to } \mathrm{m}
$$

where $\mathrm{m}=$ the number of plants in sector $s$ in county $c$, and $\mathrm{N}_{o}=$ employment in plant $o$ in sector $s$ in county $c$,
$\mathrm{IND}_{\text {_DENS }}^{c s t}$ = Industry density measure based on relative size of plants in industry, described in the section on data below.

## Local Labor Supply Characteristics

HS_ED $c=$ percent of adults ages 25-64 in county $c$ with at least high school education in 1990 Census of Population.

C_ED $c=$ percent of adults ages $25-64$ in county $c$ with college education in 1990 Census of Population.

## Additional County Characteristics

MET $=$ Dummy variable ( $1=$ Metro core county, 0 otherwise )
URB20 $=$ Dummy variable ( $1=$ Nonmetro, $20,000+$ urban residents, 0 otherwise )
$\mathrm{ADJ}=$ Dummy variable $(1=$ Adjacent to Metro core county, 0 otherwise $)$
HWY $=$ Dummy variable ( $1=$ Interstate highway through county, 0 otherwise )
COL $=$ Dummy variable ( $1=4$-year college or university, 0 otherwise )

## Year Dummies

D86-D93.

## Sector Dummies

$\mathrm{D} 1 \mathrm{M}=$ Dummy variable $(1=$ Meatpacking, 0 otherwise $)$
$\mathrm{D} 2 \mathrm{~F}=$ Dummy variable ( $1=$ Other food processing, 0 otherwise )
D3C = Dummy variable ( $1=$ Textiles apparel \& leather, 0 otherwise )
$\mathrm{D} 4 \mathrm{~W}=$ Dummy variable $(1=$ Furniture $\&$ wood products, 0 otherwise $)$
D5P = Dummy variable ( $1=$ Printing \& publishing, 0 otherwise )
D6C = Dummy variable ( $1=$ Chemicals \& petroleum, 0 otherwise )
D7P = Dummy variable ( $1=$ Plastics products, 0 otherwise )
$\mathrm{D} 8 \mathrm{M}=$ Dummy variable $(1=$ Metals \& equipment, 0 otherwise $)$
D9E = Dummy variable ( $1=$ Electronics \& instruments, 0 otherwise $)$
The year 1994 and the paper, rubber glass \& misc. sector are the omitted categories.

## Data

Data on Iowa county earnings and employment by 4-digit SIC code were obtained from ES 202 data. The dataset covers 6,664 manufacturing establishments that existed in Iowa's 99 counties at some point during 1986-94, and includes all manufacturing workers covered under unemployment insurance. ${ }^{3}$ Measures of local industry structure and weighted average plant size required employment for individual plants. When a 4-digit SIC code in a county contained multiple establishments, the 1987 and 1992 Census of Manufacturing data by ZIP Code (by employment size code), five editions of The Official Iowa Manufacturers Directory (1985-86 through 1995), and three editions of the Iowa Business Directory (1985,

1989 and 1994) were used to estimate the relative size of the plants in each year. The employment estimated for individual firms always add up to ES-202 industry totals for that year. Census of Manufacturing by ZIP Code for 1992 and 1987 and County Business Patterns 1983-1994 were used to estimate the sizes of an additional 4,443 manufacturing plants in the first two tiers of counties in neighboring states. All these data are by place of work, rather than by place of residence. The 1994 Iowa Industry-Occupation Matrix provided employment in 880 occupations by 3-digit SIC code, which was used to determine which manufacturing SIC codes employ unusually large proportions of the same occupations.

The model is estimated with pooled cross-section time-series data using weighted least squares. In order to take account of greater measurement error for smaller sectors, continuous variables for all observations were transformed with a weight equal to the square root of sector employment. All continuous variables are in natural log form. Dummy variables for years and sectors allow for the intercept to change.

More sophisticated procedures for pooled regressions exist, which take account of cross-section and time-series disturbances or correct for autocorrelation. However, these require a full panel of data for the years 1986-1994. This would require me to discard observations for those counties where there was no employment in the sector in some years due to either plant closures or startups. In plastics products, for instance, this would eliminate almost one-third of the counties with employment in 1994, and observations for an additional 7 counties that had plastics employment only in earlier years (see Table 1).

Table 1. Counties with employment and number of plants, by manufacturing sector

|  | Meat Packing | Other Food Process. | $\begin{gathered} \hline \hline \text { Textile } \\ \& \\ \text { Leather } \end{gathered}$ | Wood <br>  <br> Furn. | Printing \& Publ. | Chemical |  | Metals \& Equip. | Electr. <br>  <br> Instr. | Paper, Rubber, Glass, etc. |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Number of counties with employment in sector in: |  |  |  |  |  |  |  |  |  |  |
| All 9 years | 45 | 74 | 46 | 64 | 99 | 44 | 40 | 95 | 45 | 44 |
| Average year | 58 | 81 | 58 | 76 | 99 | 62 | 54 | 97 | 53 | 60 |
| 1994 | 55 | 82 | 59 | 84 | 99 | 60 | 58 | 98 | 54 | 63 |
| At least one year | 74 | 93 | 69 | 92 | 99 | 80 | 67 | 99 | 66 | 75 |
| Number of counties that had two or more 20+ plants in the sector in 1994 |  |  |  |  |  |  |  |  |  |  |
| 99 Iowa counties | 12 | 33 | 14 | 17 | 32 | 14 | 20 | 76 | 20 | 17 |
| 8 Metro Core | 4 | 8 | 5 | 5 | 8 | 6 | 7 | 7 | 7 | 7 |
| 9 Large Nonmetro | 1 | 7 | 1 | 3 | 7 | 5 | 2 | 9 | 2 | 5 |
| 82 Rural | 7 | 18 | 8 | 9 | 17 | 3 | 11 | 60 | 11 | 5 |
| Counties with multiple 20+ plants as a percent of all counties with employment in 1994 in the sector |  |  |  |  |  |  |  |  |  |  |
| Iowa | 22\% | 40\% | 24\% | 20\% | 32\% | 23\% | 34\% | 78\% | 37\% | 27\% |
| Metro Core | 50\% | 100\% | 63\% | 63\% | 100\% | 75\% | 88\% | 88\% | 88\% | 88\% |
| Large Nonmetro | 11\% | 78\% | 11\% | 33\% | 78\% | 63\% | 29\% | 100\% | 22\% | 63\% |
| Rural | 18\% | 28\% | 19\% | 13\% | 21\% | 7\% | 26\% | 74\% | 30\% | 11\% |
| Number of plants in 1994: Iowa |  |  |  |  |  |  |  |  |  |  |
| 20+ employees | 63 | 188 | 64 | 95 | 205 | 62 | 88 | 531 | 87 | 100 |
| All sizes | 119 | 385 | 153 | 327 | 900 | 188 | 152 | 1,217 | 208 | 257 |
| Large Nonmetro 250 |  |  |  |  |  |  |  |  |  |  |
| $20+$ employees | 8 | 31 | 5 | 17 | 28 | 20 | 9 | 71 | 13 | 26 |
| All sizes | 14 | 54 | 21 | 40 | 108 | 41 | 17 | 161 | 31 | 52 |
| Rural 5 |  |  |  |  |  |  |  |  |  |  |
| $20+$ employees | 37 | 67 | 37 | 41 | 76 | 16 | 52 | 254 | 44 | 31 |
| All sizes | 78 | 183 | 74 | 161 | 391 | 67 | 79 | 580 | 69 | 85 |

Average number of $20+$ employee plants per county with sector employment in 1994

| Metro Core | 2.3 | 11.3 | 2.8 | 4.6 | 12.6 | 3.3 | 3.4 | 25.8 | 3.8 | 5.4 |
| :--- | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: |
| Large Nonmetro | 0.9 | 3.4 | 0.6 | 1.9 | 3.1 | 2.5 | 1.3 | 7.9 | 1.4 | 3.3 |
| Rural | 1.0 | 1.0 | 0.9 | 0.6 | 0.9 | 0.4 | 1.2 | 3.1 | 1.2 | 0.7 |

Average number of <20 employee plants per county with sector employment in 1994

| Metro Core | 1.1 | 7.3 | 4.5 | 11.1 | 37.5 | 6.8 | 3.6 | 33.8 | 9.8 | 9.6 |
| :--- | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | :--- |
| Large Nonmetro | 0.9 | 2.6 | 4.0 | 3.8 | 8.9 | 3.0 | 2.0 | 10.0 | 3.6 | 3.7 |
| Rural | 2.1 | 2.8 | 1.8 | 2.4 | 4.8 | 1.5 | 1.8 | 7.2 | 1.9 | 1.8 |

Average number of plants per county with sector employment in 1994

| Metro Core | 3.4 | 18.5 | 7.3 | 15.8 | 50.1 | 10.0 | 7.0 | 59.5 | 13.5 | 15.0 |
| :--- | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: |
| Large Nonmetro | 1.7 | 6.0 | 4.6 | 5.7 | 12.0 | 5.5 | 3.3 | 17.9 | 5.0 | 7.0 |
| Rural | 3.0 | 3.8 | 2.6 | 3.0 | 5.7 | 1.9 | 3.0 | 10.3 | 3.1 | 2.5 |

## Iowa Manufacturing

Although Iowa is most often associated with farming, it is also a heavily manufacturing-dependent state: only six states had higher manufacturing value added per capita in 1992. (1992 Census of Manufactures 1995) Both metro and nonmetro Iowa manufacturing are most heavily concentrated in industrial equipment, other metalworking industries, meatpacking and other food processing (see Table 2). In 1992., 30\% of nonmetro and $45 \%$ of metro U.S. manufacturing employment was classified in SIC codes 33-38 (metals, equipment, and instruments) (Gale 1988). These SICs accounted for $47 \%$ of manufacturing in nonmetro and rural Iowa, and $46 \%$ in metro Iowa.

In the 1970 s, Iowa's manufacturing wages were between 4 th and 8 th highest in the nation. (BLS) In 1977 there were also only five states with higher value added per worker hour in manufacturing, and the combined result was that despite high wages, production wages per dollar of value added in Iowa were $94 \%$ of the U.S. average. As a result of rapid industrial restructuring during the 1980 s, both real hourly wages and productivity are now much closer to the national average.

In this study, I classify Iowa counties into four types: metro core ( 8 metro counties containing an urbanized area), large nonmetro ( 9 nonmetro counties with over 20,000 urban residents), rural adjacent ( 27 counties with fewer than 20,000 urban residents, within 35 miles of the urbanized area, including 2 metro fringe counties), and rural nonadjacent ( 55 counties).

Nonmetro Iowa manufacturing earnings in 1993 were $22 \%$ lower than metro Iowa (compared with $30 \%$ lower nationwide) (See Table 3). This average masks wide differences.
Table 2. 1994 distribution of manufacturing employment: U.S. and Iowa metro and nonmetro

| SIC Industry Group | $\begin{array}{r} \% \mathrm{All} \\ \hline \text { U.S. US Ind. } \\ \hline \end{array}$ |  | $\begin{array}{r} \hline \hline \% \mathrm{AlI} \\ \text { lowa IA Ind. } \\ \hline \end{array}$ |  | Metro Core | Share of lowa | Large Share of |  | Rural Share of <br> Adjacent lowa |  | Rural Share of <br> Nonadj. Iowa |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 20-- Manufacturing | 18,098,123 |  | 245,438 | 100.0\% | 101,326 | 41.3\% | 42,598 | 17.4\% | 39,783 | 16.2\% | 59,639 | 24.3\% |
| U.S. excluding auxiliaries | 16,813,765 | 100.0\% |  |  |  |  |  |  |  |  |  |  |
| 1 Meat Products | 420,336 | 2.5\% | 27,027 | 11.0\% | 11,40 | 42.2\% | 5,06 | 18.7\% | 2,75 | 10.2\% | ,811 | 28.9\% |
| 2 All Other Food \& Kindred | 1,068,350 | 6.4\% | 23,982 | $9.8 \%$ | 11,130 | 46.4\% | 5,522 | 23.0\% | 3,144 | 13.1\% | 4.186 | 17.5\% |
| 3 Textile \& Leather Prods. | 1,640,583 | 9.8\% | 7,664 | 3.1\% | 2,473 | 32.3\% | 287 | 3.7\% | 1,270 | 16.6\% | 3,633 | 47.4\% |
| 4 Wood Prods. \& Furniture | 1,190,769 | 7.1\% | 15,060 | $1 \%$ | 5,089 | $33.8 \%$ | 2,716 | 18.0\% | 3.492 | 23.2\% | 3,763 | 25.0\% |
| 5 Printing \& Publishing | 1,481,903 | 8.8\% | 21,202 | 8.6\% | 13,483 | 63.6\% | 2,109 | 9.9\% | 2.441 | 11.5\% | 3,169 | 14.9\% |
| 6 Chemicals \& Petroleum | 936,314 | 5.6\% | 7,947 | 3.2\% | 2,725 | 34.3\% | 3,558 | 44.8\% | 402 | 5.1\% | 1,262 | 15.9\% |
| 7 Misc. Plastics Products | 708,610 | 4.2\% | 9.656 | 3.9\% | 3,044 | 31.5\% | 1,478 | 15.3\% | 2.918 | 30.2\% | 2,216 | 23.0\% |
| 8 Metals \& Equipment | 5,475,860 | 32.6\% | 89,665 | 36.5\% | 34,841 | 38.9\% | 12.213 | 13.6\% | 18,109 | 20.2\% | 24.363 | 27.2\% |
| 9 Electronic, Electric, Instr. | 2,146,333 | 12.8\% | 21.994 | 9.0\% | 10,923 | 49.7\% | 5.009 | 22.8\% | 2.964 | 13.5\% | 3,235 | 14.7\% |
| 10 Paper Rubber Glass Misc. | 1,066,799 | 6.3\% | 16,182 | 6.6\% | 6,432 | 39.7\% | 5,183 | 32.0\% | 1,997 | 12.3\% | 2,570 | 15.9\% |

Table 3. Differences between 1993 Iowa metro and nonmetro manufacturing earnings

|  | All Manuf. | Meat Packing | Other Food Processing | Textiles \& Leather | Wood \& Furniture | Printing \& Publishing | Chemicals \& Petroleun | Plastics <br> Products | Metals \& Equip. | Electronics Instruments | Paper Rubber Glass Misc. |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Actual Manufacturing Earnings 1993 |  |  |  |  |  |  |  |  |  |  |  |
| Metro | \$33,799 | \$23,086 | \$35,232 | \$19,419 | \$23,556 | \$28,000 | \$35,625 | \$26,389 | \$40,254 | \$38,475 | \$35,557 |
| All Nonmetro | \$26,396 | \$22,492 | \$29,888 | \$16,676 | \$26,420 | \$17,174 | \$34,989 | \$21,982 | \$28,149 | \$27,383 | \$28,477 |
| Urban20k | \$31,446 | \$22,997 | \$34,450 | \$16,109 | \$33,914 | \$17,792 | \$38,826 | \$25,211 | \$32,996 | \$36,770 | \$29,753 |
| RurAdj | \$25,611 | \$21,713 | \$28,585 | \$15,136 | \$26,269 | \$18,166 | \$24,358 | \$20,456 | \$28,936 | \$19,453 | \$31,275 |
| RurNAdj | \$22,901 | \$22,446 | \$25,013 | \$17,269 | \$20,845 | \$16,068 | \$27,325 | \$21,552 | \$25,154 | \$20,229 | \$23,768 |
| Earnings Predicted by 1993 Industry Mix if Earned 1993 U.S. Average Earnings in each 4-digit SIC |  |  |  |  |  |  |  |  |  |  |  |
| Metro | \$31,431 | \$21,694 | \$32,287 | \$18,791 | \$22,923 | \$29,274 | \$37,312 | \$25,370 | \$33.521 | \$42,488 | \$32,670 |
| All Nonmetro | \$29,067 | \$21,140 | \$30,257 | \$16,686 | \$24,000 | \$27,908 | \$41,163 | \$25,638 | \$31,806 | \$32,638 | \$29,203 |
| Urban20k | \$30,632 | \$20,813 | \$32,803 | \$18,948 | \$27,276 | \$27,712 | \$41,465 | \$25,577 | \$31,881 | \$32,071 | \$30,742 |
| RurAdj | \$29,272 | \$22,048 | \$27,985 | \$17,361 | \$23,388 | \$27,743 | \$39,929 | \$25,711 | \$32,555 | \$33,548 | \$30,078 |
| RurNAdj | \$27,667 | \$21,013 | \$28,700 | \$16,245 | \$22,126 | \$28,150 | \$40,689 | \$25,592 | \$31,215 | \$32,641 | \$25,372 |
| \% Difference from Actual Iowa Metro Earnings |  |  |  |  |  |  |  |  |  |  |  |
| All Nonmetro | -22\% | -3\% | -15\% | -14\% | 12\% | -39\% | -2\% | -17\% | -30\% | -29\% | -20\% |
| Urban20k | -7\% | 0\% | -2\% | -17\% | 44\% | -36\% | 9\% | -4\% | -18\% | -4\% | -16\% |
| RurAdj | -24\% | -6\% | -19\% | -22\% | 12\% | -35\% | -32\% | -22\% | -28\% | -49\% | -12\% |
| RurNAdj | -32\% | -3\% | -29\% | -11\% | -12\% | -43\% | -23\% | -18\% | -38\% | -47\% | -33\% |
| \% Difference from lowa Metro Earnings After Adjusted for Industry Mix |  |  |  |  |  |  |  |  |  |  |  |
| All Nonmetro | -16\% | 0\% | -9\% | -3\% | $7 \%$ | -36\% | -11\% | -18\% | -26\% | -7\% | -10\% |
| Urban20k | -5\% | 4\% | -4\% | -18\% | 21\% | -33\% | -2\% | -5\% | -14\% | 27\% | -11\% |
| RurAdj | -19\% | -7\% | -6\% | -16\% | 9\% | -32\% | -36\% | -24\% | -26\% | -36\% | -4\% |
| RurNAdj | -23\% | 0\% | -20\% | 3\% | -8\% | -40\% | -30\% | -19\% | -33\% | - $32 \%$ | -14\% |

Sources: Iowa data from Iowa Department of Employment Services ES-202 data. U.S. earnings from 1993 County Business Patterns.

Large nonmetro counties have average annual manufacturing wages $5-7 \%$ lower than those in metro core counties. Adjacent rural earnings were $24 \%$ lower and nonadjacent rural earnings $32 \%$ lower than 1993 metro core earnings in lowa. Only about a fourth of this gap can be explained by differences in mix of 4-digit SIC codes. Cost of living cannot account for these large differences in Iowa manufacturing wages. Nonmetro cost of living in 1989 is estimated to be $5.3 \%$ lower than metro Iowa, and $4.4 \%$ lower when average metro and nonmetro cost of living is weighted by the number of manufacturing jobs in each county rather than by total population. ${ }^{4}$ Metro-nonmetro differences in hours worked are minimal (see Table 4).

Table 4. Average weekly hours of production workers in Iowa manufacturing

|  | $\mathbf{1 9 7 7}$ | $\mathbf{1 9 8 2}$ | $\mathbf{1 9 8 7}$ | $\mathbf{1 9 9 2}$ |
| :--- | ---: | ---: | ---: | :---: |
| Iowa Manufacturing | 37.4 | 35.6 | 38.1 | 39.0 |
| Metro | 37.4 | 35.1 | 38.0 | 39.2 |
| Nonmetro | 37.4 | 36.0 | 38.2 | 38.9 |
| Nonmetro as \% of Metro | $100.0 \%$ | $102.6 \%$ | $100.6 \%$ | $99.2 \%$ |

Source: Census of Manufacturing, various years.

Capital-labor ratios for metro core and rural manufacturing in Iowa are not equal.
During 1982-1992, new capital expenditures per employee in rural Iowa counties were 14$23 \%$ less than metro. New capital expenditures per production worker were $28-36 \%$ lower. (see Figure 1). Large nonmetro counties in Iowa appear to have manufacturing capital-labor ratios that are, on average, comparable to those of metro counties during 1982-1992.


Figure 1. Capital expenditures per manufacturing employee and per production worker

## Key-occupation Elasticities and the Definition of an "Industry"

Rosabeth Kanter (1995) writes that clusters are "concrete manifestations of more generic skills that cut across industries and outlast them." For purposes of this study, the"industry" for any plant is defined to be other plants in the same 3-digit SIC in the labor market area, plus some share of employment in those 3-digit SICs that use unusually high proportions of the same key occupations. Key occupations for a given SIC are defined to be those occupations that SIC employs in greater proportions than the (statewide) average across all SIC codes.

Two $880 \times 1$ vectors were calculated for each 3-digit SIC. The first contains an arc
elasticity $\mathrm{E}(S o)$ for each occupation. $\mathrm{E}(S o)$ is the arc-elasticity for the share of occupation o out of total employment in 3-digit SIC $S, \mathrm{SH}(\mathrm{So})$, relative to the share of occupation $o$ in the total economy, $\mathrm{SH}(\mathrm{To})$.

$$
\begin{aligned}
\mathrm{E}(\mathrm{So})= & \underline{\mathrm{SH}(S o)-\mathrm{SH}(T o)} \\
& \left(\mathrm{SH}(S o)+\mathrm{SH}(T o)^{*} 0.5\right.
\end{aligned}
$$

The higher the value of $\mathrm{E}(S o)$, the more the presence or growth of SIC $S$ will increase local or regional employment of occupation $o$. The second vector contains a set of weights. $\mathrm{WE}(R o)$ is the weight attached to occupation $o$ in SIC $R$. It is the share of occupation $o$ in the wage bill of SIC $R$ in excess of the share of occupation $o$ in the wage bill for the total economy.

$$
\mathrm{WE}(R o)=\frac{(\mathrm{SH}(R o)-\mathrm{SH}(T o))^{*} \mathrm{wo}}{\sum\left(\mathrm{SH}(R o)^{*} \mathrm{wo}\right)}
$$

where $w o$ is the average wage of occupation $o$ in the economy. Share of wages is used rather than share of employment for occupation weights on the assumption that workers with higher wages will generally have higher levels of human capital, and plants will incur higher search costs per employee for higher wage occupations. The key-occupation elasticity of SIC $S$ with respect to SIC $R$ is:

$$
\mathrm{E}(S, R)=\quad \sum\left(\mathrm{E}(S o)^{*} \mathrm{WE}(R o)\right) \quad \text { for } o=1 \text { to } 880
$$

where $\mathrm{E}(S, R)$ is the key-occupation elasticity of industry $S$ with respect to industry $R$. The matrix of key-occupation elasticities of industries with respect to other industries is not symmetric: in general, $\mathrm{E}(S, R) \neq \mathrm{E}(R, S)$.

