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# Determinants of State Labor Productivity: The Changing Role of Density

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**Abstract.** This study examines the determinants of state labor productivity during the 1989 to 2000 period. Using the model developed by Carlino and Voith (1992), we estimate how state characteristics such as population density, education, industrial structure, and business amenities (such as crime rates), influence state labor productivity. We also estimate our model over two sub-periods (1989 to 1995 and 1996 to 2000) in order to isolate the labor productivity boom of the late 1990s. Our aggregate results for the full 1989 to 2000 period were consistent with previous research. However, the determinants of labor productivity changed during the productivity boom of the late 1990s. During the period 1996 to 2000 greater industrial diversity appeared to have stimulated labor productivity, whereas in the earlier period, 1989 to 1995, specialization promoted labor productivity. Finally, while population density contributed to labor productivity during the earlier period, population density proved *not* to be a statistically significant determinant of labor productivity during the period 1996 to 2000.

## 1. Introduction

Many studies have identified a significant and sustained acceleration in U.S. productivity growth starting in the second half of the 1990s. Authors using industry-level data to examine this acceleration have highlighted that investment in information technology spurred broad-based productivity gains across most major industries (Stiroh, 2002). Indeed, Stiroh (2002, p. 1559) goes so far as to state that sufficient consensus appears to be emerging that "both the production and the use of IT have contributed substantially to the US aggregate productivity revival in the late 1990s."[1] Moreover, the broad-based nature of growth suggests that it is useful to examine the causes of aggregate productivity growth, rather than focusing on productivity in selected industries.[2]

While it is generally agreed that the acceleration in US productivity is widespread over many industries, the existing research on this issue has paid little attention to the regional implications of IT's impact on productivity. Nor has this literature explored the ramifications of IT's impact on the traditional determinants of regional productivity. Such a focus is important for a number of reasons. For instance, it offers insights as to observed changes in locational preferences of industries that appear to be shifting away from urban settings in favor of more rural areas. Moreover, there are subsequent state policy directives that would be impacted. It may be that in order to further promote productivity gains, and thereby state income growth and wealth accumulation, state legislators may need to direct scarce public funds toward, say, road infrastructure projects, health services and educational facilities in rural areas.

[1] As with many so called economic consensuses, there is less than universal acceptance of Stiroh's claim which the author explains in detail. The reader is referred to his 2002 study for details.
[2] This is not to imply that investigating productivity differentials across industries is no longer important. Indeed, such research may find aspects of productivity determinants that are hidden by focusing on aggregate productivity growth. That said, if indeed IT is having a broad impact across sectors, then this effect should be revealed in an analysis of aggregate productivity.

Therefore, it is indeed useful to examine the determinants of *state productivity* over sub-periods, a period that examines the early 1990s as well as the late 1990s, in an effort to shed light on how IT may have altered the regional economic landscape. Clearly, doing so would make it possible to determine whether the factors contributing to productivity growth changed during that period. An examination of the data in Figures 1A and 1B helps to illustrate why it is prudent to break our data into two sub-periods (1989 to 1995 and 1996 to 2000). Following Carlino and Voith (1992), Smoluk and Andrews (2005), and other researchers that proxy