If secretaries are $6 \%$ of the wage bill for a particular industry, and $5 \%$ for Iowa as a
whole, the industry's weight for this occupation $\mathrm{WE}(R o)$ is 0.01 , not 0.06 . The construction of this measure does not say that ubiquitous occupations such as secretaries are unimportant. Rather, it is intended to reflect that the growth or presence of a particular 3-digit industry that employs 0.06 secretaries will do little more to increase the available pool of trained and experienced secretaries than general growth in the local economy. Obviously, individual firms may differ widely in the their staffing patterns, and will often substitute away from scarce occupations in a particular labor market. These "elasticities" derived from state averages are intended only to develop a measure of which other industries also tend to employ large numbers of the same unusual or specialized occupations.

These key occupation elasticities can be used to attach relative weights to plant employment in closely related 3-digit SICs in a straightforward manner and with a clear interpretation. The key occupation elasticity of 3820 (measuring and controlling devices) with respect to 3570 (computer equipment) is two-thirds that of 3570 with respect to itself $(17.7 / 26.8=0.66)$. Thus, on average, the presence of a 3820 plant with 300 employees will have roughly the same impact as a 3570 plant with 200 employees, when we define impact to be raising local employment in key occupations to 3570 .

Any given 3-digit manufacturing industry group includes a share of employment from, on average, ten other 3-digit SIC codes (see Appendix Table A1). This is roughly the same level of detail as 2-digit SIC codes. 3690 (Misc. Electrical Equipment \& Supplies) pulls in some share of employment from 28 other 3-digit SICs, while at the other extreme, there are not any other 3-digit SICs judged to be closely related to 2010 (Meat Products) according to
key-occupation elasticities.

## Definition of a "Sector"

3-digit industries were grouped into 10 manufacturing sectors: 1) meatpacking, 2) other food processing, 3) textiles apparel and leather, 4) furniture and wood products, 5) printing and publishing, 6) chemicals and petroleum, 7) plastics products, 8) metalworking \& industrial \& transportation equipment 9) electronics, electrical equipment and instruments, and 10) a miscellaneous sector containing paper products, rubber products, glass ceramic and pottery products, and misc. manufacturing (all of these "miscellaneous" industries had observations in a relatively small number of counties when taken by themselves). 3630 Household Appliances is grouped with SIC 33, 34, 35 and 37, rather than with the rest of SIC 36, while 3570 Computer Equipment is categorized with SICs 36 and 38.

Grouping paper rubber glass \& miscellaneous manufacturing in a single sector should not be a major cause for concern. A labor market area with just six 250-employee paper plants located together will have an industry size of 1,500 and industry density of 6 in this sector. A labor market area that has just six 250-employee plants located next to each other, with two in paper, two in rubber, and two in glass products can be expected to have an industry size of 500 and industry density of 2 in this sector. The principal drawback is that differences in parameters between these four largely unrelated industry groups will, of course, be blurred. The alternatives are to throw out this information or have an insufficient number of observations.

SICs 3240 (Cement, Hydraulic), 3250 (Structural Clay Products), 3270 (Concrete,

Gypsum and Plaster Products) and 3280 (Cut Stone and Stone Products) were not included in any sector. Due to classic location theory weight and transport cost considerations, these industries generally locate either near the source of raw materials (gypsum, clay, etc.), or near the source of final demand (ready mixed concrete).

## Definition of a "Labor Market Area"

Many studies of agglomeration use metro areas or BEA labor market areas as the unit of observation. Where the commuting area has a dense core and relatively sparsely populated boundaries, this unit can capture most of the establishments and workers within commuting distance of each other fairly well. In this study with only 99 counties, it is not feasible to group counties into labor market areas because this would throw away too much information and result in too few observations.

Using only employment within county borders can be a misleading indicator of labor market size in many nonmetro areas. There are nearly as many metalworking workers (around 5,000) within 25 minutes drive of Ottumwa (population 30,000) as there are within 25 minutes of any point in the Des Moines metro area (population near 400,000). But they are located in at least six different counties in the area around Ottumwa, while most of the Des Moines metro metalworking jobs are in Polk County. A rural county that borders a metro is also part of a much larger labor market than its own county employment suggests.

When I calculate overall workforce size, industry size, and industry density in this study, I include some fraction of plant employment in neighboring counties. This fraction of employment is a declining bell-shaped function of distance that drops off rapidly beyond 15
miles, has a weight near 0.50 at 25 miles, and a weight close to 0.10 at 50 miles (see Figure 2).
This was derived from journey to work data in the 1990 Census, assuming that average commute times reflect the distribution of manufacturing workers' places of residence around their place of work, and taking the percent of workers who commute at least a given


Figure 2. Distance function used for workforce size, industry size, and industry density
number of minutes as the percent who would be willing to travel that distance to a manufacturing job at a second point. ${ }^{5}$ Distance between any two ZIP Code points is calculated as the sum of the vertical and horizontal distances rather than the shortest diagonal distance, since most roads either are laid out on a NSEW grid or else meander as they follow rivers and other natural features. (Swenson 1996) Beyond a fixed minimum time for trips of
all distances, I treat minutes and miles as interchangeable. ${ }^{6}$
The resulting measures of industry size and workforce size within the labor market area will nearly always be larger than measures based only on own county employment. Given employment evenly and uniformly distributed across space and lowa's average county size, the size of the labor market area around a plant will be 3.5 to 4 times larger than a single county. For small counties near larger ones, the difference is even larger. The maximum workforce size is 219,347 for Polk County (own county workforce of 173,353 , and 206,854 for the Des Moines MSA), while the minimum is 15,610 and the average for all Iowa counties is 55,315. (see Appendix Table A4).

## Measure of Industry Density

In addition to measuring industry size, this analysis utilizes a measure of industry density. In cases where multiple units are owned by a single firm, this study defines a plant to be a unit with a distinct street address found in either the Directories of Manufacturing or the Iowa Business Directories. Regression results are reported for industry density, which is simply the reciprocal of the Herfindahl index. If there are $m$ plants in the industry, the industry density for plant $o$ is:

$$
\text { Industry density }_{o t}=\frac{1}{\sum\left(\mathrm{~s}_{p t}\right)^{2}} \text { for } p=1 \text { to } \mathrm{m}
$$

where $\mathrm{S}_{p t}$ is the share of plant $p$ in total industry employment at time $t$ in the labor market area about plant $o$.

$$
\text { and } \mathrm{s}_{p t}=\frac{\mathrm{N}_{p t}}{\sum \mathrm{~N}_{p t}} \text { for } p=1 \text { to } \mathrm{m}
$$

where $\mathrm{N} p t=$ employment of plant $p$ at time $t$.
I take the reciprocal of the standard Herfindahl index because this makes it far easier to interpret the resulting regression coefficients. Transformed in this way, one plant in the industry has industry density of 1 , three equally sized plants in the same 3-digit SIC at the same location results in industry density of 3 , etc.. Industry density for one plant with $50 \%$, one with $30 \%$, and one with $20 \%$ of the industry employment is 2.63 , the same as that of 2.6 equally-sized establishments. The easiest way to imagine a $100 \%$ increase in industry density is to think of creating a twin for each plant in the labor market area (or if we wish to hold industry size constant, each plant would become half as large).

The value of industry density for sector $s$ in county $c$ at time $t$ is the weighted average of all plants $o$ in sector $s$ in county $c$ at time $t:^{7}$

$$
\text { industry density }_{c s t}=\sum\left(\mathrm { N } o ^ { * } \left(\frac{\text { Density-Mot }))}{\sum \mathrm{N} o}\right.\right.
$$

## Industry Size and Density Incorporating Distance and Industry Weights

Since plants in different (but closely related) 3-digit industries are given weights between 0.30 and 1.00 , and plants located in other ZIP Codes have a weight attached to them that is a declining function of distance, the equivalent size of a plant $\mathrm{N}_{p}$ is:

$$
\mathrm{N}_{p}=\mathrm{NA}_{p} * \mathrm{~W}\left(S_{p}, R_{o}\right) * \mathrm{f}\left(\text { miles }_{p o}\right)
$$

where $\mathrm{NA}_{p}=$ actual employment of plant $p$ in 3-digit SIC $S, \mathrm{~W}(R, S)$ is the relative weight attached to employment in closely related SIC S with respect to any plant in SIC $R$

$$
\mathrm{W}(S, R)=\frac{\mathrm{E}(S, R)}{\mathrm{E}(R, R)}
$$

where $\mathrm{E}(R, R)$ is the key-occupation elasticity of SIC $R$ with respect to itself, $\mathrm{E}(S, R)$ is the key-occupation elasticity of SIC $S$ with respect to key occupations of SIC $R$.
and $f$ (miles) is a bell-shaped declining function of distance with a value between 0 and 1 .
Industry size in the labor market area around plant $g$ in SIC R is:
Industry Size $=\sum \mathrm{N}_{p}$, for $p=1$ to m
where m is the number of plants in the Industry of plant ${ }_{o}$, (both in SIC $R$, and in all closely related SICs).

Similarly, we incorporate the equivalent employment sizes, adjusted for plants in closely related SICs and for plants at some distance from plant g , into the calculation of industry density.

Industry density $=\frac{1}{\sum \mathrm{~s}_{p} \wedge^{2}}$, for $p=1$ to m
where $\mathrm{S}_{p}$ is the share of plant i in total industry employment.

$$
\mathrm{S}_{p}=\frac{\mathrm{N} p}{\sum \mathrm{~N} p} \text { for } p=1 \text { to } \mathrm{m}
$$

Industry density as I have measured it is nearly equal for metro and nonadjacent rural counties, on average, which is not what I would have expected. While industry density is generally higher in metro core counties than it is in completely remote rural counties, by far the highest values are in exurban counties located 20-60 miles from metro areas. This measure will reflect the diversity of places of work for the employees within commuting distance of a
plant, and not just the density of plants actually located near the plant. It is unclear whether these high values for exurban counties are an accurate reflection of industry density relative to urbanized areas.

Other plant and SIC-level variables are aggregated to observations for a sector in a county in the same fashion. Industry density, plant size, actual earnings, U.S. weighted earnings, and other measures for the printing and publishing sector in Linn County are each the weighted average for all the printing and publishing plants located in that county.

## Results

Do increases in industry localization (greater industry size and industry density) raise manufacturing wages in nonmetro areas, and are urbanization economies responsible for a large share of the differences in manufacturing earnings among counties? In nine of the ten sectors, we find that greater industry size and density do not lead to higher wages. Indeed, in at least half of the sectors, the estimated coefficient for both measures of clustering is significantly negative. Only in metals does the combined effect of industry size and industry density have a significant positive effect. We find that workforce size, on the other hand, has a quite strong effect on wages in most sectors. A quite large share of the differences in manufacturing earnings among nonmetro county types are not predicted by either industry size and density or by workforce size (or the other control variables included in my model), which points to a need to explore what other factors contribute to high or low nonmetro manufacturing earnings.

Because natural logarithms were used for all continuous variables, their coefficients can be interpreted as elasticities. I compare results of two specifications: the first is a more basic model (see Tables 5 and 6), and the second one includes dummy variables for several additional county characteristics (see Tables 7 and 8 ). Because the detailed model contains multiple measures of urbanization using both a continuous variable (workforce size) and dummy variables (metro core, large nonmetro and adjacent), it requires us to combine an elasticity and a discrete change to obtain a unified measure of urbanization. While the addition of these dummy variables does not significantly alter the coefficient for workforce size in the overall regression, it does for many individual sectors. ${ }^{8}$ Thus, the major advantage of the basic model is that it allows me to report a single measure of urbanization, particularly in graphs.

I begin with results for the overall regression for all 10 sectors combined. Discussion of results for individual sectors will follow. In the overall regression for all ten sectors, workforce size was significant and positive. Doubling the total number of workers in the labor market area is estimated to increase manufacturing earnings by $7.4 \%$ (see Table 5). Estimated coefficients for both industry size and industry density are negative and significant. A $100 \%$ increase in industry size is estimated to lower earnings $1.9 \%$, while a $100 \%$ increase in industry density decreases earnings by $2.8 \%$, holding all other variables constant. The estimated coefficients for MET and URB20 dummy variables in the detailed model indicate that manufacturing wages are $5.3 \%$ higher in metro core counties and $6.4 \%$ higher in large nonmetro counties, all else being equal. In general, urbanization clearly raises manufacturing wages, but localization does not.
Table 5. Basic model: WLS results for county manufacturing earnings by sector, 1986-1994

|  | All 10 | Meat | Other Food | Textiles | Wood \& | Printing \& Chemicals \& | Plastics | Metals \& | Electronics Paper Rubber |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Sectors | Packing | Processing | \& Leather | Furniture | Publishing | Petroleum | Products | Equipment | Instruments Glass Misc. |  |
| US PR EA | $0.742^{* *}$ | $1.994^{* *}$ | $0.634^{* *}$ | $0.653^{* *}$ | $1.027^{* *}$ | $0.974^{* *}$ | 0.211 | $0.706^{* *}$ | $0.716^{* *}$ | $0.547^{* *}$ | $0.722^{* *}$ |

                                    \({ }_{*}^{*} \stackrel{*}{*}\)
                                    \(1.164 \quad 2.763^{* *} \quad 1.170\)
    *     * 

0.001

*     *         *             * 

-0.014
0.161
0.168
-0.040
-0.043
-0.054 -0.029
-0.014 $-0.022$
0.022
-0.019
$1.164-2.763^{* *}$
Table 6. Basic model: T-ratios for WLS on county earnings by manufacturing sector, 1986-1994

|  | All 10 Sectors | Meat Packing | Other Food Processing | Textiles \& Leather | Wood \& Furniture | Printing \& Publishing | Chemicals \& Petroleum | Plastics Products | Metals \& Equipment | Electroni Instrume | Paper Rubber Glass Misc. |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| US_PR_EA | 21.250 | 12.350 | 6.487 | 5.704 | 12.640 | 6.806 | 1.596 | 3.858 | 9.353 | 4.474 | 5.562 |
| PLANTSZ | 12.580 | -2.986 | 10.770 | 0.095 | 10.190 | 11.410 | 3.445 | 0.032 | 3.793 | 1.397 | 3.555 |
| WKFC_SZ | 7.465 | -4.129 | 4.361 | -0.035 | 1.465 | 8.195 | 5.417 | 1.488 | 6.141 | 6.543 | 2.686 |
| IND_SZ | -3.083 | -1.406 | -4.868 | 2.427 | -1.117 | -6.449 | -5.887 | -2.308 | 1.836 | -1.703 | -2.414 |
| IND_DENS | -3.570 | 0.223 | 1.925 | -2.922 | -4.091 | -2.287 | -0.133 | 1.990 | 0.015 | -0.525 | 1.704 |
| HS_ED | 1.851 | -3.479 | 1.356 | 3.007 | -2.966 | -2.299 | 3.703 | 1.967 | 1.627 | 0.796 | 1.275 |
| C_ED | 6.153 | 2.810 | -1.861 | 2.161 | 4.546 | 2.586 | -0.536 | 0.056 | 1.425 | 2.703 | 0.070 |
| D86 | 1.622 | -1.314 | -0.378 | 0.922 | -1.205 | 0.838 | 0.045 | 0.839 | 2.512 | -0.606 | 1.342 |
| D87 | -0.601 | -2.424 | -0.892 | -0.438 | -0.599 | 0.636 | 0.040 | -0.836 | 1.414 | -0.654 | 0.302 |
| D88 | -0.048 | -2.420 | -0.524 | -0.431 | 0.142 | 0.476 | 1.035 | -0.392 | 0.648 | -0.821 | 0.122 |
| D89 | -0.400 | -1.838 | -1.389 | -0.637 | -0.372 | 0.279 | 0.693 | 0.266 | 0.334 | -0.442 | 0.793 |
| D90 | -0.738 | -1.260 | -1.239 | -0.795 | -0.066 | 0.184 | 0.435 | -0.633 | 0.836 | -0.216 | 0.905 |
| D91 | -0.085 | 0.095 | -1.300 | -0.601 | 0.664 | 0.635 | 0.920 | -0.473 | 0.491 | -0.338 | 0.110 |
| D92 | 1.047 | -0.689 | -0.296 | -0.265 | 0.459 | 0.015 | 1.667 | -0.028 | -0.007 | 0.336 | 1.282 |
| D93 | -0.183 | -0.188 | -0.540 | -0.278 | 0.294 | -0.326 | 0.036 | -0.435 | 0.454 | -0.301 | 0.781 |
| CONSTANT | 5.092 | -4.648 | 2.752 | 2.341 | 0.014 | -1.112 | 4.434 | 1.013 | 1.502 | 2.217 | 0.898 |
| DIM | 12.600 |  |  |  |  |  |  |  |  |  |  |
| D2F | 10.470 |  |  |  |  |  |  |  |  |  |  |
| D3C | -0.900 |  |  |  |  |  |  |  |  |  |  |
| D4W | 5.144 |  |  |  |  |  |  |  |  |  |  |
| D5P | -4.603 |  |  |  |  |  |  |  |  |  |  |
| D6C | 8.212 |  |  |  |  |  |  |  |  |  |  |
| D7P | 5.291 |  |  |  |  |  |  |  |  |  |  |
| D8M | 6.241 |  |  |  |  |  |  |  |  |  |  |
| D9E | -0.027 |  |  |  |  |  |  |  |  |  |  |
| CONSTANT | 5.092 |  |  |  |  |  |  |  |  |  |  |

Table 7. Detailed model: WLS results for county earnings by manufacturing sector, 1986-1994

|  | All 10 Sectors | Meat Packing | Other Food Processing | Textiles \& Leather | Wood \& Furniture | Printing \& Publishing | Chemicals \& Petroleum | Plastics Products | Metals \& Equipment | Electronics Instruments | Paper Rubber Glass Misc. |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| US_PR_EA | 0.719 ** | 1.966 ** | $0.471^{* *}$ | 0.673 ** | 0.948 ** | $0.916^{* *}$ | 0.186 | $0.626^{* *}$ | $0.702^{* *}$ | 0.490 ** | $0.688{ }^{* *}$ |
| PLANTSZ | 0.083 ** | -0.110 ** | 0.191 ** | -0.015 | 0.158 ** | $0.173^{* *}$ | 0.068 ** | 0.036 | $0.043^{\text {** }}$ | 0.027 | $0.121^{* *}$ |
| WKFC_SZ | 0.076 ** | -0.017 | 0.183 ** | -0.059 | 0.064 * | $0.284^{* *}$ | $0.184^{* *}$ | $0.125^{* *}$ | 0.061 ** | $0.171^{* *}$ | $0.239^{* *}$ |
| IND_SZ | -0.015 ** | -0.034 | -0.106 ** | 0.039 | -0.027 ** | -0.202 ** | -0.147 ** | -0.060 ** | 0.039 ** | -0.026 | -0.051 ** |
| IND_DENS | -0.028 ** | -0.004 | 0.042 * | -0.116 ** | -0.059 ** | -0.048 ** | -0.001 | $0.062^{* *}$ | 0.005 | -0.025 | 0.044 |
| HS_ED | $0.164^{* *}$ | -0.867 ** | $0.424^{* *}$ | $0.863^{* *}$ | -0.188 | -0.356 * | 0.859 ** | $0.497^{* *}$ | 0.268 ** | 0.221 | 0.141 |
| C_ED | $0.055^{* *}$ | $0.353^{* *}$ | -0.218 ** | -0.058 | $0.107^{*}$ | $0.155^{* *}$ | 0.006 | -0.117 | -0.023 | $0.213^{* *}$ | 0.008 |
| MET | $0.053^{* *}$ | 0.043 | 0.088 | $0.164^{*}$ | -0.101 * | $0.128^{* *}$ | 0.099 | 0.096 | $0.123^{* *}$ | 0.072 | -0.206 ** |
| URB20 | $0.064^{* *}$ | -0.107 | $0.207^{* *}$ | $0.361^{* *}$ | -0.032 | -0.064 ** | $0.157^{* *}$ | $0.111^{* *}$ | $0.161^{* *}$ | 0.001 | -0.113 |
| ADJ | -0.013 | -0.158 ** | -0.002 | 0.053 | -0.003 | $0.082^{* *}$ | 0.030 | -0.131 ** | 0.008 | 0.076 | -0.141 ** |
| HWY | $-0.036^{* *}$ | -0.225 ** | -0.146 ** | -0.092 ** | -0.038 | 0.029 | 0.056 | -0.088 ** | 0.019 | -0.101 ** | -0.034 |
| COL | 0.042 ** | -0.125 ** | 0.097 ** | $0.161^{* *}$ | 0.163 ** | $-0.073^{* *}$ | -0.081 | 0.024 | 0.010 | -0.019 | 0.038 |
| D86 | 0.031 | -0.106 | -0.019 | 0.071 | -0.057 | 0.024 | 0.004 | 0.041 | 0.071 ** | -0.043 | 0.109 |
| D87 | -0.011 | -0.195 ** | -0.042 | -0.036 | -0.028 | 0.018 | -0.001 | -0.056 | 0.041 | -0.045 | 0.027 |
| D88 | 0.000 | -0.185 ** | -0.026 | -0.031 | 0.007 | 0.014 | 0.074 | -0.030 | 0.020 | -0.056 | 0.013 |
| D89 | -0.007 | -0.130 * | -0.071 | -0.052 | -0.020 | 0.009 | 0.050 | 0.014 | 0.010 | -0.032 | 0.068 |
| D90 | -0.014 | -0.098 | -0.067 | -0.058 | -0.006 | 0.006 | 0.034 | -0.038 | 0.022 | -0.017 | 0.076 |
| D91 | -0.002 | 0.008 | -0.069 | -0.039 | 0.028 | 0.020 | 0.073 | -0.031 | 0.012 | -0.026 | 0.014 |
| D92 | 0.019 | -0.050 | -0.014 | -0.019 | 0.021 | 0.003 | 0.132 | -0.004 | -0.002 | 0.021 | 0.100 |
| D93 | -0.004 | -0.011 | -0.025 | -0.021 | 0.013 | -0.010 | 0.003 | -0.026 | 0.012 | -0.017 | 0.063 |
| CONSTANT | $1.934^{* *}$ | -9.432 ** | $3.821^{* *}$ | $2.764^{* *}$ | 0.292 | -0.605 | $6.832^{* *}$ | 2.043 | $1.624^{* *}$ | $3.505^{* *}$ | 0.355 |
| DIM | $0.311^{* *}$ |  |  |  |  |  |  |  |  |  |  |
| D2F | 0.225 ** |  |  |  |  |  |  |  |  |  |  |
| D3C | -0.038 |  |  |  |  |  |  |  |  |  |  |
| D4W | $0.107^{* *}$ |  |  |  |  |  |  |  |  |  |  |
| D5P | $-0.103^{* *}$ |  |  |  |  |  |  |  |  |  |  |
| D6C | $0.204^{* *}$ |  |  |  |  |  |  |  |  |  |  |
| D7P | $0.121^{* *}$ |  |  |  |  |  |  |  |  |  |  |
| D8M | $0.162^{* *}$ |  |  |  |  |  |  |  |  |  |  |
| D9E | 0.003 |  |  |  |  |  |  |  |  |  |  |
| R-Sq Adj | 0.921 | 0.920 | 0.922 | 0.887 | 0.941 | 0.950 | 0.846 | 0.904 | 0.968 | 0.918 | 0.927 |
| $\mathrm{N}$ | 6284 | 520 | 733 | 522 | 688 | 891 | 555 | 486 | 872 | 473 | 544 |

[^0]Table 8. Detailed model: T-ratios for WLS on county earnings by manufacturing sector, 1986-1994

|  | All 10 Sectors | Meat Packing | Other Food Processing | Textiles \& Leather | Wood \& Furniture | Printing \& Publishing | Chemicals \& Petroleum | Plastics Products | Metals \& Equipment | Electronics Instrument | Paper Rubbe Glass Misc. |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| US_PR_EA | 20.470 | 12.220 | 4.691 | 6.065 | 11.420 | 6.400 | 1.361 | 3.382 | 9.195 | 3.879 | 5.087 |
| PLANTSZ | 12.630 | -2.836 | 10.450 | -0.507 | 9.684 | 11.410 | 2.957 | 0.931 | 3.741 | 0.996 | 3.966 |
| WKFC_SZ | 5.479 | -0.312 | 4.592 | -1.113 | 1.812 | 7.053 | 3.029 | 2.469 | 2.722 | 3.598 | 3.891 |
| IND_SZ | -2.530 | -1.180 | -5.174 | 1.390 | -1.995 | -7.404 | -5.626 | -2.248 | 2.911 | -1.578 | -2.147 |
| IND DENS | -3.473 | -0.128 | 1.804 | -3.326 | -3.454 | -2.513 | -0.029 | 2.013 | 0.332 | -0.904 | 1.333 |
| HS_ED | 2.898 | -4.310 | 2.608 | 4.926 | -1.317 | -1.886 | 3.397 | 2.013 | 2.378 | 1.003 | 0.603 |
| C ED | 2.224 | 3.142 | -3.267 | -0.663 | 1.729 | 3.347 | 0.049 | -1.551 | -0.600 | 2.605 | 0.084 |
| MET | 2.328 | 0.426 | 1.353 | 1.940 | -1.659 | 3.021 | 1.032 | 1.418 | 3.520 | 0.937 | -2.230 |
| URB20 | 3.752 | -1.550 | 4.337 | 6.120 | -0.747 | -2.079 | 2.041 | 2.001 | 6.143 | 0.013 | -1.628 |
| ADJ | -0.962 | -2.906 | -0.055 | 0.985 | -0.087 | 4.028 | 0.524 | -3.165 | 0.438 | 1.427 | -2.544 |
| HWY | -3.119 | -4.727 | -4.720 | -2.060 | -1.314 | 1.536 | 1.046 | -2.379 | 1.158 | -2.326 | -0.682 |
| COL | 2.856 | -1.987 | 2.484 | 3.012 | 4.269 | -2.877 | -1.182 | 0.514 | 0.462 | -0.365 | 0.647 |
| D86 | 1.614 | -1.353 | -0.386 | 0.959 | -1.189 | 0.775 | 0.045 | 0.657 | 2.589 | -0.647 | 1.387 |
| D87 | -0.571 | -2.458 | -0.843 | -0.489 | -0.592 | 0.601 | -0.016 | -0.909 | 1.482 | -0.685 | 0.351 |
| D88 | -0.018 | -2.373 | -0.529 | -0.428 | 0.148 | 0.471 | 0.920 | -0.492 | 0.722 | -0.843 | 0.174 |
| D89 | -0.388 | -1.700 | -1.448 | -0.716 | -0.431 | 0.285 | 0.617 | 0.233 | 0.366 | -0.486 | 0.887 |
| D90 | -0.762 | -1.275 | -1.374 | -0.828 | -0.125 | 0.188 | 0.418 | -0.656 | 0.822 | -0.264 | 1.002 |
| D91 | -0.126 | 0.109 | -1.416 | -0.562 | 0.600 | 0.651 | 0.898 | -0.533 | 0.437 | -0.393 | 0.185 |
| D92 | 1.030 | -0.644 | -0.278 | -0.274 | 0.458 | 0.083 | 1.637 | -0.066 | -0.059 | 0.321 | 1.294 |
| D93 | -0.185 | -0.145 | -0.516 | -0.302 | 0.278 | -0.323 | 0.040 | -0.451 | 0.437 | -0.272 | 0.822 |
| CONSTANT | 5.230 | -4.948 | 3.722 | 2.342 | 0.323 | -0.405 | 4.871 | 1.076 | 2.083 | 2.631 | 0.261 |
| DIM | 12.350 |  |  |  |  |  |  |  |  |  |  |
| D2F | 10.700 |  |  |  |  |  |  |  |  |  |  |
| D3C | -1.450 |  |  |  |  |  |  |  |  |  |  |
| D4W | 4.893 |  |  |  |  |  |  |  |  |  |  |
| D5P | -4.408 |  |  |  |  |  |  |  |  |  |  |
| D6C | 8.556 |  |  |  |  |  |  |  |  |  |  |
| D7P | 5.281 |  |  |  |  |  |  |  |  |  |  |
| D8M | 6.781 |  |  |  |  |  |  |  |  |  |  |
| D9E | 0.115 |  |  |  |  |  |  |  |  |  |  |

Doubling individual plant size is estimated to raise earnings by $8.3 \%$. Clearly the assumption of constant returns to scale in plant output needs to be relaxed. This may be due to economies of size in producing identical products, or may also be because larger plants produce different products from smaller plants. ${ }^{9}$

The model accurately predicts metro earnings relative to nonmetro earnings in general, but accounts for just over half the differences among nonmetro county types. When estimated coefficients are applied to means for the three nonmetro county types, the basic model ${ }^{10}$ predicts rural adjacent earnings to be $7.4 \%$ less than large nonmetro, only about half the actual difference of $14.4 \%$ (see Table 9). The model also predicts Rural Nonadjacent counties to earn $9.0 \%$ less than Rural Adjacent, when in fact they earn $15.3 \%$ less. This tells us that, while urbanization, industry mix, and plant size are all important factors in explaining nonmetro manufacturing earnings, other unmeasured factors (perhaps capital per worker or unionization $)^{11}$ make a large difference as well. The omission of capital data might alter my results for urbanization and reduce the ability of my model to predict nonmetro earnings in general, but I see no reason why it should bias my coefficients for industry clustering. ${ }^{12}$

The model was also estimated separately for ten manufacturing sectors. I report results for the more detailed model in the text unless otherwise noted. ${ }^{13}$ (see Table 7 and Figures 3 and 4) The results are quite mixed for many variables, but the only sector where industry clustering clearly raises manufacturing wages is metals \& equipment. Doubling industry size raises manufacturing wages by a modest $3.9 \%$, while the effect of industry density is near zero. (see Table 7) This is an important sector for rural development in Iowa,
Table 9. 1994 means for four county types and wage differences predicted by basic model

|  | Means by county type, counties in each type weighted by number of manufacturing workers |  |  |  | BasicModelEstimatedCoefficient | Predicted effect on wages due to differences in mean between: |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  |  |  | Type: | Lg NMet | RurAdj | RurNAdj | RurAdj | RurNAdj | RurNAdj |
|  | Metro | Nonmetro | Adjacent | Nonadjent |  | Type: | Metro | Metro | Metro | Lg Nmet | RurAdj | Lg Nmet |
| Actual Earnings | \$34,388 | \$32,010 | \$27,416 | \$23,223 |  |  |  |  |  |  |  |  |  |
| US_WT_EA | \$31,346 | \$30,585 | \$28,987 | \$27,947 | 0.742 |  | -1.8\% | -5.6\% | -8.2\% | -3.9\% | -2.7\% | -6.5\% |
| PLANTSZ | 158\% | 104\% | 112\% | 77\% | 0.082 |  | -3.4\% | -2.8\% | -5.7\% | 0.6\% | -3.0\% | -2.4\% |
| WKFC_SZ | 128,173 | 60,449 | 70,882 | 34,865 | 0.074 |  | -5.4\% | -4.3\% | -9.2\% | 1.2\% | -5.1\% | -4.0\% |
| IND_SZ | 2,878 | 1.251 | 1,835 | 999 | -0.019 |  | 1.6\% | 0.8\% | 2.0\% | -0.7\% | 1.1\% | 0.4\% |
| IND DENS | 6.5 | 5.7 | 6.6 | 6.5 | -0.028 |  | 0.4\% | -0.1\% | 0.0\% | -0.4\% | 0.1\% | -0.4\% |
| HS_ED | 87.4\% | 86.1\% | 86.3\% | 86.6\% | 0.098 |  | -0.1\% | -0.1\% | -0.1\% | 0.0\% | 0.0\% | 0.1\% |
| C_ED | 23.9\% | 18.1\% | 13.9\% | 14.2\% | 0.117 |  | -3.2\% | -6.1\% | -5.9\% | -3.1\% | 0.3\% | -2.8\% |
| MET | 1 | 0 | 0 | 0 |  |  |  |  |  |  |  |  |
| URB20 | 0 | 1 | 0 | 0 |  |  |  |  |  |  |  |  |
| ADJ | 0 | 0.25 | 1 | 0 |  |  |  |  |  |  |  |  |
| HWY | 0.875 | 0.222 | 0.407 | 0.218 |  |  |  |  |  |  |  |  |
| COL | 0.875 | 0.111 | 0.148 | 0.164 |  |  |  |  |  |  |  |  |
| D1M (meatpacking) | 11.3\% | 11.9\% | 6.9\% | 13.1\% | 0.317 |  | 0.2\% | -1.4\% | 0.6\% | -1.6\% | 2.0\% | 0.4\% |
| D2F (other food) | 11.0\% | 13.0\% | 7.9\% | 7.0\% | 0.221 |  | 0.4\% | -0.7\% | -0.9\% | -1.1\% | -0.2\% | -1.3\% |
| D3C (textile) | 2.2\% | 0.3\% | 2.4\% | 4.9\% | -0.023 |  | 0.0\% | 0.0\% | -0.1\% | 0.0\% | -0.1\% | -0.1\% |
| D4W (wood \& furn.) | 5.0\% | 6.4\% | 8.8\% | 6.5\% | 0.112 |  | 0.2\% | 0.4\% | 0.2\% | 0.3\% | -0.3\% | 0.0\% |
| D5P (printing/publ.) | 13.3\% | 5.0\% | 6.1\% | 5.3\% | -0.108 |  | 0.9\% | 0.8\% | 0.9\% | -0.1\% | 0.1\% | 0.0\% |
| D6C (chemicals) | 2.7\% | 8.2\% | 1.0\% | 2.1\% | 0.196 |  | 1.1\% | -0.3\% | -0.1\% | -1.4\% | 0.2\% | -1.2\% |
| D7P (plastics) | 3.0\% | 3.5\% | 7.3\% | 3.7\% | 0.121 |  | 0.1\% | 0.5\% | 0.1\% | 0.5\% | -0.4\% | 0.0\% |
| D8M (metals) | 34.5\% | 28.7\% | 45.5\% | 38.1\% | 0.148 |  | -0.9\% | 1.6\% | 0.5\% | 2.5\% | -1.1\% | 1.4\% |
| D9E (electronics etc.) | , $10.7 \%$ | 11.8\% | 7.5\% | 8.2\% | -0.001 |  | 0.0\% | 0.0\% | 0.0\% | 0.0\% | 0.0\% | 0.0\% |
| (paper rubber glass) | 6.3\% | 11.2\% | 6.6\% | 11.1\% |  |  |  |  |  |  |  |  |



Sector employment as a share of total nonadjacent rural employment, 1994


Workforce size, industry size and density, and sum of all three: detailed model

© Workforce size 坥 Industry size + industry density * Sum of all three O
Figure 3. Clustering effect on wages, sector share of rural nonadjacent


Figure 4. Clustering effect on wages, nonmetro share


Nonmetro Share of Iowa Employment by Sector, 1994


Change in Nonmetro Share of Iowa Employment by Sector, 1979-1994


Figure 5. Workforce size effect on wages, nonmetro share


Figure 6. Combined agglomeration effects on wages, nonmetro share
since metals \& equipment accounted for $38 \%$ of rural lowa manufacturing jobs in 1994. In all other cases with positive and significant coefficients for industry size (textiles apparel \& leather) or industry density (plastics, other food processing, and paper rubber glass \& misc.), the coefficient for the other industry cluster variable is negative and at least as large in absolute value.

In contrast to industry clustering, workforce size was significant and positive for six of ten sectors in the basic model (see Table 5), and eight of ten sectors in the more detailed model (see Table 7). More densely populated labor market areas have higher earnings, holding all other factors constant. There are wide differences in the estimated effects of urbanization across sectors (see Figure 5). Printing \& publishing consistently shows the strongest effect, with or without a metro dummy variable. Doubling workforce size raises wages in chemicals \& petroleum products and in electronics \& instruments by $17 \%$ or more in either specification, and in both the paper rubber glass \& miscellaneous sector and in food processing sector by at least $12 \%$. The coefficients for metals \& equipment and plastics vary considerably when additional dummy variables are added (in different directions), but the general picture is that they are an intermediate case. The combined effect of workforce size and the metro dummy has the smallest impact on wages in meatpacking, textiles apparel \& leather, and wood \& furniture.

With the exception of plastics, we find the wage effect of industry clustering (coefficients for industry size and industry density combined) is most negative in those industries which are a comparatively small share of total manufacturing employment for rural
nonadjacent areas (see Figure 3). The correlation between sectors' industry clustering coefficients and sectors' share of nonadjacent rural employment is 0.57 ( 0.52 basic model): in general, the smaller the sector, the more negative the coefficient (see Table 10). If two sectors (in two otherwise identical counties) both have high productivity relative to the rest of their local economy, but one sector makes up a much larger share of total local employment, it is reasonable to expect that the supply of labor to the large sector will be more inelastic than the supply of labor to the small sector. Increases in productivity and higher demand for labor in a small sector may translate into large (percent) increases in employment with only a small increase in wages above prevailing local wage rates, while an increased labor demand in a comparatively large sector may require relatively large increases in wages to elicit substantial increases in employment. However, this cannot explain the substantial negative wage effects we see in sectors like chemicals or printing and publishing. If higher productivity within a small sector translates into small wage effects (and large employment effects) due to more elastic labor supply to that sector, then negative wage effects from lower productivity should be dampened in the same way (leading mainly to large negative effects on employment).

We also see that five of the six sectors with the most negative effects of clustering on wages are not growing in nonmetro counties (see Figure 4, bottom panel). It is the sectors with less negative or moderately positive effects on wages from clustering where nonmetro counties are gaining jobs: the correlation between the combined clustering coefficients and 1979-1994 change in nonmetro share of employment for the ten sectors is $0.67(0.64$ basic model) (see Table 10).

Table 10. Correlation matrix: agglomeration coefficients and nonmetro job shares, 10 sectors

|  |  |  |  |
| :--- | ---: | ---: | ---: | ---: |
| Detailed model coefficients: | Nonmetro <br> Share of 1994 <br> Sector Empl. | Change in <br> Nonmetro <br> Share | Sector Share of <br> Rural NonAdj |
|  | -0.59 | 0.04 | -0.24 |
| Empl. | 1994 |  |  |
| Urbanization (Workforce Size) | 0.56 | 0.67 | 0.57 |
| Clustering (IND_SZ + IND_DENS) | -0.17 | 0.56 | 0.20 |
| Agglom. (WKFC SZ + IND SZ + IND DENS) |  |  |  |
|  |  |  |  |
| Basic model coefficients | Nonmetro | Change in | Sector Share of |
|  | Share of 1994 | Nonmetro | Rural NonAdj |
|  | Sector Empl. | Share $79-94$ | Empl. 1994 |
| Urbanization (Workforce Size) | -0.50 | -0.21 | -0.14 |
| Clustering (IND SZ + IND_DENS) | 0.52 | 0.64 | 0.52 |
| Agglom. (WKFC SZ + IND SZ + IND DENS) | -0.26 | 0.18 | 0.18 |

Note:Correlations are among values for the ten manufacturing sectors.

It seems surprising that workforce size effect on wages is unrelated or weakly negatively related to emloyment share growth in nonmetro counties, while cluster effect on wages is strongly and positively related to employment share growth in nonmetro areas. This could simply reflect strong growth in exurban counties. Particularly in metals and plastics, maps indicate employment growth is strongest in rural counties adjacent to or at least within 50 miles of metro counties. Counties at these distances from metro areas also tend to produce much higher industry density values than either metro counties or more remote rural counties.

Many workers live in rural places and commute considerable distances to jobs in metro areas. One plausible explanation for this pattern of exurban manufacturing growth is that, by locating in exurban counties, these firms locate nearer to an established pool of rural workers who may be willing to accept lower wages in return for a shorter commute. This might also explain why we sometimes find that a single company establishes several smaller plants scattered across several counties rather than a single larger plant (such clustering of
branch plants owned by the same firm is particularly evident in electrical equipment, apparel, plastics, and metal stampings).

It is interesting to note that the four sectors with the most negative impacts of clustering (see Figure 3, bottom panel), are characterized by a much larger share of plants that produce for local markets in rural areas. To the extent that manufacturers produce for a local market, clustering means competition in final product markets, and we can expect isolated firms to enjoy a comparative degree of market power (and thus higher value of marginal product). While $27 \%$ of metro core printing and publishing workers are employed by newspapers, newspapers make up $46 \%$ of large nonmetro and fully $62 \%$ of all rural nonadjacent printing and publishing employment. For local newspapers, greater workforce size in the labor market area generally translates into a larger market of potential subscribers and advertisers, while greater industry density means a smaller market for each paper. ${ }^{14}$ More than half the rural chemical firms in the state produce agricultural chemicals, and it is evident from SIC classifications and from product and firm descriptions that many of these primarily serve farmers in the immediate area. ${ }^{15}$ Many of the rural wood products firms can similarly be identified as businesses which sell a large share of their products locally. Feed mixing and grinding (SIC 2048) accounts for $31 \%$ of employment and $47 \%$ of the plants in rural nonadjacent food processing (other than meatpacking), and most of these plants are small, local feed mills. ${ }^{16}$ Naturally, rural nonadjacent counties have the lowest workforce size. So in these four sectors, in the places where we find urbanization is low and industry clustering is high, this often means increased competition for local markets which leads to
lower value of marginal product and lower wages than where plants are isolated. ${ }^{17}$
With the exception of chemicals and meatpacking, we see that those sectors where workforce size has a smaller effect on wages also tend to be those sectors where a larger share of employment is found in nonmetro counties: the correlation between these is $-0.59(-0.50$ basic model) (see Figure 5, top and middle panels and Table 8.). This is consistent with a view that wage differences are at least broadly associated with differences in productivity, and that in the long run rural areas find their competitive advantage in those sectors where urbanization effects are weakest.

However, there is no apparent correspondence between urbanization effect on wages and change in nonmetro market share over time across the ten sectors: the correlation between these is 0.04 ( -0.21 basic model) (see Figure 5, bottom panel and Table 8). This result is true regardless of what base year is chosen. Thus the dynamic picture suggests that, in the short run, observed metro-nonmetro wage differences may not correspond so closely to current productivity differences. We might assume that because some sectors are shifting to nonmetro areas, then wage differences must now exceed productivity differences resulting in lower rural unit labor costs. It is not so clear that this is the case. The five sectors where rural areas are gaining market share account for $68 \%$ of Iowa manufacturing employment. Yet in the aggregate, Census of Manufacturing data indicates that rural unit labor costs are as high or higher than in Iowa's metro areas (see Figure 6). Large nonmetro counties have the lowest unit labor costs of all, but they are neither increasing or decreasing their share of total manufacturing jobs.


Figure 6. Unit labor costs: Payroll and production wages per dollar value added 18

When we look at agglomeration effects combined (workforce size, industry size, and industry density coefficients added together), it is paradoxically the sectors where the combined effects of agglomeration are the largest that nonmetro Iowa is gaining the most jobs (see Figure 7 and Table 8). But when we look at clustering and urbanization separately, we can see that this combined result is primarily related to clustering effects and not urbanization, particularly when we compare correlations for the basic and detailed model (see Table 8 and Figures 4 and 5). ${ }^{19}$ Although industry size tends to be higher in metro core counties, industry density (as I have measured it) is roughly equal for metro and nonmetro
counties, on average (an outcome I find odd in itself). So while urbanization is fairly clearcut, it is more difficult to interpret why rural areas would systematically either gain or lose jobs in particular sectors based on clustering effects, one way or the other.

## Conclusions

The impact of urbanization economies on wages is significant and positive in six of ten manufacturing sectors, and in eight of ten sectors when additional dummy variables are added for other county characteristics. By contrast, when estimated coefficients for both industry size and industry density are combined, the impact of industry clustering is significantly negative in at least half of the ten sectors. The only sector with clear and unequivocal evidence that industry clustering raises wages is metalworking \& equipment, although this one sector accounts for $36 \%$ percent of Iowa manufacturing employment. In the case of metals, the estimated coefficient for workforce size is still larger than the coefficient for industry size ( 0.061 vs. 0.039 ).

The industry mix, plant size, education, and agglomeration variables included in the model can only partially explain why some nonmetro counties have considerably higher earnings than others. Rural nonadjacent counties earn $15.3 \%$ less than rural adjacent counties and $27.5 \%$ less than large nonmetro counties, while the basic model predicts them to earn $9.0 \%$ and $16.4 \%$ less, respectively. If data on capital investment and unionization were available, these might be able to explain the difference. The answer to this question is potentially important, because the large nonmetro counties have an even larger advantage in
labor productivity, which gives them 15-20\% lower unit labor costs than rural Iowa counties in spite of nearly $30 \%$ higher average annual earnings per worker.

Those sectors where clustering lowers wages are the sectors where rural and nonmetro Iowa is not gaining share of Iowa manufacturing jobs. We see that those sectors where urbanization has a relatively weaker effect on manufacturing wages tend to be the same sectors where a larger share of employment is concentrated in nonmetro areas. We also find that the sectors where jobs are shifting from metro to rural locations are not necessarily those with the lowest (or the highest) metro-nonmetro earnings differences.

Most previous studies of urbanization and localization economies have focused on job growth, rather than wages. It is quite possible that urbanization raises productivity in most manufacturing industries, and localization does not. A second possibility is that industry clusters do raise productivity, but that the primary effect is to increase job growth rather than wages. If labor supply to a single sector is fairly elastic, then when a single sector has higher productivity, firms in this sector may be able to attract workers from other lowpaying sectors to expand production with relatively small increases above prevailing local wage rates. If clustering does increase job growth, then over long periods of time higher industry growth would eventually increase the size of the local economy, and thus increase wages only indirectly through increased urbanization. Many of Henderson's models explicitly assume that increases in local industry productivity translate entirely into job growth, and that cities achieve an equilibrium size when they grow to the point where higher productivity due to both localization and urbanization economies is exactly offset by
increases in wages and rents due to congestion and diseconomies of city size. ${ }^{20}$ No such conclusions can be drawn from this study, without expanding the analysis to include rates of job growth.

## Notes

1. This rose dramatically from 1979 , when $19.3 \%$ of nonmetro manufacturing workers earned hourly wages below the same level. In 1987 a job that paid $\$ 5.58$ an hour, 40 hours a week, 52 weeks a year earned $\$ 11,611$ : an income equal to the poverty line for a family of four.
2. For instance, in SIC 3523 Farm machinery and equipment, all the plants with over 1,000 workers produce tractors, farm implements, and other heavy machinery. By contrast, SIC 3523 plants with between 25 and 50 employees produce relatively far less complicated and less highvalue products including bins and bunks, wagon boxes, sprayer units, fertilizer tanks, grain and manure handling equipment, livestock pens, feeders and ventilation systems, farrowing crates, floor slats, gates and fencing. Even if the assumption of constant returns to scale in plant size needs to be relaxed, we can expect the list of relevant explanatory variables to be much the same.
3. Thus, the dataset excludes the self-employed. Self-employed persons account for just $1.7 \%$ of U.S. manufacturing employment, compared with almost $10 \%$ across all industries and $19 \%$ of all construction employment (Aronson 1991)
4. A study by the Office of the Legislative Auditor for the state of Minnesota (Yunker et. al., 1989) found nonshelter costs in the Minneapolis-St. Paul MSA and the remainder of the state differed by just one-tenth of one percent. Thus, regional cost of living differences within Minnesota were based entirely on differences in housing costs. I assume the same result holds for lowa, and use appropriate BLS market basket weights for the North Central region to determine the share of housing costs in total expenditures. 1989 median house values and gross rents from the 1990 Census of Population were used to produce estimates of cost of living differences among Iowa counties. Assuming housing of equal quality in all counties, the metro-nonmetro difference in cost of living was $8.0 \%$. After making adjustments for differences in age, size, and characteristics of housing, the metro-nonmetro lowa cost of living difference was $5.3 \%$. These adjustments were made using the coefficients estimated by the BLS to adjust value of the housing stock for depreciation (in the shelter portion of the CPI) and county-level Census data (Lane et. al., 1988). When metro and nonmetro counties are weighted by number of manufacturing workers (rather than total population), the cost of living for the average manufacturing worker narrows further to $4.4 \%$.
5. The resulting weights correspond closely with empirical results obtained in a study by Khan, Orazem, and Otto (1997), which estimated increases in county population resulting from increases in employment one and two counties away relative to increases in own county employment for the Upper Midwest.
6. Most of Iowa's urbanized areas are less than eight miles across. I assume beyond 10 minutes, commuters spend additional minutes in the middle of the commute traveling at highway speeds.
7. If industry density, industry size, and weighted average plant size were all calculated for the same set of plants (for instance, those in the county, or those in the larger labor market area), there is almost perfect three-way dependence among these three variables (see Appendix Table A5). Since plants across county borders may influence external economies from urbanization and localization, but do not affect internal economies of scale from plant size, it is appropriate that these three measures are not all calculated for the same set of firms, and inclusion of all three variables in the model does not result in collinearity. Because of this three-way relationship, it is still the case that the only way to increase (labor market) industry size while holding (labor market) industry density and (county) plant size constant is to increase the plant size of firms in other counties. Similarly, the only way to increase (labor market) industry density while holding (labor market) industry size and (county) plant size constant is to decrease the plant size of firms outside the county. So to the extent that these three variables are not collinear, multivariate regression coefficients for industry size and industry density will only be based on characteristics of plants in other counties. Even when plant size is excluded from the model specification, however, the coefficients for industry size and density match the same general patterns I have reported here. For this reason, I feel confident that multicollinearity does not substantially bias my results.
8. For instance, in paper rubber and glass, the estimated coefficient for workforce size more than doubles from 0.118 to 0.239 when these dummy variables are added, but the estimated coefficient for the metro dummy is -0.206 . Combining workforce size and the metro dummy in some fashion generally results in a rank ordering of urbanization effects for sectors very similar to the basic model (such as when we scale the estimated elasticity up by 2.3 and add it to the estimated coefficient for the metro core dummy, to reflect 2.3 times greater workforce size, on average, in metro core counties).
9. We might suspect that if this variable was missing from the model, part of this effect would be picked up by industry size (or industry density). But when I estimated the model without the plant size variable to test this, the coefficients for industry size, industry density and workforce size in the overall regression did not increase for the overall regression. Results for individual sectors may be another matter.
10. The detailed model coefficients are able to account for more of the difference between large nonmetro and rural adjacent counties, but less of the difference between rural adjacent and nonadjacent counties than the basic model. The addition of dummy variables for metro, large nonmetro, and adjacent counties in the detailed model naturally improves the predicted differences among these types, but dummy variables for the same county types we try to predict do not tell us anything about what factors cause these differences.
11. We know that unionization is higher in large nonmetro counties than in rural counties, and we know from Census of Manufacturing data that in 1992, large nonmetro capital investment per worker was $47-59 \%$ higher (see Figure 1), labor productivity was $58-68 \%$ higher, and unit labor costs $17-25 \%$ lower than in rural adjacent and rural nonadjacent counties in Iowa. But data on capital, productivity, and unionization simply was not available at the county-industry level. The large nonmetro towns have a long history of manufacturing: most had several thousand manufacturing workers dating back at least to the 1920 s, at a time when most of Iowa's rural counties had between 25 and 250 . It is quite possible that 1929 manufacturing employment could be a stronger predictor of 1990 s manufacturing earnings than 1989 manufacturing employment.
12. If clustering increased productivity directly given the same level of capital, and this increased wages, we would expect to see this in the coefficients for industry size and density. If clustering altered productivity in ways that led to increased capital investment and this in turn raised wages, we would expect this indirect effect to show up in these coefficients, as well. But the combined coefficients for industry size and industry density were not significant and positive in any sectors other than metals. To the extent that capital or unionization are correlated with urbanization, their effects will be captured by workforce size or the metro and large nonmetro dummy variables, and to the extent that they are correlated with particular industries nationwide, their impact will be captured by the U.S. weighted earnings based on 4-digit SIC codes. All that we miss are differences in capital or unionization that deviate from these patterns of correlation. During the study period rural capital per worker decreased relative to metro, while rural nonadjacent industry size and density increased, and rural nonadjacent earnings relative to metro remained almost unchanged. But unmeasured time series changes in capital clearly do not bias my results, either: coefficients for industry size and density are virtually identical for 1994 in cross-section as they are for the pooled dataset of all nine years. The omission of capital simply means these results do not enable us to draw conclusions about what the relative wages (and productivity) of rural, large nonmetro, and metro labor would be if they had equal levels of capital per worker.
13. Alternative specifications were estimated that included county earnings outside the given manufacturing sector and cost-of-living adjustments. Both variables interacted with workforce size such that the coefficient for one variable was extremely large and negative while the other would be extremely large and positive (which was negative and which was positive switched from sector to sector). I chose to limit my model to the variables I was most interested in.
14. When the basic model was estimated for printing and publishing only for the 55 rural nonadjacent counties, the estimated coefficient for workforce size was more than three times larger and for industry size was three times more negative than the same regression on only the 44 more urban counties. Industry density is statistically insignficant among more urban counties but substantially negative among rural nonadjacent counties.

|  | Workforce | Industry | Industry |
| :--- | :---: | :---: | :---: |
|  | Size | Size | Density |
| 44 Metro core, large nonmetro, rural adjacent | 0.126 | -0.081 | 0.023 |
| 55 Rural nonadjacent | 0.419 | -0.259 | -0.169 |

These regression results are consistent with the observation that, the more an industry consists of plants producing for a local market, the more we can expect low industry density to represent monopoly power and the more we can expect workforce size to represent market size (increasing value of marginal product by spreading substantial fixed costs in publishing over a larger subscriber base). It is only among firms that export a substantial portion of their production that we might expect clustering to potentially raise value of marginal product.
15. Half are classified as SIC 2875 , which indicates the only chemical manufacturing they perform is to mix fertilizers from prepurchased ammonia, phosphate, etc. A significant portion of the other half of agricultural chemical firms are also engaged primarily in providing chemicals and services to local farmers, as evidenced both by product descriptions and by firm names such as "Taylor County Agri-Center", "Cedar Johnson Farm Service Co.", "Gold-Eagle Co-op" and "Farm Service Agriland Inc."
16. There were 139 feed mills in the 1994 DES data. Particularly in northern Iowa, there are often several in each county. While some mills may ship mixed feeds considerable distances, most of the small mills are local elevators and co-ops of the type that primarily market to farmers in the area.
17. In general, fabricated metals sell a large portion of their products locally as well. But here the situation is reversed. In Iowa's rural counties, the overwhelming majority of fabricated metals are automotive stampings, tools, and other products which are primarily exported outside the region. Structural metal, metal plating, and other firms which primarily serve customers in the immediate area make up $10 \%$ or less of fabricated metals employment among counties not adjacent to metro areas (compared to roughly a third in metro core counties). Because fabricated metals, in turn, are only a quarter of the total employment in metals and equipment, such local plants make up a comparatively small portion of employment in this sector.
18. I show both total payroll and production wages because, to the extent that nonproduction
workers in metro areas (in headquarters, design, marketing, etc.) perform functions for rural branch plants (or vice versa), payroll per dollar of value added at the plant level may give a misleading picture of unit labor costs. These graphs bracket the possible range for unit labor costs if all services performed within a firm could be allocated to the production site receiving them.
19. When Bernat (1995) performed estimates of agglomeration economies for the U.S. in the 1970s and the late 1980s, he found that agglomeration effects were important but had declined in significance over time. My model specification assumes the slope parameters remain constant over time. If agglomeration economies have declined, this could be consistent with the largest erosion of metro employment in those sectors where advantages of agglomeration effects were highest. But the change in Iowa nonmetro share is tied to clustering effects and not urbanization effects, so it is difficult to fit this interpretation to the evidence.
20. It is clear that rural-urban earnings differences in Iowa cannot be accounted for by cost-ofliving differences alone. Table 3 indicates that nonmetro manufacturing earnings are $16 \%$ lower than metro after adjusting for industry mix, while the estimated metro-nonmetro cost-of-living difference for manufacturing workers averages only $4.4 \%$ (See Note 4).

## DATA AND METHODS OF MEASUREMENT

## Data Sources

Data on employment, earnings, and number of units for Iowa counties by 4-digit SIC came from ES 202 data for the years 1983-1994, obtained from the Iowa Department of Employment Services. Data on employment by 3-digit SIC broken down by 881 occupations were obtained from the Iowa Industry-Occupation matrix for 1994 (Iowa Department of Employment Services). Average wages by occupation came from The Iowa Wage Survey 1994 (Iowa Department of Employment Services) supplemented by the 1994 Occupational Outlook Handbook (U.S. Bureau of Labor Statistics 1996). County Business Patterns data were used for average earnings and weighted average firm size by 4-digit SIC for the United States for the years 1986-1993 (1994 for earnings). 1986 was the earliest year available in electronic form on CD-ROM. County Business Patterns also provided data on establishments by employment size code in the nearest two tiers of counties in neighboring states (1983-94 in printed form, and 1986-1994 on CD-ROM).

Education and number of workers were from the 1990 Census of Population. 1992 and 1987 Census of Manufacturing by ZIP Code, Official Iowa Directory of Manufacturing, and Iowa Business Directories were used in estimating individual plant employment where there were several plants in one 4-digit SIC code in a county. MapInfo 3.0 contained point latitude-longitude coordinates for ZIP Codes. Iowa DOT maps and the 1992-93 Blue Book were used to identify 4-year colleges.

## ES 202

The most important source of data for this project was ES 202 data on employment, earnings, and number of units by 4-digit SIC for lowa counties covering the years 1983-1994. ES-202 data is collected by the Iowa Department of Employment Services when firms report payroll and employment by quarter for unemployment insurance, in accordance with federal law and the Bureau of Labor Statistics. Because publicly available sources of economic data do not disclose information for units where this would reveal information about individual units, it is ordinarily very difficult to compare firms in clusters with firms that are the only firm in their industry. We obtained permission to use this data through a cooperative agreement with Director Cynthia Eisenauer. To maintain strict confidentiality, industry and county data from ES-202 will only be reported at levels of aggregation that avoid disclosure of information about individual units, in accordance with standard BLS and DES procedures for nondisclosure.

The employment and earnings data are annual averages that include any and all wage-and-salary employment and payroll throughout the course of the year, rather than data collected for a particular week or month. All firms with wage-and-salary employment covered under unemployment insurance are legally required to provide accurate data on a quarterly basis. Therefore, the data is a complete Census rather than a survey sample, and the level of accuracy is quite high.

Self-employment or other proprietors' income and employment is not included in ES
202. This makes very little difference in this study, because the share of self-employment
in total employment is smaller in U.S. manufacturing than in any other sector. Only $1.7 \%$ of manufacturing employment is self-employed, compared with almost $10 \%$ across all industries and $19 \%$ of all construction employment (Aronson 1991).

Most surveys of establishments ask firms to report their principal SIC code. In the Iowa ES 202 data, DES analysts decide what SIC code to classify each firm in based on information provided by the firms. This generally results in far more consistent classification of firms at the same particular time and area. SIC classifications changed quite frequently for some units, presumably due to changes in product mix. Sometimes the classification for a unit changed mid-year, though usually they changed at the beginning of a new year. In such cases, I assigned the unit that year to the SIC code with the larger share of annual employment. In some counties, large numbers of firms changed SIC codes all at once at just a few points in time, suggesting that either a different analyst was assigned to that county, or that SIC classifications in counties are reevaluated at a few points in time.

## Variables

## Earnings

Earnings are the dependent variable. The measure used for earnings in this study is real average annual earnings per job in all manufacturing plants classified in a particular manufacturing sector in a particular county in a particular year (deflated by the CPI to obtain earnings in constant 1994 dollars). No data on hours is collected in ES-202.

## U.S. Weighted Earnings

This measure indicates what the average annual earnings in a
county in a particular sector would be if each worker earned the U.S. average earnings for that year. County Business Patterns data is used for U.S. average earnings by 4-digit SIC code. It captures whether the mix of 4-digit SIC codes within a sector are in comparatively high-wage or low-wage SIC codes. Since it is based on U.S. average earnings in that year, it also controls for business cycle and other time-series changes particular to that industry. For instance, this measure reflects that at the national level in SIC 2011 Meatpacking, average annual earnings in constant 1994 dollars were $\$ 25,302$ in 1986, but declined to $\$ 21,268$ by 1993. U.S. weighted earnings for individual plants are weighted by the employment in each plant that year to arrive at a value for U.S. weighted earnings for an entire sector in a county.

Both ES 202 and County Business Patterns data switched from the 1977 SIC Classification to the 1987 SIC Classification beginning in 1988. SIC codes for all Iowa plants that existed 1983-87 were translated to 1987 SIC definitions, in order to make use of the additional five years of information. Some 1987 SIC codes do not correspond on a one-toone basis with 1977 SIC codes. In these cases, U.S. average earnings for 4-digit (1987) SIC codes 1986 and 1987 were estimated based on trends in 3-digit SIC codes 1986-1989 and observed trends in the continuing 4-digit SIC codes 88-94.

## Plant Size

This is weighted average plant size in the county in a particular sector relative to the expected plant size based on U.S. weighted average plant size. If the size of an individual
plant is the same as the U.S. weighted average size in that 4-digit SIC code, Plant Size $=1.00$. If a plant employs 50 workers in a 4-digit SIC code where the U.S. weighted average size is 250 , Plant Size $=0.20$ for that plant. Since the unit of observation is a sector in a county, the Plant Size value for a particular sector in a county is the weighted average of all the individual plants in that sector in that county.

If there is a single plant with 1,000 workers in Industry A in county C, the average plant size and the weighted average plant size are both 1,000 . However, if there are four plants with 1 worker each and one plant with 996 workers, the average plant size in the county drops to 200 , while the weighted average plant size in the county drops just slightly to $992\left(996^{*}(996 / 1000)+1^{*}(1 / 1000)+1^{*}(1 / 1000)+1^{*}(1 / 1000)+1^{*}(1 / 1000)=992\right)$. Since we are measuring determinants of manufacturing wages, and $99.6 \%$ of the workers earning wages in the industry in this county work in a large plant with 1,000 workers, it is more appropriate to use weighted average plant size. Adding less than $1 \%$ additional employment in the county will do little to change average earnings, and ideally our explanatory variable measuring plant size should not be highly sensitive to such small changes, either. Since individual plant sizes already had to be determined in order to measure changes in industry density, it was a simple matter to calculate weighted average plant size in each sector rather than average plant size.
U.S. weighted earnings are based on 4-digit SIC codes. The weighted U.S. average plant size in 3599 Industrial machinery, nec in 1990 was 54 employees, while in 3531 Construction machinery it was 1,122 . Average earnings in 3599 were $\$ 28,921$, while they were $\$ 36,019$ in 3531 . If there is a direct relationship between plant size and average earnings,
then we might expect that a plant with 200 employees in SIC 3599 will earn more than the U.S. average for that SIC, while if a plant this size is in SIC 3531 we might expect it to earn less than the U.S. average for its industry. The average earnings for any 4-digit SIC code will already implicitly reflect that the firms in that industry tend to be larger or smaller, on average. What remains to be explained by the Plant Size variable is whether or not this plant is large for its industry. Average U.S. earnings in SIC 37 are quite high, and weighted average plant size is near 3,000. Most Iowa plants in SIC 37 are both considerably smaller and earn considerably less than the U.S. average. Iowa plants in SIC 35 often earn wages above the national average. Although not much larger than Iowa plants in SIC 37 in absolute terms, we find they are considerably larger when national average sizes are taken into account. Using absolute plant sizes (rather than relative plant sizes) in conjunction with national average earnings, the regression likely would not perform as well predicting manufacturing earnings in Iowa across different SIC codes.

## U.S. weighted average firm sizes were approximated using County Business

 Patterns, which provides data on the number of employees and the number of units in each of nine employment size classes. The average plant size in each size class was multiplied times a weight equal to the share of that size class in total employment for that 4-digit SIC code. When summed across all size codes, this results in the weighted average size of plants in that industry. The resulting weighted average should be the expected value you would obtain, on average, if you randomly sampled workers in the industry and found out the employment of the plant they worked in. By contrast, dividing industry employment by the total number ofunits (simple average plant size) gives equal weight to all plants.
Average plant size and weighted average plant size can be quite different, and suggest quite different trends. Between 1988 and 1993 the average establishment size in SIC 2011 Meatpacking grew just $3 \%$, from 87 to 90 workers. Although the number of very small meatpacking plants grew, evidently the share of total employment shifted towards the largest plants, because weighted average plant size in meatpacking grew from 871 workers in 1988 to 1,077 workers in 1993 (a 23\% increase in five years time). Since average annual U.S. earnings per worker are weighted by the number of workers, then in order to predict wages, the appropriate measure of plant size is ideally also one that is weighted by workers. In an industry where earnings rise as a function of plant size, then all other things being equal, we would expect a worker in a plant of the average U.S. plant size to actually earn less than the U.S. average earnings for that industry. The weighted average plant size, on the other hand, would likely be a far better indicator of the size of plant that we would expect to earn the U.S. average earnings in that 4-digit SIC code.

Employment for some size classes for some 4-digit SIC codes were nondisclosed at the national level (usually because there were fewer than three units in that size class), although total employment by 4-digit SIC code was always disclosed. In nondisclosed size classes, the number of units in that size class was still reported. A formula in FileMaker Pro (a relational database) automatically determined the next most detailed SIC level at which employment in that plant size class was disclosed and subtracted employment and units for all the disclosed 4-digit SIC codes to find the average plant size within that size class of all
the (residual) undisclosed 4-digit SIC codes within the disclosed level. This average size was multiplied by the number of units in the undisclosed size class. After this first stage, if average size was understated in one undisclosed SIC, it was overstated in one or more other undisclosed SICs by an equal amount. Within a particular 4-digit SIC code, this estimated employment for all nondisclosed size classes was then automatically compared with the actual total for all nondisclosed size classes (the residual after the total of all disclosed size classes is subtracted from total 4-digit SIC employment). A formula automatically flagged major disparities and adjustments were made manually if they did not agree closely. While not as exact as methods using Maximum Likelihood Estimation, any remaining discrepancies were small enough that they would not change my estimates of weighted average plant size for entire 4-digit SIC codes by a substantial amount. Another formula automatically flagged any 4-digit SIC codes that jumped dramatically from one year to another, I checked these manually, and generally found evidence from the unit counts by size code that a large plant had either actually entered or left the SIC code, or else had grown or declined dramatically (so either due to reclassification to another SIC code or else due to an actual plant startup/ closure/expansion/contraction, as opposed to some fluke due to my method of estimation).

As mentioned above under U.S. Average Earnings, some 1987 SIC codes do not correspond on a one-to-one basis with 1977 SIC codes. Where 1977 SIC codes combined, 1987 Classification weighted average plant sizes are simply a weighted average of the joined 1977 SIC codes (weighted by employment in each 1977 SIC code). Where 1977 SIC codes were split into multiple 1987 SIC codes, U.S. weighted average plant sizes for these 4-digit
(1987) SIC codes in 1986 and 1987 were estimated based on trends in average earnings for 1977 Classification 3-digit SIC codes (or 1987 Classification 4-digit codes with relevant 1987 Codes recombined) over 1986-1989 and observed trends in the continuing 4-digit SIC codes 88-93.

## Workforce Size

Workforce size is used as a measure of urbanization. Data on the number of workers residing in each county is from the 1990 Census of Population. Workers as defined in the Census were used rather than labor force, because outside of manufacturing, self-employment is a significant portion of the general economy. This is a measure of the size of the labor market area available to a county, and a portion of the workforce from surrounding counties is included using the same distance function used to calculate industry size and clustering. Ideally I would have liked a measure of workers (including self-employed) by place of work rather than by place of residence, since place of work data was used for industry size and industry density (and that is how the distance function was derived).

MapInfo generated coordinates for the weighted average of all the Census block groups in each county, and these resulting county centers of population were used to determine the effective distance between counties. Using the center of population makes a large difference only in those counties where most of the population is concentrated at one side of the county (principally those along rivers and those in or near metro areas). This reflects, for instance, that most of the population in Pottawattamie County (Council Bluffs) is very close to Omaha (Omaha MSA), much of the population in Warren County is
concentrated close to Polk County (Des Moines MSA), and most of the population in Scott County (Davenport) is close to Moline County (Quad Cities MSA).

## Industry Size

This is a measure of how many workers within commuting distance are employed by plants in the same 3-digit SIC code or closely related 3-digit SIC codes. The industry for a given plant in a particular 3-digit SIC code is defined to be all plants in its own 3-digit SIC code, adjusted by a distance function according to how miles away the other plant is located, plus plants in closely related 3-digit SIC codes adjusted by both the distance function and a weight based on their impact on increasing key occupations to that 3-digit SIC.

The distance function was derived from 1990 Census of Population journey to work data for Iowa. Using a 5 mile $\times 5$ mile grid, the share of total workers who commute a given distance to work was divided by the number of 5 mile blocks at that distance, to give the average density of workers' places of residence distributed about their place of work. The density of this distribution drops off quite rapidly. Since manufacturing jobs generally pay above average wages (especially relative to many retail and service jobs) and thus may induce workers to commute farther, these may be somewhat conservative assumptions.

A second distribution represents the percentage of workers who are willing to commute a given distance from their place of residence to a plant. This is based on the same share of workers willing to commute a given distance (if $50 \%$ commute over 15 minutes, then I assume $50 \%$ are willing to commute to a plant at a distance of 15 miles). This again seems to be a conservative assumption, since this is the percent that have already chosen to work at
a job at the distance. However, since they are presumably willing to commute this distance in any direction, in this second case the density is not divided by the number of blocks at that distance, so this function doesn't drop off as rapidly.

The two distributions are overlapped, centered on the same point to begin with, and then one "plant" is moved away by five mile increments. It seems logical to assume that those workers who in fact commute greater distances in the first distribution will be the same workers willing to commute greater distances in the second. The overlap between the two distributions then indicates what share of the workers actually employed at Plant B are willing to commute to Plant A, calculated by taking the minimum densities of the two distributions across all 5 mile blocks as a share of the total area under the distribution about Plant B.

What results is a bell-shaped density function that drops off fairly rapidly beyond 10-15 miles, but has a tail that extends to 70 miles. This function has a value near 0.50 at 25 miles and a value near 0.10 at 50 miles. Keep in mind that, at a distance of 50 miles between plants, the workers in question are those who live more or less midway between the two plants (necessarily only those willing to commute distances over 25 miles).

While this seems an accurate way to come up with a conservative estimate of the total share of workers at one plant willing to commute to another plant at a given distance, it is also true that workers will be more willing to commute at closer distances than farther distances. Perhaps a count that gives equal weight to those workers who might just barely be willing to commute that far (under the right circumstances) and to those located much closer
still results in a distance function that reaches too far.
It is reassuring that these weights derived from average commuting times do correspond closely to empirical results obtained by Khan, Orazem and Otto (1997) in a study of counties in the Upper Midwest, which estimated the relative impact of an increase in employment in one county on population growth in the same county, one county, and two counties away, respectively. An "average" Iowa county is roughly 24 miles by 24 miles.

## Industry Density

Data on individual firm sizes were derived using electronic 1987 and 1992 Census of Manufacturing by ZIP Code (and employment size code) records entered into a relational database, matching this with the ES 202 data by industry, and combining this with information from Directories of Manufacturing and Business Directories to identify the relative size of firms, and births/deaths/contractions/expansions over the period 1983-1994. See Appendix C for a description of this procedure. All individual firm employment was allocated in such a way that it added up to industry totals for each year in the ES 202 data, and the ES 202 SIC classification was the one used in all cases except when the other sources clearly indicated a misclassification according to the descriptions in 1987 SIC Manual.

## High School Education and College Education

These variables are measured as percent of adults in prime working years (ages 25-64) who have completed high school and who have completed four years or more of college, respectively. These were derived from 1990 Census of Population data. Education for all adults was available on CD-ROM, while education for adults $65+$ was found in printed
reports and was subtracted to obtain education among the population ages 25-64. While many adults 65 and over continue to work, this is generally not true in manufacturing. It turned out that, once retirement age adults are excluded, levels of high school completion are lowest in the larger, manufacturing-dependent nonmetro counties (those with 20,000 or more urban residents, not part of a metro area). Because the more rural and farming-dependent counties tend to have proportionally larger shares of retirement age adults, education levels for all adults in these counties are sometimes among the lowest in the state. However, high school completion rates among rural adults 25-65 were frequently as high and sometimes higher than in metro counties. College completion rates were highest in metro counties, as expected.

## Metro Core

This is a dummy variable for metro core counties - those metro counties that contain an urbanized area. According to the Census, an urbanized area has over 50,000 residents who live in contiguous places with sufficient population density. In the 1990 Census, two-thirds of the U.S. population and roughly one-third of Iowans lived in urbanized areas.

## URB20 (Large Nonmetro)

This is a dummy variable for more urban nonmetro counties - those with over 20,000 residents living in urban areas. According to the Census Bureau, urban areas are defined to be places with a population of 2,500 or more. Three-fourths of the U.S. population and close to two-thirds of Iowans lived in urban areas in 1990.

Nonmetro towns in Iowa show a remarkably strong correlation between town size
and economic base. Seven of the ten nonmetro counties where the largest town has a population of $12,000-40,000$ are heavily manufacturing-dependent (manufacturing accounts for between 28 and $52 \%$ of all earnings in 1992, BEA REIS), while only one of these counties has a 4-year college. Ten of the twelve counties where the largest town has a population of $8,000-12,000$ have 4 -year private colleges, while only three smaller towns have 4 -year colleges. The counties where the largest town is less than 8,000 are mostly either manufacturing or farming dependent (or both). Manufacturing in large nonmetro counties is quite different from other nonmetro manufacturing, as evidenced by average manufacturing earnings almost equal to those in metro areas.

## Adjacent to Metro Core

A third dummy variable indicates which counties are adjacent to a metro core county (and have their nearest county border within 35 miles of the metro urbanized area). Note that this is a slightly different set of counties from those considered "adjacent" in the Beale codes. "fringe" metro counties (Dallas and Warren) in this study are classified as "rural adjacent" (not "metro core"). Such counties are classified as metro by the Census Bureau based on the significant share of county residents who commute to work in a Metro Core county, and because of this tend to have higher incomes than nonmetro counties. However I am focusing on the jobs actually located in the county by place of work, not incomes by place of residence. The manufacturing jobs actually located in metro fringe counties (Dallas and Warren) during 1986-94 have far more in common with other rural adjacent counties than they do with metro core counties (based on characteristics such as average earnings and value-
added per worker).
The Beale codes in turn classify those counties adjacent to Dallas and Warren counties as "adjacent" (such as Guthrie, Lucas, Clarke). Most of the population in these counties are nearly an hour if not more than an hour from the urbanized area of the Des Moines MSA, and I do not classify these as "adjacent." In addition, because the Council Bluffs and Sioux City urbanized areas are located at the extreme west edge of Pottawattamie and Woodbury counties (unusually wide counties), I do not classify Cass County and Crawford County as adjacent. It is a 50 mile drive to Atlantic and a 54 mile drive to Denison, the county seats of Cass and Crawford counties. 50 miles is ordinarily the distance to a county seat two counties almost anywhere else in Iowa (the average county size is 24 miles across). If I include counties nearly an hour from an urbanized area as "adjacent," then I would need to include a lot of other "nonadjacent" counties as adjacent as well, to be consistent. When I report summary data grouped into metro, large nonmetro, rural adjacent and rural nonadjacent, I use standard Beale code classifications for consistency with other reports. However, in my regressions I do not classify counties as "adjacent" when the MSA urbanized area is 35 miles or more from the nearest county border.

## Interstate Highway

This dummy variable simply indicates whether an interstate highway passes through the county during the study period.

## College

A dummy variable indicates whether a 4-year college is located in the county. This information was obtained from Iowa DOT road maps and the 1992-93 Blue Book.

## Methods of Measurement

## Definition of a Plant

In some cases, several manufacturing establishments in a county were owned by a single firm. The Census of Manufacturing by ZIP Code reports these as multiple plants. Prior to 1990, the DES data usually classified these as a single unit (even when the individual establishments would not otherwise be assigned to the same SIC code). After 1990, these were reported as separate units - in a few cases as many as nine different units in the same ZIP Code. It appears that some of these "units"are probably management and other auxiliary functions located at the same street address and the in same establishment where production occurs. Thus, a count of firms, establishments, and units may give three different numbers.

In this study, I focus on establishments (plants) rather than firms or payroll units. In cases where multiple units are owned by a single firm, this study defines a plant to be a unit with a distinct street address found in either the Directories of Manufacturing or the Iowa Business Directories. My reasoning is that, if a unit doesn't have its own distinct address and phone listed in either the Manufacturing Directories or the yellow pages (the source of listings in the Iowa Business Directories), then it's very likely that it doesn't handle its own hiring and personnel policies, purchases, shipping, etc.

Using this definition, some "clusters" may consist partly or entirely of plants owned by the same firm. Hon Industries has a number of distinct plants listed in the Directories of Manufacturing, all located in Muscatine. It is particularly common in textiles and apparel to find more than one plant owned by a single firm in the same labor market area, with the second or third plant often located 15-25 miles away. Multiple local establishments also occur frequently in printing and publishing. Other examples include a number of plants in south central Iowa that manufacture wiring harnesses, metal stampings plants in rural central and northeast Iowa, plastics plants in central and east central Iowa, other metalworking and industrial equipment firms like John Deere in metro counties, and several millwork and furniture manufacturers located in Waterloo, Council Bluffs, and other metro locations. It is most common of all in ready-mixed concrete, but these plants were not included in any of the ten manufacturing sectors.

If we tried to classify multiple establishments owned by one firm as a single unit, then our job becomes far more complex. As a practical matter, when equally sized plants are located 20 miles apart in the same county we must decide where to assign all the employment. And then we must consider whether we will be consistent if plants are located 20 miles apart in neighboring counties, instead. We must also attempt to learn whether plants with different names are in fact owned by the same parent company. We have to decide what to do in cases with partnerships and other shared ownership. (Should we treat the MeredithBurda printing plant to be a part of Meredith, but then treat it as a separate plant after it was sold to R. R. Donnelley?) Given the far more incomplete information available, it would be
much more difficult to come up with an objective definition of plants that was based on firm ownership. It is far more straightforward and consistent to simply look up a plant and determine whether it was listed in the phone book.

## Key-occupation Elasticity of One Industry with Respect to Another

Limitations and Considerations The key occupation elasticity is sensitive to the way occupations are grouped and classified. In the beginning, I used the occupation distribution at the next most detailed level (with 110 occupation groups) rather than the most detailed level (with 811 occupations). The BLS and the Iowa DES use a set of occupations that group both certain meat cutters and semiconductor workers under a category "Other machine setters, operators and tenders" at the third level of detail. So until I turned to the fourth, most detailed breakdown of occupations, computer equipment plants were classified as one of the closest industries to meat packing plants!

Using only the more detailed occupations means that, for instance, pattern and moldmakers in metal industries and pattern and moldmakers in plastics are treated as different even if they construct the patterns from the same materials. These occupations are grouped together at the next level of detail. The fourth (highest) level of detail defines many occupations that are specific to meatpacking. As a result, other food processing industries are not classified as using similar skills/occupations to meatpacking using the key-occupation elasticities, and there is not a single industry which is treated as similar to meatpacking in my analysis. Whether meatpacking and other food processing occupations are really this distinctly different is an open question.

I considered a weighted combination of these two levels of detail $(70 \%, 30 \%)$ that would reflect some crossover of skills among occupations grouped together at the third level of detail, while setting a minimum threshhold at a level that would safely exclude any erroneous similarities like that in "miscellaneous operators" in semiconductor and meatpacking plants. However, in most industries the weighted combination of the third and fourth level of detail was not a substantial change from simply using the 880 most detailed occupations.

This measure may also change somewhat if we take the occupational distribution of the U.S. or some other area as the base, rather than that for Iowa. Since Iowa specializes in metalworking, industrial equipment, and food processing and has comparatively high numbers of workers in these occupations, key occupations elasticities for these industries will be lower. The highest key occupation elasticities in Iowa manufacturing are for textiles and apparel industries, since there are relatively so few of these workers.

However, this sensitivity to the area chosen as a base seems appropriate. Where textile workers are scarce, locating near other textile firms will have a greater impact than within a region where textiles are ubiquitous. It is simply important to choose a base that is most relevant for the questions that we want to ask.

## Three Alternative Measures of Industry Density

## Density-M

In addition to measuring Industry Size, this analysis utilizes a measure of Industry density. Regression results are reported for Density-M (M for Marshallian, to be explained
below), which is simply the reciprocal of the Herfindahl index.
If there are m firms in the industry,
Density $-\mathrm{M}_{\mathrm{g}}=\frac{1}{\sum \mathrm{~S}_{\mathrm{i}} \wedge 2}$ for $\mathrm{i}=1$ to m
where $\mathrm{S}_{\mathrm{i}}$ is the share of plant i in total industry employment.

$$
S_{i}=\frac{N_{i}}{\sum N_{i}} \text { for } \mathrm{i}=1 \text { to } \mathrm{m}
$$

I take the reciprocal of the standard Herfindahl index because this makes it far easier to interpret the resulting regression coefficients. A single firm in the industry results in a Density-M index of 1 , three equally sized firms results in a HCI of 3 , etc. A market with unequally sized firms is thus assigned a value that indicates this degree of concentration is the same as that associated with this given number of equally sized firms: One firm with $50 \%$ and one with $30 \%$, and one with $20 \%$ of the industry have a Herfindahl Cluster Index of 2.63, the same as that of 2.6 equally-sized firms. If we started with three firms with shares of $50 \%, 30 \%$ and $20 \%$, then a $100 \%$ increase in Density-M could be six firms with shares of $25 \%, 25 \%, 15 \%, 15 \%, 10 \%$ and $10 \%$. Two or more firms in the same 4-digit industry at the same location will have the same Density-M, even if they are of unequal sizes.

## Density-H

Two other clustering measures were developed as well. Density-H (for "Hub-and-spoke" cluster) for a plant is equal to the number of plants at least as large as itself, with smaller plants treated as a fraction of a plant. If there are m plants in Industry K ,
and N is plant employment, then the Cluster Index for plant g is

$$
\text { Density }-\mathrm{Hg}=\frac{\sum \min (\mathrm{Ng}, \mathrm{Ni})}{\mathrm{Ng}} \text {, for } \mathrm{i}=1 \text { to } \mathrm{m}
$$

Two unequally-sized firms in the same 4-digit industry at the same location will not have the same Density-H. Large firms will have very few other firms as large as themselves, while small firms at the same location can have very high values for MCI. When all the firms in the industry are the same size, Density-H returns the exact same value as Density-H: four equally sized firms in the Industry give a Density- H value of 4 .

When all the firms are the same size, Density-H gives the exact same value as Density-M: four equally sized firms in the Industry give an Density-H of 4. However, when there is a single large firm and many small firms, Density- $M$ gives relatively far more weight to the larger firm(s). Thus Density-M is good at measuring "Marshallian" industry clusters, but not "Hub and Spoke" industry clusters which are dominated by one or several large, vertically integrated firms. Since Density-H returns nearly the same value as Density-M where firms are of relatively equal size, Density-H detects both Marshallian and hub-andspoke clusters, while Density-M does a comparatively good job only with the Marshallian type. The only reason for using Density-M rather than Density-H is because Density-H has far more severe problems with inflated values on the boundary between densely and sparsely populated areas, when large firms are in the labor market area but outside the county, which I discuss below.

As one example, there were over 200 establishments in the printing and publishing industry in Polk County (core of Des Moines metro area) with total county employment of
nearly 8,000 employees in 1990. The largest three firms had over half of county employment, and there are another 15 with more than 50 workers (not counting neighboring counties). While Density-H gave a value of 5.5 to Printing and Publishing in Polk County in 1990, Density-M gave it a value of 17.7. In spite of the size of the three largest firms, the "average" worker in Polk County printing and publishing (if they were randomly sampled) has nearly 18 other firms at least as large as the one they work in, if you count smaller firms as a fraction of a firm. (consider that while the largest firm will have a Density-H less than three and will receive the most weight in the weighted average for the sector, many of the smallest of the 200 establishments will have a Density-H around 200). From the point of view of the person hiring for a firm, on average there are nearly 18 other firms at least as large as their own. Not only is there a large pool of workers experienced in occupations specific to printing and publishing (already measured by Industry Size), but the firm also has access to workers who come from a comparatively diverse range of different work environments, with a potentially wider variety of experience, new ideas and skills. This wider variety means there is likely a higher chance that at least one of the applicants will already have experience with a particular type of client, software program, piece of equipment, procedure, or printing process.

While I believe these are sound indicators at a local level, it seems that any pure measure of structure runs into problems when I give firms declining weight as a function of distance. The highest values for either the Density-M or Density-H are found not in the county where the largest cluster of firms is located, but in counties with a few very small
firms located 30-60 miles away from cities and other large clusters. Guthrie County, located about 40 miles west of Polk County with fewer than 30 printing and publishing employees in the county, had an Density-M of 8.6 (56\% higher than Polk) and a Density-H of 45.4 (156\% higher) for this sector, because even when Polk County firms are weighted at 0.10 or 0.15 , this still results in roughly 45 firms as large as one of the handful of small printing firms in Guthrie County). As you can see, this "exurban fringe" effect is far more severe with Density-H than with Density-M, even though in general I prefer Density-H as a local indicator of clustering because it picks up clusters even in the presence of large firms, such as the 200 printing and publishing firms in the Des Moines metro area.

As a result, the mean value of Density-M is actually as high or even slightly higher in non-adjacent rural counties than in the metro and more urban nonmetro counties because some counties on the "exurban fringe" (25-50 miles from metro areas) with only small plants have astronomically high values. Consider that when a firm 50 miles away is given a weight roughly 0.10 , a plant with 100 employees will be treated like a plant with 10 employees and a plant with 20 employees like one with 2 , reflecting the comparatively small number of workers who live within commuting distance of both plants. In many industries like Printing and Publishing or Metals, there may easily be $30-60$ plants within 60 miles most places in the state, and far more near the largest metros. Most are treated as equivalent to very small firms because of the distance. Usually, a county contains some sizeable firms so the distant firms don't have such a large impact. But when none of the plants in a county have more than 2-5 employees, then all these distant plants mean dozens of plants at least as large (in the case of

Density-H), or an industry with lots of very small firms and no large ones (in the case of Density-M). Values for truly remote counties and metro counties make sense, and I believe both would produce a meaningful measure of clustering, if it wasn't for this strange effect on the boundary between them.

Because Density-H emphasizes clusters of smaller firms, Density-H is inflated even more than Density-M in these exurban fringe counties that are not adjacent but are within one hour of metros. These inflated values in exurban fringe counties swamp any other differences between Density-M and Density-H.

These problems do not arise with my measures of Industry Size, only with the measures of Clustering. This effect occurs with any "pure" measure of structure that only takes account of the relative size of firms (measures that remain the same if the size of all firms were scaled up or down by the same number). Excluding sectors with fewer than 20 employees could probably remove only the worst effects. The only real solution seems to be to eliminate the declining weight for employment as a function of distance. The best alternative is probably to include all plants within, say, 30 miles at full weight. I believe this would eliminate the problems with Density-M, but some problems might remain with Density-H since small firms across a county border can still take on such larger Density-H values than large firms. So long as the large firm is in the same county (and it's low DensityH is averaged in with the small firms), this isn't a problem.

## Cluster-S - Size-Standardized Cluster Index

While the first two measures are measures of pure structure (double the size of all firms and the Density- M and Density- H are unchanged), Cluster- S is a measure that combines both the relative size of firms and the absolute size of the cluster.

> Standardized Cluster Index $g=\sum \min (N k, N i)$, for $i=1$ to $m$, at location of plant $g$ Nk

where $\mathrm{Nk}=$ Weighted average U.S. size of plants in industry K
Although multiple regression can distinguish the relative contributions of industry structure after controlling for plant size and industry size, I believe Cluster-S is a better indicator to use in policy applications, and for creating maps that show high values that correspond with the perception one has when looking at a map of firm locations and sizes. Cluster-S values often comes close to the value you would obtain by multiplying Density-H times weighted average firm size of the firms for which the measure is taken, so estimating a model that includes plant size with Cluster-S in place of Density-H makes little difference.

Discussions of industry clusters generally discuss both size ("critical mass") and structure (and usually linkages, communication, networks, and institutions as well). DensityM and Density-H only become really meaningful in combination with some measure of firm or industry size, as in a multiple regression. Cluster-S captures both size and structure in a single measure.

## GENERAL CONCLUSIONS

This study used data on Iowa manufacturing 1986-1994 to examine whether industry size and industry density increase manufacturing earnings. The most important finding was that we found only a quite modest impact on wages in metals and equipment, and the combined effects of industry size and industry clustering was significantly negative in half the sectors. The sectors with the largest negative effects of clustering are sectors where a substantial portion of the rural firms serve local markets. Additional study is required to learn whether or not clustering has a substantial effect on job growth, particularly for rural areas. Given that many rural areas currently have strong manufacturing job growth but relatively low wages, rural development practitioners should view claims about the benefits of industry clusters for rural areas with some caution.

When the 55 nonadjacent rural counties were sorted into equally sized groups with relatively high, middle and low manufacturing wages, the low-wage rural nonadjacent counties had higher rates of job growth through startups, but lower rates of subsequent expansion and higher rates of plant contraction/closure. The net effect was that high manufacturing wage counties had net job growth over 1986-94 nearly equal to that of low manufacturing wage counties, and their level of manufacturing employment was considerably less cyclical.

The characteristic that distinguished the high manufacturing wage counties most clearly from the others was larger plant size. Rural development professionals might achieve more success in raising wages by targeting plants and industries with greater internal economies of size, rather than those where external economies are important. Internal
economies of size are far more important relative to urbanization in wood products and furniture, and equally large in other food processing. ${ }^{1}$ The effects of both plant size and industry size come close to the effect of urbanization in metals (because the effect of urbanization is small, not because the other two are large): and this is one of the two sectors where rural Iowa has gained the most jobs over the past two decades. In most other sectors, the effects of urbanization on wages are considerably larger than the effects of plant size.

The impact of urbanization, as measured by workforce size in the labor market area, varied across sectors, but was generally quite strong. The largest effect was in printing \& publishing, followed by electronics electrical equipment $\&$ instruments and by chemicals. The weakest impacts were in textiles appparel \& leather, wood products \& furniture, and meatpacking. These results agree with general perceptions of which are traditional sectors for rural manufacturing today. More surprising was the quite strong effect of urbanization on food processing wages, a sector often considered to be a mainstay of rural manufacturing. We found that nonmetro Iowa tends to have has a larger share of the state's employment in those sectors where the estimated impact of urbanization on wages is relatively small.

Shifts in nonmetro market share of Iowa manufacturing do not correspond very closely with these estimated urbanization effects. In most sectors, it was nonmetro Iowa that gained market share 1979-1994, yet Census of Manufacturing data does not indicate a rural advantage in unit labor costs. Further research into these shifts is justified.

Finally, key-occupation elasticities may have other uses for economic development practitioners. For communities where important local industries are in decline, they could
serve as a guide to which stable or growing industries would make the most use of the skills that already exist. A list of closely related industries could be examined to see which ones are growing and which ones exhibit different cycles of expansion and decline. Using this tool, local economies could diversify into other industries and product markets without abandoning their comparative advantage they have already developed in particular skills and technologies.

## Notes

1. Other food processing in rural nonadjacent Iowa consists heavily of prepared feeds, rendering, and other industries which often locate near raw inputs, rather than "footloose" food processing industries producing products for direct human consumption. Meat and poultry products (a sector of their own in my analysis, which often locates near inputs but also does produce products for direct human consumption) locates frequently in rural nonadjacent lowa as well.

## APPENDIX A. ADDITIONAL TABLES AND FIGURES

## Closely Related 3-Digit SICs Defined to be in the Same Industry

The 3 -digit Industry Groups on the right are those which use unusually large proportions of one or more key occupations to the 3-digit Industry Group listed on the left hand side. Key occupations for any given Industry Group are defined to be those occupations that the Industry Group employs in greater proportions than the statewide average across all industries.
${ }^{1}$ Fewer than 150 employees statewide. When odd results are obtained, it is often the case that at
least one of the SICs is quite small or had just one or two plants in the state.
2 For very small 3-digit SICs not included in the 1994 Industry-Occupation Matrix, values for the 3-digit Industry Group in brackets were substituted.

Table A1. Closely related 3-Digit SICs

| 3-digit (1994) |  |  |
| :---: | :---: | :---: |
| SIC of | f (Iowa) | Related 3-digit SICs (based on key-occupation elasticities) |
| Plant | (Empl.) | (Weight for own industry is 1.000 , for other 3-digit SICs in parentheses.) |
| 2010 (25,505) |  |  |
| 2020 | $(4,035)$ | 2070 (0.399), 2030 (0.336) |
| 2030 | $(1,880)$ | $\begin{aligned} & 2080(0.518), 2090(0.456), 3410(0.451), 2050(0.446), 2020(0.440), \\ & 3250(0.399), 2040(0.364), 2840(0.304) \end{aligned}$ |
| 2040 | $(9,880)$ | 3570 (0.340) |
| 2050 | $(2,945)$ | 2030 (0.519), 3230 (0.300), 3220 (0.300) |
| 2060 | (590) | 2020 (0.468), 2030 (0.466), 2080 (0.367), 2090 (0.337) |
| 2070 | $(1,905)$ | $\begin{aligned} & 2890(0.758), 3010(0.454), 2630(0.450), 3050(0.424), 2840(0.403), \\ & 2850(0.400), 2020(0.316) \end{aligned}$ |
| 2080 | $(1,555)$ | $\begin{aligned} & 2030(0.722), 3410(0.641), 2090(0.579), 2020(0.543), 3250(0.467), \\ & 2040(0.402), 2840(0.331) \end{aligned}$ |
| 2090 | $(1,400)$ | $\begin{aligned} & 2030(0.717), 2080(0.640), 2620^{1}(0.620), 2020(0.616), 2840(0.606), \\ & 3350(0.600), 3410(0.549), 3110(0.542), 2070(0.538), 3250(0.525), \\ & 2040(0.509), 3950(0.474), 2630(0.419), 2650(0.408), 29901(0.390), \\ & 2850(0.382), 2810(0.379) \end{aligned}$ |
| 22102 | [2250] | $\begin{aligned} & 2330^{1}(0.905), 2320(0.873), 2310(0.873), 2340(0.731), 2360(0.692), \\ & 2350(0.692), 2380^{1}(0.612), 2370^{1}(0.612), 3150^{1}(0.609), 3130^{1}(0.609), \\ & 2270(0.605), 2290(0.307) \end{aligned}$ |
| 22202 | [2250] | $\begin{aligned} & 2330^{1}(0.905), 2320(0.873), 2310(0.873), 2340(0.731), 2360(0.692), \\ & 2350(0.692), 2380^{1}(0.612), 2370^{1}(0.612), 3150^{1}(0.609), 3130^{1}(0.609), \\ & 2270(0.605), 2290(0.307) \end{aligned}$ |
| 22302 | [2250] | $2330^{1}$ (0.905), 2320 ( 0.873 ), 2310 ( 0.873 ), 2340 ( 0.731 ), 2360 ( 0.692 ), <br> 2350 (0.692), 23801 (0.612), $2370^{1}$ (0.612), $3150^{1}$ (0.609), $3130^{1}$ ( 0.609 ), <br> 2270 (0.605), 2290 (0.307) |

Table A1. (continued)

| 3-digit SIC | (Iowa) (Empl.) | Related 3-digit SICs (based on key-occupation elasticities) (Weight for own industry is 1.000 , for other 3-digit SICs in parentheses.) |
| :---: | :---: | :---: |
| 2250 | (520) | $\begin{aligned} & 2330^{1}(0.905), 2320(0.873), 2310(0.873), 2340(0.731), 2360(0.692), \\ & 2350(0.692), 2380^{1}(0.612), 2370^{1}(0.612), 3150^{1}(0.609), 3130^{1}(0.609), \\ & 2270(0.605), 2290(0.307) \end{aligned}$ |
| 22601 | (105) | 23801 (0.431), 23701 (0.431), 2390 (0.355), 2750 (0.331), 2780 (0.330) |
| 22701 | (10) | $\begin{aligned} & 3160(0.751), 2290(0.711), 2390(0.594), 3190^{1}(0.513), 2320(0.393), \\ & 2310(0.393), 2510(0.370), 2450(0.347), 2330^{1}(0.335), 2340(0.309), \\ & 3730^{1}(0.301), 2250(0.300), 2230(0.300), 2220(0.300), 2210(0.300) \end{aligned}$ |
| 22901 | (100) | $\begin{aligned} & 2270^{1}(1.071), 3160(0.961), 2390(0.825), 31901(0.691), 2510(0.563), \\ & 2450(0.464), 2320(0.443), 2310(0.443), 3840(0.396), 3730^{1}(0.383), \\ & 2380^{1}(0.302), 2370^{1}(0.302) \end{aligned}$ |
| 23102 | [2320] | $\begin{aligned} & 2330^{1}(0.928), 2340(0.862), 2250(0.848), 2230(0.848), 2220(0.848), \\ & 2210^{(0.848),} 2270^{1}(0.739), 2360(0.724), 2350(0.724), 31501(0.719), \\ & 3130^{1}(0.719), 2380^{1}(0.682), 2370^{1}(0.682), 2290^{1}(0.422), 3160(0.342) \end{aligned}$ |
| 2320 | $(2,350)$ | $2330^{1}$ (0.928), 2340 ( 0.862 ), 2250 ( 0.848 ), 2230 ( 0.848 ), 2220 ( 0.848 ), 2210 (0.848), $2270^{1}$ ( 0.739 ), 2360 ( 0.724 ), 2350 ( 0.724 ), $3150^{1}$ ( 0.719 ), $3130^{1}$ ( 0.719 ), $2380^{1}$ ( 0.682 ), $2370^{1}$ ( 0.682 ), 22901 ( 0.422 ), 3160 ( 0.342 ) |
| 23301 | (65) | $\begin{aligned} & 2320(0.840), 2310(0.840), 2340(0.782), 2250(0.736), 2230(0.736), \\ & 2220(0.736), 2210(0.736), 2360(0.708), 2350(0.708), 31501(0.603), \\ & 3130^{1}(0.603), 2270^{1}(0.594), 2380^{1}(0.515), 2370^{1}(0.515), 2290^{1}(0.364), \\ & 3160(0.316) \end{aligned}$ |
| 2340 | (280) | $\begin{aligned} & 2330^{1}(0.907), 2320(0.884), 2310(0.884), 2250(0.787), 2230(0.787), \\ & 2220(0.787), 2210(0.787), 3150^{1}(0.718), 3130^{1}(0.718), 2380^{1}(0.709), \\ & 2370^{1}(0.709), 2360(0.709), 2350(0.709), 2270^{1}(0.675), 2290^{1}(0.465), \\ & 2390(0.314) \end{aligned}$ |
| 2350 | $(1,625)$ | $2330^{1}$ (0.748), 2320 ( 0.721 ), 2310 ( 0.721 ), 2340 ( 0.660 ), 2250 ( 0.636 ), 2230 ( 0.636 ), 2220 ( 0.636 ), 2210 ( 0.636 ), $2380^{1}$ ( 0.556 ), $2370^{1}$ ( 0.556 ), $3150^{1}(0.533), 3130^{1}(0.533), 2270^{1}(0.503), 2290^{1}(0.382)$ |
| $2360{ }^{2}$ | [2350] | $\begin{aligned} & 2330^{1}(0.748), 2320(0.721), 2310(0.721), 2340(0.660), 2250(0.636), \\ & 2230(0.636), 2220(0.636), 2210(0.636), 2380^{1}(0.556), 2370^{1}(0.556), \\ & 3150^{1}(0.533), 3130^{1}(0.533), 2270^{1}(0.503), 2290^{1}(0.382) \end{aligned}$ |
| 237012 [23 | 23801] | $\begin{aligned} & 2320(0.713), 2310(0.713), 2250(0.625), 2230(0.625), 2220(0.625), \\ & 2210(0.625), 2340(0.555), 2330^{1}(0.550), 2360(0.482), 2350(0.482), \\ & 22601(0.453), 31501(0.434), 3130^{1}(0.434), 2270^{1}(0.405), 2290^{1}(0.403), \\ & 2390(0.389), 3160(0.366) \end{aligned}$ |

Table A1. (continued)

| 3-digit |
| :---: | ---: | :--- |
| SIC |$\quad$| (Iowa) <br> (Empl.) |
| :---: | | Related 3-digit SICs (based on key-occupation elasticities) |
| :--- |
| (Weight for own industry is 1.000, for other 3-digit SICs in parentheses.) |,

Table A1. (continued)

| 3-digit SIC | $\begin{gathered} \hline \hline \text { (Iowa) } \\ \text { (Empl.) } \end{gathered}$ | Related 3-digit SICs (based on key-occupation elasticities) (Weight for own industry is 1.000 , for other 3-digit SICs in parentheses.) |
| :---: | :---: | :---: |
| 2630 | (220) | $\begin{aligned} & 3110(0.550), 2070(0.407), 2650(0.406), 2890(0.364), 3350(0.318), \\ & 2670(0.313), 2620^{1}(0.308) \end{aligned}$ |
| 2650 | $(3,030)$ | $\begin{aligned} & 2670(0.962), 2620^{1}(0.881), 3110(0.535), 3350(0.475), 2630(0.441), \\ & 3210^{1}(0.376), 3190^{1}(0.368) \end{aligned}$ |
| 2670 | $(2,780)$ | 2650 (0.732), 26201 (0.648), 3110 (0.312) |
| 2710 | $(6,995)$ | $\begin{aligned} & 2720(0.697), 2740(0.617), 2790(0.570), 2730(0.553), 2750(0.434), \\ & 2780(0.343), 2760(0.338) \end{aligned}$ |
| 2720 | $(1,750)$ | $\begin{aligned} & 2740(0.764), 2710(0.706), 2750(0.528), 2780(0.482), 2730(0.439), \\ & 2760(0.424), 2790(0.363) \end{aligned}$ |
| 2730 | $(1,430)$ | $\begin{aligned} & 2750(0.596), 2780(0.494), 2790(0.481), 2760(0.474), 2710 \text { ( } 0.427) \text {, } \\ & 2720(0.392) \end{aligned}$ |
| 2740 | $(1,030)$ | 2720 (0.745), 2710 (0.597), 2790 (0.524), 2780 (0.349), 2750 (0.316) |
| 2750 | $(6,930)$ | 2760 (0.621), 2780 (0.522), 2730 (0.442), 2790 (0.360), 2720 (0.345) |
| 2760 | $(1,280)$ | 2750 (0.824), 2780 (0.761), 2730 (0.488), 2720 (0.396) |
| 2780 | (540) | 2760 (0.585), 2750 (0.516), 2730 (0.405), 2790 (0.381), 2720 (0.369) |
| 2790 | (625) | 2750 (0.430), 2710 (0.414), 2730 (0.409), 2780 (0.339), 2740 (0.337) |
| 2810 | (255) | $\begin{aligned} & 3240(0.628), 2870(0.426), 3250(0.381), 3210^{1}(0.379), 3010(0.379), \\ & 2820(0.370), 2850(0.356) \end{aligned}$ |
| 2820 | (710) | 2870 (0.789), 2890 (0.449) |
| 2830 | $(2,055)$ |  |
| 2840 | (830) | $\begin{aligned} & 2890(0.553), 2620^{1}(0.430), 2070(0.394), 3250(0.366), 2630(0.352) \text {, } \\ & 2090(0.320), 2850(0.317) \end{aligned}$ |
| 2850 | $(1,395)$ | 2810 (0.463), 2870 (0.454) |
| 2860 | (195) | 2830 (0.309) |
| 2870 | $(1,695)$ | 2820 (1.078), 2890 (0.573), 2810 (0.373) |
| 2890 | (340) | 2820 (0.564), 2870 (0.506), 2070 (0.445), 2850 (0.353), 2840 (0.323) |
| 29101 | (10) |  |
| 29501 | (115) | 2830 (0.683), 2870 (0.671), 2820 (0.640) |

Table A1. (continued)

| $\begin{aligned} & \hline \text { 3-digit } \\ & \text { SIC } \\ & \hline \end{aligned}$ | (Iowa) (Empl.) | Related 3-digit SICs (based on key-occupation elasticities) (Weight for own industry is 1.000 , for other 3-digit SICs in parentheses.) |
| :---: | :---: | :---: |
| $2990{ }^{1}$ | (120) | 2850 (0.712), 3410 (0.657), 3650 (0.620), 3250 (0.522) |
| 3010 | $(3,040)$ |  |
| 30202 | [3060] | $\begin{aligned} & 2520(0.424), 3110(0.419), 3010(0.309), 31901(0.307) \\ & 3050(530) \quad 3060(0.341), 3020(0.341), 3010(0.332), 2070(0.331) \end{aligned}$ |
| 3060 | $(1,500)$ | 2520 (0.424), 3110 (0.419), 3010 (0.309), 31901 (0.307) |
| 3080 | (8,920) | $\begin{aligned} & \left.3640(0.700), 3960(0.499), 3610(0.348), 3170^{1}(0.323), 3450 \text { ( } 0.309\right) \text {, } \\ & 3750^{1}(0.304) \end{aligned}$ |
| 3110 | (185) | $3190^{1}(0.496), 2630$ (0.446), $3210^{1}(0.434), 2650$ (0.363), 2670 (0.327) |
| 31301 | [31501] | $2330^{1}$ ( 0.673 ), 2320 ( 0.665 ), 2310 ( 0.665 ), 2340 ( 0.654 ), 2250 ( 0.595 ), 2230 ( 0.595 ), 2220 ( 0.595 ), 2210 ( 0.595 ), 2360 ( 0.529 ), 2350 ( 0.529 ), $2270^{1}$ ( 0.524 ), 3160 ( 0.466 ), $2380^{1}$ ( 0.459 ), $2370^{1}$ ( 0.459 ) |
| 31401 | (5) | 2390 (0.707), $3150^{1}(0.342), 3130^{1}(0.342)$ |
| 31501 | (60) | $\begin{aligned} & 2330^{1}(0.673), 2320(0.665), 2310(0.665), 2340(0.654), 2250(0.595), \\ & 2230(0.595), 2220(0.595), 2210(0.595), 2360(0.529), 2350(0.529), \\ & 2270^{1}(0.524), 3160(0.466), 2380^{1}(0.459), 2370^{1}(0.459), 3140^{1}(0.417) \end{aligned}$ |
| 3160 | (585) | $\begin{aligned} & 2270^{1}(0.944), 2290^{1}(0.810), 2390(0.780), 3190^{1}(0.614), 2510(0.465), \\ & 2450(0.426), 3840(0.360), 3730^{1}(0.354) \end{aligned}$ |
| 31701 | (30) | $\begin{aligned} & 2450(0.642), 3860^{1}(0.598), 3750^{1}(0.565), 3840(0.554), 3580(0.500), \\ & 3690(0.473), 3930^{1}(0.462), 2490(0.456), 2430(0.428), 2530(0.406), \\ & 3480(0.392), 3430(0.381), 3710(0.351), 3790(0.320), 3510(0.315) \text {, } \\ & 3910(0.310), 3730^{1}(0.303) \end{aligned}$ |
| 31901 | (75) | $\begin{aligned} & 2270^{1}(0.665), 2290^{1}(0.631), 3160(0.619), 2390(0.555), 3110(0.453), \\ & 2510(0.398), 2450(0.317), 3730^{1}(0.305) \end{aligned}$ |
| 32101 | (30) | $\begin{aligned} & 3010(0.497), 3110(0.428), 3250(0.422), 3290(0.416), 2670(0.341) \text {, } \\ & 3190^{1}(0.328), 3240(0.316), 2810(0.308) \end{aligned}$ |
| 32202 | [3230] | 2050 (0.386), $3210^{1}(0.376), 3250$ (0.337), 3240 (0.308) |
| 3230 | (405) | 2050 (0.386), $3210^{1}$ (0.376), 3250 (0.337), 3240 (0.308) |
| 3240 | (540) | 2810 (0.714), 3010 (0.473), 32101 (0.414), 3250 (0.402) |
| 3250 | (480) | $\begin{aligned} & \left.3010(0.616), 3210^{1}(0.472), 2850(0.412), 3280^{1}(0.406), 2810 \text { ( } 0.367\right) \text {, } \\ & 3240(0.349) \end{aligned}$ |
| 32601 | (50) | 3990 (0.308) |

Table A1. (continued)

| 3-digit SIC | $\begin{gathered} \hline \hline \text { (Iowa) } \\ \text { (Empl.) } \end{gathered}$ | Related 3-digit SICs (based on key-occupation elasticities) (Weight for own industry is 1.000 , for other 3-digit SICs in parentheses.) |
| :---: | :---: | :---: |
| 3270 | $(3,800)$ | 29501 (0.503) |
| $3280{ }^{1}$ | (45) | 3470 (0.378), 37501 (0.340), 2490 (0.331), 3010 (0.316), 3250 (0.308) |
| 3290 | (595) | $\begin{aligned} & 3210^{1}(0.465), 3390^{1}(0.443), 3870(0.429), 3490(0.328) \\ & 3310 \quad(945), 3340(0.621), 3330(0.621) \end{aligned}$ |
| 3320 | $(1,990)$ | 3360 (0.651), 3310 (0.398), 3490 (0.347) |
| 33302 | [3340] | 3310 (0.589) |
| 3340 | (320) | 3310 (0.589) |
| 3350 | $(2,915)$ | $\begin{aligned} & 26201(0.709), 3110(0.517), 3190^{1}(0.439), 2650(0.408), 3950(0.343) \text {, } \\ & 2630(0.341) \end{aligned}$ |
| 3360 | $(1,220)$ | 3320 (0.645), 3490 (0.441), 3420 (0.366), 3590 (0.338) |
| 33901 | (45) | 3340 (0.456), 3330 (0.456), 3510 (0.333) |
| 3410 | (265) | $3460(0.411), 2530(0.394), 3450(0.381), 3340(0.365), 3330(0.365)$, $3430(0.361), 3250(0.316), 3650(0.314), 2030(0.300)$ |
| 3420 | $(1,255)$ | $\begin{aligned} & 3440(0.657), 3430(0.560), 3490(0.487), 3450(0.467), 3790(0.447), \\ & 3540(0.436), 3530(0.430), 3360(0.419), 3590(0.398), 3510(0.397), \\ & 3410(0.366), 3560(0.357), 3460(0.341), 3520(0.337), 3710(0.335), \\ & 2530(0.329), 3750^{1}(0.307), 3580(0.306), 2520(0.302) \end{aligned}$ |
| 3430 | (645) | $\begin{aligned} & 2530(0.583), 3420(0.582), 3450(0.538), 3510(0.531), 3410(0.521), \\ & 3590(0.471), 3580(0.470), 3170^{1}(0.451), 2520(0.438), 3440(0.425), \\ & 3710(0.396), 3750^{1}(0.387), 3490(0.375), 3530(0.372), 3540(0.364) \text {, } \\ & 3480(0.364), 3690(0.354), 3550(0.344), 3460(0.341), 3520(0.340), \\ & 3860^{1}(0.339), 3790(0.331), 3610(0.317) \end{aligned}$ |
| 3440 | $(4,045)$ | $\begin{aligned} & 3420(0.541), 3460(0.450), 37501(0.426), 3790(0.416), 3430(0.384), \\ & 3530(0.362), 3520(0.349), 3510(0.340), 2530(0.332), 3410(0.315) \text {, } \\ & 3590(0.312), 2520(0.301), 3580(0.300) \end{aligned}$ |
| 3450 | $(1,395)$ | $\begin{aligned} & 3560(0.538), 3720(0.416), 3490(0.384), 3590(0.380), 3460(0.376), \\ & 3520(0.352), 3540(0.351), 3430(0.343), 3420(0.343), 3510(0.341), \\ & 3710(0.338), 3410(0.338), 3910(0.305) \end{aligned}$ |
| 3460 | $(2,580)$ | $3410(0.364), 3050(0.354), 37501(0.341), 3450(0.320), 3290$ ( 0.312 ), $2540(0.309), 3520(0.306)$ |
| 3470 | (330) |  |

Table A1. (continued)

| 3-digit SIC | (Iowa) <br> (Empl.) | Related 3-digit SICs (based on key-occupation elasticities) (Weight for own industry is 1.000 , for other 3-digit SICs in parentheses.) |
| :---: | :---: | :---: |
| 3480 | $(1,175)$ | $3170^{1}(0.553), 3580(0.509), 3690(0.444), 3430(0.436), 3860^{1}(0.388)$, $3840(0.379), 2450(0.365), 2520(0.357), 3710(0.353), 3550(0.352)$, $3810(0.348), 3760(0.348), 3610(0.341), 2530(0.339), 3750^{1}(0.336)$, $2430(0.334), 3930^{1}(0.322)$ |
| 3490 | $(2,910)$ | $3360(0.576), 3420(0.549), 3320(0.546), 3450(0.537), 3590(0.533)$, $3290(0.530), 3460(0.499), 37501(0.478), 3560(0.473), 3710(0.399)$, $32801(0.396), 3870(0.389), 3540(0.386), 3510(0.386), 3430(0.375)$, $3470(0.363), 3520(0.354), 3530(0.347), 3440(0.342), 3630(0.305)$ |
| 3510 | (945) | $\begin{aligned} & 3550(0.606), 3590(0.585), 3560(0.564), 3540(0.521), 3430(0.505) \text {, } \\ & 3530(0.495), 3450(0.458), 3360(0.422), 3710(0.414), 3720(0.411), \\ & 3340(0.379), 3330(0.379), 3420(0.368), 3490(0.366), 3610(0.358), \\ & 31701(0.356), 3520(0.353), 3440(0.348), 3790(0.346), 3630(0.331) \text {, } \\ & 3730^{1}(0.314), 3390^{1}(0.311), 3750^{1}(0.304), 3580(0.302) \end{aligned}$ |
| 3520 | $(14,010)$ | $3530(0.669), 3720(0.660), 3460(0.647), 3450(0.637), 3590(0.617)$, $3440(0.578), 3560(0.574), 3510(0.569), 3490(0.563), 3710(0.560)$, $3430(0.546), 3420(0.537), 3540(0.526), 3790(0.522), 37501(0.521)$, $2530(0.519)$ |
| 3530 | $(9,730)$ | $\begin{aligned} & 3510(0.668), 3720(0.599), 3590(0.598), 3420(0.558), 3560(0.555), \\ & 3730^{1}(0.546), 3520(0.532), 3790(0.528), 3540(0.507), 3440(0.487), \\ & 3430(0.460), 3550(0.459), 3450(0.447), 3490(0.438), 3630(0.425), \\ & 3580(0.412), 3710(0.402) \end{aligned}$ |
| 3540 | $(2,990)$ | $3590(0.473), 3720(0.418), 3450(0.383), 3550$ (0.375), 3460 ( 0.373 ), $3510(0.369), 3560(0.365), 3420(0.348), 3360(0.317), 3620(0.304)$ |
| 3550 | $(2,445)$ | $\begin{aligned} & 3510(0.704), 3560(0.685), 3590(0.660), 3540(0.600), 3620(0.527), \\ & 3360(0.518), 3450(0.472), 3720(0.421), 3430(0.394), 3530(0.392), \\ & 3820(0.387), 3170^{1}(0.366), 3580(0.323), 3860^{1}(0.322) \end{aligned}$ |
| 3560 | $(2,265)$ | $3450(0.833), 3550(0.731), 3590(0.717), 3510(0.680), 3720(0.641)$, $3360(0.631), 3540(0.612), 3490(0.533), 3530(0.513), 3320(0.462)$, $3710(0.455), 3520(0.440), 3420(0.426), 3910(0.401), 3430(0.367)$, $3620(0.351)$ |
| 3570 | (690) | 3820 (0.660), 38601 (0.410), 2040 (0.360), 3660 (0.321), 3620 (0.319) |
| 3580 | $(3,845)$ | $\begin{aligned} & 3170^{1}(0.620), 2620^{1}(0.538), 3690(0.476), 3610(0.465), 3480(0.457), \\ & 3860^{1}(0.445), 3750^{1}(0.444), 3430(0.428), 2530(0.420), 2450(0.420), \\ & 2430(0.418), 3840(0.396), 3710(0.377), 3930^{1}(0.373), 3530(0.343), \\ & 3810(0.340), 3760(0.340), 3790(0.317), 3550(0.315), 2490(0.313), \\ & 3590(0.303) \end{aligned}$ |

Table A1. (continued)

| 3-digit SIC | $\begin{gathered} \text { (Iowa) } \\ \text { (Empl.) } \end{gathered}$ | Related 3-digit SICs (based on key-occupation elasticities) (Weight for own industry is 1.000 , for other 3-digit SICs in parentheses.) |
| :---: | :---: | :---: |
| 3590 | $(3,735)$ | $3720(0.775), 3540(0.763), 3510(0.709), 3560(0.697), 3550(0.682)$, $3450(0.633), 3490(0.540), 3530(0.534), 3430(0.533), 3360(0.501)$, $3520(0.444), 3420(0.427), 3620(0.389), 3460(0.379), 3710(0.365)$, $3440(0.365), 2530(0.340), 3580(0.339)$ |
| 3610 | (1,150) | $\begin{aligned} & 3810(0.504), 3760(0.504), 3580(0.482), 3510(0.352), 31701(0.337), \\ & 3640(0.336), 3430(0.327), 3710(0.321), 3690(0.312), 3080(0.310) \text {, } \\ & 3630(0.307), 3670(0.302) \end{aligned}$ |
| 3620 | $(3,800)$ | $\begin{aligned} & 3870(0.644), 3810(0.386), 3760(0.386), 3660(0.376), 3570(0.348), \\ & 3640(0.335), 3820(0.318), 3860^{1}(0.311) \end{aligned}$ |
| 3630 | (7,715) | $3510(0.427), 3530(0.411), 37501(0.410), 3460(0.396), 3050(0.392)$, $3690(0.379), 3470(0.369), 37301(0.360), 3960(0.343), 3580(0.327)$, $3810(0.319), 3760(0.319), 3610(0.319), 3560(0.318), 3410(0.317)$, $3080(0.317), 2430(0.316), 3490(0.315)$ |
| 3640 | (400) | $\begin{aligned} & 3080(0.541), 3620(0.416), 3570(0.362), 3810(0.358), 3760(0.358) \text {, } \\ & 3960(0.342), 3610(0.322) \end{aligned}$ |
| 3650 | (330) | $\begin{aligned} & 3210^{1}(0.554), 3410(0.509), 2430(0.500), 3250(0.458), 29901(0.417), \\ & 2420(0.361), 3630(0.319) \end{aligned}$ |
| 3660 | $(1,185)$ | 3670 (0.604), 3690 (0.461), 3820 (0.334), 3620 (0.325) |
| 3670 | $(1,365)$ | 3660 (0.417) |
| 3690 | $(3,110)$ | $\begin{aligned} & 3660(0.893), 31700^{1}(0.776), 3670(0.640), 3580(0.623), 3750^{1}(0.592), \\ & 3860^{1}(0.534), 3840(0.511), 2450(0.511), 3480(0.484), 2530(0.474), \\ & 3430(0.471), 3630(0.468), 2430(0.446), 3930^{1}(0.439), 3710(0.422), \\ & 2490(0.403), 3610(0.402), 3080(0.400), 3990(0.389), 3510(0.387), \\ & 3820(0.382), 3940(0.353), 2520(0.348), 3790(0.342), 3550(0.325), \\ & 3640(0.314), 3360(0.314) \end{aligned}$ |
| 3710 | $(9,765)$ | $\begin{aligned} & 3170^{1}(0.716), 3510(0.653), 3580(0.625), 3430(0.625), 3450(0.604), \\ & 3490(0.593), 2530(0.583), 3560(0.579), 3520(0.543), 37501(0.542), \\ & 3690(0.530), 3420(0.524), 3790(0.517), 38601(0.501), 3590(0.499), \\ & 3610(0.490), 3530(0.489), 3550(0.482), 2450(0.480), 3480(0.479), \\ & 3840(0.462), 3290(0.451), 3440(0.445) \end{aligned}$ |
| 3720 | (760) | $\begin{aligned} & 3590(0.499), 3450(0.419), 3540(0.386), 3560(0.384), 3530(0.377) \text {, } \\ & 3730^{1}(0.367), 3870(0.350), 3520(0.301) \end{aligned}$ |
| 37301 | (70) | 3870 (0.499), 3720 (0.479), 3530 (0.331) |
| 3740 | (220) |  |

Table A1. (continued)

| $\overline{\text { 3-digit }}$ SIC | $\begin{gathered} \text { (Iowa) } \\ \text { (Empl.) } \end{gathered}$ | Related 3-digit SICs (based on key-occupation elasticities) (Weight for own industry is 1.000 , for other 3-digit SICs in parentheses.) |
| :---: | :---: | :---: |
| 37501 | (20) | $\begin{aligned} & 2490(0.441), 3170^{1}(0.438), 2530(0.436), 2520(0.368), 3280^{1}(0.367), \\ & 3460(0.358), 3490(0.354), 2450(0.330), 3790(0.325), 2540(0.322), \\ & 3440(0.305) \end{aligned}$ |
| 37602 | [3810] | 3620 (0.462), 3610 (0.373), 3640 (0.322), 3720 (0.318), 3570 (0.310) |
| 3790 | $(1,025)$ | 3420 ( 0.544 ), 37501 ( 0.535 ), 3530 ( 0.518 ), 3440 ( 0.517 ), 3470 ( 0.470 ), 3510 (0.439), 2530 ( 0.438 ), $3170^{1}$ (0.427), 2520 (0.414), 3580 (0.398), 3430 ( 0.392 ), 3520 ( 0.388 ), 3710 ( 0.381 ), 3050 ( 0.348 ), 2490 ( 0.347 ), $3730^{1}(0.340), 3860^{1}(0.336), 2450$ ( 0.333 ), 2430 ( 0.309 ), 3460 ( 0.307 ), 3630 (0.304), 3740 (0.302) |
| 3810 | $(8,735)$ | 3620 (0.462), 3610 (0.373), 3640 (0.322), 3720 (0.318), 3570 (0.310) |
| 3820 | $(1,120)$ | 3570 (0.686), 3660 (0.334), 3620 (0.312) |
| 3840 | (335) | 2450 (0.327), 31701 (0.309) |
| 38501 | (70) |  |
| 38601 | (80) | $\begin{aligned} & 31701(0.695), 3570(0.616), 3870(0.479), 3840(0.436), 3580(0.428), \\ & 3820(0.411), 2450(0.407), 3690(0.393), 3620(0.392), 37501(0.374), \\ & 39301(0.352), 3430(0.342), 2530(0.342), 2490(0.340), 2430(0.338), \\ & 3480(0.332), 3550(0.308), 3610(0.300) \end{aligned}$ |
| 3870 | (260) | 3620 (0.526), $3860{ }^{1}$ (0.362) |
| 3910 | (195) | 3450 (0.331), 3720 (0.317) |
| 39301 | (40) | $\begin{aligned} & 2450(0.703), 2540(0.644), 2430(0.449), 3170^{1}(0.319), 2440(0.317), \\ & 2520(0.309), 2490(0.301) \end{aligned}$ |
| 3940 | $(3,235)$ | $\begin{aligned} & 2270^{1}(0.902), 2290^{1}(0.824), 3160(0.796), 2450(0.783), 3840(0.740), \\ & 2390(0.700), 2510(0.659), 3170^{1}(0.656), 3190^{1}(0.584), 3690(0.556) \end{aligned}$ |
| 3950 | (700) | $\begin{aligned} & 2260^{1}(0.511), 3350(0.502), 2380^{1}(0.462), 2370^{1}(0.462), 2620^{1}(0.389), \\ & 2390(0.338), 2650(0.326), 3170^{1}(0.324), 3050(0.324), 2320(0.324), \\ & 2310(0.324), 3160(0.315), 3610(0.312), 2090(0.308), 3110(0.305) \end{aligned}$ |
| 3960 | (250) | 31901 (0.398), 3080 (0.385), 3640 (0.340), 3250 (0.317) |
| 3990 | $(1,410)$ | 3660 (0.559), 3670 (0.542), $3260^{1}$ (0.431), 3690 (0.396) |

${ }^{1}$ Fewer than 150 employees statewide. When odd results are obtained, it is often the case that at least one of the SICs is quite small or had just one or two plants in the state.
${ }^{2}$ For very small 3-digit SICs not included in the 1994 Industry-Occupation Matrix, values for the 3 -digit Industry Group in brackets were substituted.
Table A2. Variable means for four county types by sector

|  | Average EarningsU.S. AvgActual Ind. Mix |  | Weighted Avg Plant Size U.S. Avg. PLANT |  |  | LaborMkt Workforce Size | Industry Size | Industry Density | $\begin{aligned} & \text { H.S. } \\ & \text { Educ. } \end{aligned}$ | County <br> Coll. Cost of <br> Educ. Living |  | County Empl in Sector | Cty Net <br> Job Chg <br> 86-94 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| All 10 Manufacturing Sectors |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Metro Core | \$34,388 | \$31,346 | 1,453 | 919 | 1.58 | 128,173 | 2,878 | 6.48 | 87.4\% | 23.9\% | 0.98 | 4,477 | 0.8\% |
| Large Nonmetro | \$32,010 | \$30,585 | 553 | 532 | 1.04 | 68,820 | 1,251 | 5.72 | 86.1\% | 18.1\% | 0.95 | 1,372 | 0.1\% |
| Rural Adjacent | \$27,416 | \$28,987 | 839 | 749 | 1.12 | 70,882 | 1,835 | 6.64 | 86.3\% | 13.9\% | 0.94 | 1,127 | 4.7\% |
| Rural Nonadjacent | \$23,223 | \$27,947 | 424 | 551 | 0.77 | 34,865 | 999 | 6.52 | 86.6\% | 14.2\% | 0.92 | 808 | 3.4\% |
| Meatpacking |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Metro Core | \$24,088 | \$23,238 | 1,264 | 824 | 1.84 | 121,417 | 3,556 | 3.65 | 86.3\% | 20.8\% | 0.98 | 1,634 | 4.4\% |
| Large Nonmetro | \$23,770 | \$21,490 | 886 | 781 | 1.24 | 70,184 | 1,482 | 2.03 | 84.3\% | 15.5\% | 0.95 | 1,039 | 5.0\% |
| Rural Adjacent | \$23,939 | \$23,090 | 793 | 849 | 0.90 | 70,934 | 1,824 | 3.68 | 85.8\% | 13.8\% | 0.94 | 816 | 4.6\% |
| Rural Nonadjacent | \$23,356 | \$22,529 | 558 | 753 | 0.72 | 35,189 | 1,383 | 4.02 | 86.6\% | 14.8\% | 0.93 | 937 | 0.8\% |
| Other Food Processing |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Metro Core | \$34,883 | \$33,112 | 346 | 369 | 0.85 | 145,427 | 1,652 | 6.28 | 88.2\% | 23.8\% | 0.99 | 2,346 | 0.7\% |
| Large Nonmetro | \$37,127 | \$35,684 | 478 | 312 | 1.49 | 85,314 | 1,147 | 3.52 | 83.1\% | 14.8\% | 0.96 | 1,255 | -1.6\% |
| Rural Adjacent | \$29,449 | \$28,516 | 267 | 274 | 1.18 | 68,808 | 614 | 7.06 | 87.5\% | 15.8\% | 0.95 | 387 | 5.2\% |
| Rural Nonadjacent | \$25,772 | \$28,596 | 202 | 311 | 0.67 | 40,096 | 391 | 3.99 | 86.3\% | 14.0\% | 0.93 | 435 | 3.0\% |
| Textiles, Apparel, and Leather |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Metro Core | \$18,349 | \$18,538 | 196 | 318 | 0.64 | 119,975 | 411 | 4.33 | 86.6\% | 21.2\% | 0.97 | 421 | 5.0\% |
| Large Nonmetro | \$15,707 | \$16,765 | 50 | 184 | 0.37 | 70,037 | 228 | 5.98 | 86.4\% | 18.1\% | 0.94 | 73 | -10.0\% |
| Rural Adjacent | \$15,415 | \$17,256 | 170 | 302 | 0.58 | 52,430 | 490 | 3.91 | 85.6\% | 13.5\% | 0.93 | 189 | 5.2\% |
| Rural Nonadjacent | \$18,255 | \$16,863 | 278 | 293 | 0.98 | 39,415 | 426 | 2.02 | 86.4\% | 16.1\% | 0.93 | 395 | 3.6\% |
| Wood Products and Furniture |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Metro Core | \$24,393 | \$23,759 | 284 | 338 | 0.96 | 123,485 | 814 | 6.56 | 86.5\% | 21.1\% | 0.98 | 1,015 | 6.3\% |
| Large Nonmetro | \$35,755 | \$30,769 | 342 | 1,010 | 0.32 | 104,331 | 2,370 | 8.10 | 81.2\% | 14.5\% | 0.98 | 1,450 | 2.6\% |
| Rural Adjacent | \$29,298 | \$25,074 | 1,737 | 346 | 4.53 | 70,572 | 2,185 | 3.09 | 85.2\% | 14.8\% | 0.96 | 1,772 | 3.0\% |
| Rural Nonadjacent | \$21,084 | \$22,126 | 278 | 308 | 0.91 | 39,617 | 536 | 4.03 | 87.6\% | 16.1\% | 0.94 | 436 | 8.5\% |
| Printing and Publishing |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Metro Core | \$27,901 | \$29,980 | 518 | 409 | 1.27 | 164,612 | 2,288 | 15.44 | 88.3\% | 24.9\% | 0.99 | 3,515 | 1.6\% |
| Large Nonmetro | \$17,419 | \$28,443 | 67 | 430 | 0.18 | 86,291 | 771 | 16.42 | 87.9\% | 23.5\% | 0.96 | 290 | 1.6\% |
| Rural Adjacent | \$19,030 | \$28,200 | 73 | 441 | 0.28 | 76,756 | 763 | 21.35 | 86.6\% | 14.4\% | 0.95 | 147 | 0.5\% |
| Rural Nonadjacent | \$16,248 | \$28,599 | 66 | 477 | 0.20 | 36,825 | 322 | 11.90 | 87.1\% | 15.3\% | 0.93 | 164 | 1.0\% |

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Table A2. continued

|  | Average E <br> Actual | arnings U.S. Avg Ind. Mix | Weighted <br> Actual | Avg Plant U.S. Avg. Ind. Mix | $\begin{aligned} & \hline \hline \text { Size } \\ & \text { RELSZ } \end{aligned}$ | Workforce Size | Industry Size | Industry Density | HS <br> Educ. | Coll. Educ. | County Cost of Living | Empl in Sector | $\begin{array}{r} \text { Net } \\ \text { Jobs } \\ 86-94 \end{array}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Chemicals |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Metro Core | \$35,882 | \$36,413 | 226 | 455 | 0.47 | 134,972 | 430 | 3.45 | 88.7\% | 28.7\% | 0.99 | 539 | 2.5\% |
| Large Nonmetro | \$39,953 | \$41,050 | 333 | 589 | 0.64 | 78,176 | 677 | 2.35 | 85.1\% | 16.8\% | 0.95 | 703 | 1.6\% |
| Rural Adjacent | \$24,990 | \$38,102 | 55 | 830 | 0.07 | 78,959 | 172 | 5.41 | 85.9\% | 14.6\% | 0.94 | 64 | 5.2\% |
| Rural Nonadjacent | \$28,862 | \$39,567 | 172 | 811 | 0.26 | 41,717 | 235 | 2.17 | 86.3\% | 15.1\% | 0.93 | 226 | 2.2\% |
| Plastics Products |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Metro Core | \$27,918 | \$25,391 | 391 | 220 | 1.76 | 144,468 | 1,219 | 5.86 | 89.6\% | 30.2\% | 1.00 | 733 | 2.3\% |
| Large Nonmetro | \$26,812 | \$25,407 | 268 | 203 | 1.27 | 93,854 | 943 | 5.43 | 83.2\% | 14.7\% | 0.96 | 475 | 5.1\% |
| Rural Adjacent | \$21,079 | \$25,507 | 158 | 228 | 0.70 | 78,400 | 900 | 8.15 | 86.2\% | 13.5\% | 0.95 | 212 | 14.3\% |
| Rural Nonadjacent | \$21,754 | \$26,089 | 111 | 218 | 0.52 | 39,847 | 334 | 4.80 | 86.4\% | 15.4\% | 0.93 | 147 | 8.9\% |
| Metals and Equipment |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Metro Core | \$41,499 | \$34,251 | 1,515 | 693 | 2.23 | 127,034 | 4,152 | 9.74 | 87.0\% | 21.8\% | 0.98 | 6,578 | -1.3\% |
| Large Nonmetro | \$35,494 | \$31,978 | 677 | 584 | 1.50 | 68,243 | 1,966 | 8.83 | 85.8\% | 17.2\% | 0.95 | 1,934 | 0.9\% |
| Rural Adjacent | \$29,708 | \$32,751 | 1,294 | 1,176 | 0.92 | 79,659 | 2,938 | 9.33 | 86.2\% | 14.2\% | 0.95 | 1,809 | 4.4\% |
| Rural Nonadjacent | \$26,437 | \$32,052 | 575 | 726 | 0.86 | 38,107 | 1,445 | 6.77 | 87.2\% | 15.8\% | 0.93 | 1,168 | 3.7\% |
| Electronics, Electrical Equipment, and Instruments |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Metro Core | \$37,338 | \$41,554 | 5,183 | 1,991 | 2.41 | 130,827 | 5,968 | 2.49 | 89.8\% | 25.1\% | 1.00 | 8,069 | 1.5\% |
| Large Nonmetro | \$35,582 | \$32,788 | 978 | 535 | 2.20 | 78,431 | 657 | 2.85 | 87.8\% | 20.8\% | 0.95 | 994 | -9.6\% |
| Rural Adjacent | \$20,439 | \$32,691 | 221 | 914 | 0.29 | 61,278 | 1,089 | 4.43 | 85.6\% | 12.8\% | 0.95 | 400 | 2.7\% |
| Rural Nonadjacent | \$25,458 | \$33,622 | 384 | 974 | 0.44 | 42,496 | 846 | 2.99 | 86.3\% | 15.2\% | 0.95 | 1,071 | 1.1\% |
| Paper, Rubber, Glass and Miscellaneous Manufacturing |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Metro Core | \$34,016 | \$32,754 | 630 | 701 | 0.91 | 173,591 | 1,301 | 3.49 | 88.9\% | 26.2\% | 0.99 | 2,484 | -1.0\% |
| Large Nonmetro | \$31,450 | \$31,209 | 576 | 483 | 1.76 | 76,956 | 960 | 2.34 | 85.2\% | 16.7\% | 0.96 | 1,455 | 0.2\% |
| Rural Adjacent | \$31,743 | \$30,726 | 334 | 294 | 1.40 | 75,202 | 460 | 2.35 | 85.2\% | 14.7\% | 0.96 | 357 | 1.7\% |
| Rural Nonadjacent | \$24,534 | \$27,348 | 218 | 324 | 0.73 | 36,853 | 303 | 2.33 | 87.0\% | 16.1\% | 0.93 | 253 | 4.2\% |

Table A3. Relationship between weighted average plant size, industry size, and industry density

| Changing weighted average plant size while holding industry size and Density-M constant |  |  |  |  |  |  |  |  |  |  |  |  | Ratio of |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | to Min Plant Size |
| Industry Size | 90 | 90 | 90 | 90 | 90 | 90 | 90 | 90 | 90 | 90 | 90 | 90 |  |
| (Avg. Plant Size) | 30 | 30 | 45 | 30 | 30 | 30 | 18 | 18 | 18 | 18 | 30 | 30 |  |
| Weighted Avg Plant Size | 30.0 | 44.0 | 45.0 | 45.0 | 45.1 | 45.0 | 45.0 | 44.9 | 44.9 | 44.9 | 50.4 | 56.7 | 0.4\% |
| Cluster-M | 3.00 | 2.04 | 2.00 | 2.00 | 2.00 | 2.00 | 2.00 | 2.00 | 2.00 | 2.00 | 1.79 | 1.59 |  |
| Cluster-H | 3.00 | 2.02 | 2.00 | 1.89 | 1.84 | 2.00 | 1.91 | 1.98 | 2.04 | 2.56 | 1.83 | 1.67 |  |
| Plant A | 30 | 45 | 45 | 51 | 55 | 60 | 55 | 60 | 60 | 62 | 65 | 70 |  |
| Plant B | 30 | 44 | 45 | 38 | 32 | 15 | 32 | 19 | 20 | 7 | 12.5 | 10 |  |
| Plant C | 30 | 1 |  | 1 | 3 | 15 | 1 | 9 | 5 | 7 | 12.5 | 10 |  |
| Plant D |  |  |  |  |  |  | , | 1 | 3 | 7 |  |  |  |
| Plant E |  |  |  |  |  |  | 1 | 1 | 2 | 7 |  |  |  |
| Changing weighted average plant size while holding industry size and Density-H constant |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 |  |
| Industry Size | 90 | 90 | 90 | 90 | 90 | 90 | 90 | 90 | 90 | 90 | 90 | 90 |  |
| (Avg. Plant Size) | 30 | 30 | 45 | 30 | 30 | 30 | 18 | 18 | 18 | 18 | 18 | 30 |  |
| Weighted Avg Plant Size | 30.0 | 44.1 | 45.0 | 41.7 | 41.7 | 45.0 | 44.3 | 47.4 | 50.7 | 58.9 | 65.0 | 56.7 | 56\% |
| Cluster-M | 3.0 | 2.04 | 2.00 | 2.16 | 2.16 | 2.00 | 1.99 | 1.82 | 1.70 | 1.40 | 1.25 | 1.6 |  |
| Cluster-H | 3.0 | 2.00 | 2.00 | 2.00 | 2.00 | 2.00 | 2.00 | 2.00 | 2.00 | 2.00 | 2.00 | 1.7 |  |
| Plant A | 30 | 46 | 45 | 50 | 55 | 60 | 52 | 63 | 67 | 75 | 80 | 70 |  |
| Plant B | 30 | 43 | 45 | 35 | 25 | 15 | 37 | 21 | 12 | 9 | 5 | 10 |  |
| Plant C | 30 | 1 |  | 5 | 10 | 15 | 1 | 6 | 11 | 6 |  | 10 |  |
| Plant D |  |  |  |  |  |  | 1 | 2 | 3 | 4 | 5 |  |  |
| Plant E |  |  |  |  |  |  | 1 | 2 | 1 | 4 | 5 |  |  |



Figure A1. Iowa: metropolitan core counties, large nonmetro counties, and rural counties.
Metro core counties have heavy shaded boundaries, large nonmetro counties ( $20,000+$ urban residents) have double boundaries. Source: 1990 Census of Population and Housing.


Figure A2. Own county workforce
Source: 1990 Census of Population and Housing.


Figure A3. Workforce size in labor market area.
Note: Workforce size in labor market area equals own county workforce plus a fraction of surrounding counties based on distance. Source: 1990 Census of Population and Housing.


Figure A4. Average wage and salary earnings per manufacturing job by place of work, 1994.
Source: Iowa Department of Employment Services.


Figure A5. Average wage and salary earnings per nonmanufacturing job by place of work, 1994.
Source: Iowa Department of Employment Services.


Figure A6. Manufacturing employment, 1994.
Source: Iowa Department of Employment Services.


Figure A7. Manufacturing as a percent of wage and salary employment, 1994.
Source: Iowa Department of Employment Services.


Figure A8. Meatpacking, sausages \& other prepared meats, poultry slaughtering \& egg processing (SIC 2011, 2013, 2017 ), 1994. Sources: 1994 \& 1995 Iowa Manufacturers Directory, 1992 Census of Manufacturing, Iowa DES, 1994 County Business Patterns.


Figure A9. Own county employment in meatpacking, 1994.
Source: Department of Employment Services.


Figure A10. Labor market area industry size in meatpacking, egg and poultry processing, 1994.
Industry size is calculated based on plants in those 3-digit SIC codes that use unusually large proportions of the same occupations. Source: Department of Employment Services (Iowa counties) and County Business Patterns 1994 (counties in neighboring states).


Figure A11. Labor market area industry density in meatpacking, egg and poultry processing, 1994.
Industry density is a function of the relative size and distance of plants in 3-digit SIC codes that use the same specialized occupations. Source: Department of Employment Services (Iowa counties) and County Business Patterns 1994 (counties in neighboring states).


Figure A12. Other food processing, excluding meat and poultry products (SIC 20 excl. 2010), 1994.
Sources: 1994 \& 1995 Iowa Manufacturers Directory, 1992 Census of Manufacturing, Iowa DES, 1994 County Business Patterns.


Figure A13. Own county employment in other food processing (other than meatpacking), 1994. Source: Department of Employment Services.


Figure A14. Labor market area industry size in other food processing (other than meatpacking), 1994.
Industry size is calculated based on plants in those 3-digit SIC codes that use unusually large proportions of the same occupations. Source: Department of Employment Services (Iowa counties) and County Business Patterns 1994 (counties in neighboring states).


Figure A15. Labor market area industry density in food processing (other than meat products), 1994.
Industry density is a function of the relative size and distance of plants in 3-digit SIC codes that use the same specialized occupations. Source: Department of Employment Services (Iowa counties) and County Business Patterns 1994 (counties in neighboring states).


Figure A16. Textiles, apparel, and leather products (SIC 22, 23, 31), 1994.
Sources: 1994 \& 1995 Iowa Manufacturers Directory, 1992 Census of Manufacturing, Iowa DES, 1994 County Business Patterns.


Figure A17. Own county employment in textiles, apparel, and leather products, 1994.
Source: Department of Employment Services.


Figure A18. Labor market area industry size in textiles, apparel, and leather products, 1994.
Industry size is calculated based on plants in those 3-digit SIC codes that use unusually large proportions of the same occupations. Source: Department of Employment Services (Iowa counties) and County Business Patterns 1994 (counties in neighboring states).


Figure A19. Labor market area industry density in textiles, apparel, and leather products, 1994.
Industry density is a function of the relative size and distance of plants in 3-digit SIC codes that use the same specialized occupations. Source: Department of Employment Services (Iowa counties) and County Business Patterns 1994 (counties in neighboring states).


Figure A20. Wood products and furniture (SIC 24, 25), 1994.
Sources: 1994 \& 1995 Iowa Manufacturers Directory, 1992 Census of Manufacturing, Iowa DES, 1994 County Business Patterns.


Figure A21. Own county employment in wood products and furniture, 1994. Source: Department of Employment Services.


Figure A22. Labor market area industry size in wood products and furniture, 1994.
Industry size is calculated based on plants in those 3-digit SIC codes that use unusually large proportions of the same occupations. Source: Department of Employment Services (Iowa counties) and County Business Patterns 1994 (counties in neighboring states).


Figure A23. Labor market area industry density in wood products and furniture, 1994.
Industry density is a function of the relative size and distance of plants in 3-digit SIC codes that use the same specialized occupations. Source: Department of Employment Services (Iowa counties) and County Business Patterns 1994 (counties in neighboring states).


Figure A24. Printing and publishing (SIC 27), 1994.
Sources: 1994 \& 1995 Iowa Manufacturers Directory, 1992 Census of Manufacturing, Iowa DES, 1994 County Business Patterns.


Figure A25. Own county employment in printing and publishing, 1994.
Source: Department of Employment Services.


Figure A26. Labor market area industry size in printing and publishing, 1994.
Industry size is calculated based on plants in those 3-digit SIC codes that use unusually large proportions of the same occupations. Source: Department of Employment Services (Iowa counties) and County Business Patterns 1994 (counties in neighboring states).


Figure A27. Labor market area industry density in printing and publishing, 1994.
Industry density is a function of the relative size and distance of plants in 3-digit SIC codes that use the same specialized occupations. Source: Department of Employment Services (Iowa counties) and County Business Patterns 1994 (counties in neighboring states).


Figure A28. Chemicals and petroleum products (SIC 28 and 29), 1994.
Sources: 1994 \& 1995 Iowa Manufacturers Directory, 1992 Census of Manufacturing, Iowa DES, 1994 County Business Patterns.


Figure A29. Own county employment in chemicals and petroleum products, 1994. Source: Department of Employment Services.


Figure A30. Labor market area industry size in chemicals and petroleum products, 1994.
Industry size is calculated based on plants in those 3-digit SIC codes that use unusually large proportions of the same occupations. Source: Department of Employment Services (Iowa counties) and County Business Patterns 1994 (counties in neighboring states).


Figure A31. Labor market area industry density in chemicals and petroleum products, 1994.
Industry density is a function of the relative size and distance of plants in 3 -digit SIC codes that use the same specialized occupations. Source: Department of Employment Services (Iowa counties) and County Business Patterns 1994 (counties in neighboring states).


Figure A32. Plastics products (SIC 3081-3089), 1994.
Sources: 1994 \& 1995 Iowa Manufacturers Directory, 1992 Census of Manufacturing, Iowa DES, 1994 County Business Patterns.


Figure A33. Own county employment in plastics products, 1994.
Source: Department of Employment Services.


Figure A34. Labor market area industry size in plastics products, 1994.
Industry size is calculated based on plants in those 3-digit SIC codes that use unusually large proportions of the same occupations. Source: Department of Employment Services (Iowa counties) and County Business Patterns 1994 (counties in neighboring states).


Figure A35. Labor market area industry density in plastics products, 1994.
Industry density is calculated based on plants in those 3-digit SIC codes that use unusually large proportions of the same occupations.
Source: Department of Employment Services (Iowa counties) and County Business Patterns 1994 (counties in neighboring states).


Figure A36. Primary \& fabricated metals, industrial equipment, transportation equipment (SIC 33, 34, 35 excl. 3570, 3630, 37), 1994. Sources: 1994 \& 1995 Iowa Manufacturers Directory, 1992 Census of Manufacturing, Iowa DES, 1994 County Business Patterns.


Figure A37. Own county employment in metals and equipment, 1994. Source: Department of Employment Services.


Figure A38. Labor market area industry size in metals and equipment, 1994.
Industry size is calculated based on plants in those 3-digit SIC codes that use unusually large proportions of the same occupations. Source: Department of Employment Services (Iowa counties) and County Business Patterns 1994 (counties in neighboring states).


Figure A39. Labor market area industry density in metals and equipment, 1994.
Industry density is calculated based on plants in those 3-digit SIC codes that use unusually large proportions of the same occupations. Source: Department of Employment Services (Iowa counties) and County Business Patterns 1994 (counties in neighboring states).


Figure A40. Electronics, instruments, electrical equipment (SIC 3570, 38, 36 excluding 3630 Household appliances), 1994. Sources: 1994 \& 1995 Iowa Manufacturers Directory, 1992 Census of Manufacturing, Iowa DES, 1994 County Business Patterns.


Figure A41. Own county employment in electronics, electrical equipment and instruments, 1994.
Source: Department of Employment Services.


Figure A42. Labor market area industry size in electronic and electrical equipment and instruments, 1994.
Industry size is calculated based on plants in those 3-digit SIC codes that use unusually large proportions of the same occupations. Source: Department of Employment Services (Iowa counties) and County Business Patterns 1994 (counties in neighboring states).


Figure A43. Labor market area industry density in electronics, electrical equipment, and instruments, 1994.
Industry density is a function of the relative size and distance of plants in 3-digit SIC codes that use the same specialized occupations. Source: Department of Employment Services (Iowa counties) and County Business Patterns 1994 (counties in neighboring states).


Figure A44. Paper, rubber, glass, and miscellaneous manufacturing (SIC 26, 30 excl. 3080, 3210-3240, 3260, 3290, 39 ), 1994. Sources: 1994 \& 1995 Iowa Manufacturers Directory, 1992 Census of Manufacturing, Iowa DES, 1994 County Business Patterns.


Figure A45. Own county employment in paper, rubber, glass and miscellaneous manufacturing, 1994.
Source: Department of Employment Services.


Figure A46. Labor market area industry size in paper, rubber, glass, and miscellaneous manufacturing, 1994.
Industry size is calculated based on plants in those 3-digit SIC codes that use unusually large proportions of the same occupations. Source: Department of Employment Services (Iowa counties) and County Business Patterns 1994 (counties in neighboring states).


Figure A47. Labor market area industry density in paper, rubber, glass, and miscellaneous manufacturing, 1994.
Industry density is a function of the relative size and distance of plants in 3-digit SIC codes that use the same specialized occupations. Source: Department of Employment Services (Iowa counties) and County Business Patterns 1994 (counties in neighboring states).


Figure A48. Prepared feeds (SIC 2048), 1994
Sources: 1994 \& 1995 Iowa Manufacturers Directory, 1992 Census of Manufacturing, Iowa DES, 1994 County Business Patterns.


Figure A49. "Footloose" food processing (SIC 20 excluding meat, dairy, rendering, feeds, corn \& soybean milling, \& bottling), 1994 Sources: 1994 \& 1995 Iowa Manufacturers Directory, 1992 Census of Manufacturing, Iowa DES, 1994 County Business Patterns.


Figure A50. Printing \& publishing other than newspapers (SIC 27 excluding 2711), 1994
Sources: 1994 \& 1995 Iowa Manufacturers Directory, 1992 Census of Manufacturing, Iowa DES, 1994 County Business Patterns.


Figure A51. Newspapers (SIC 2711), 1994
Sources: 1994 \& 1995 Iowa Manufacturers Directory, 1992 Census of Manufacturing, Iowa DES, 1994 County Business Patterns.


Figure A52. Pharmaceuticals, medicinals, diagnostic \& other biological products (SIC 2830), 1994
Sources: 1994 \& 1995 Iowa Manufacturers Directory, 1992 Census of Manufacturing, Iowa DES, 1994 County Business Patterns.


Figure A53. Nitrogenous \& phosphatic fertilizers, fertilizer mixing, pesticides, \& other agricultural chemicals (SIC 2870), 1994
Sources: 1994 \& 1995 Iowa Manufacturers Directory, 1992 Census of Manufacturing, Iowa DES, 1994 County Business Patterns.


Figure A54. Chemicals other than drugs and agricultural chemicals (SIC 28 excl. 2830, 2870), 1994
Sources: 1994 \& 1995 Iowa Manufacturers Directory, 1992 Census of Manufacturing, Iowa DES, 1994 County Business Patterns.


Figure A55. Hydraulic cylinders, valves, and other fluid power equipment (SIC 3593, 3594), 1994
Sources: 1994 \& 1995 Iowa Manufacturers Directory, 1992 Census of Manufacturing, Iowa DES, 1994 County Business Patterns.


Figure A56. Metal stampings \& forgings (SIC 3460), 1994
Sources: 1994 \& 1995 Iowa Manufacturers Directory, 1992 Census of Manufacturing, Iowa DES, 1994 County Business Patterns.


Figure A57. "High tech" electronics, controlling instruments and computers (SIC 3570, 3620, 3660, 3670, 3810, 3820, 3860), 1994 Sources: 1994 \& 1995 Iowa Manufacturers Directory, 1992 Census of Manufacturing, Iowa DES, 1994 County Business Patterns.


Figure A58. Elect. distrib., lighting \& wiring, audio \& video media, batteries, \& engine elect. eq. (SIC 3610, 3640, 3650, 3690 ), 1994 Sources: 1994 \& 1995 Iowa Manufacturers Directory, 1992 Census of Manufacturing, Iowa DES, 1994 County Business Patterns.


Figure A59. Medical prosthetics, instruments \& supplies, ophthalmic goods, watches \& clocks (SIC 3840, 3850, 3870), 1994 Sources: 1994 \& 1995 Iowa Manufacturers Directory, 1992 Census of Manufacturing, Iowa DES, 1994 County Business Patterns.

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[^0]:    ** Significant at $5 \%$ level * Significant at $10 \%$ level

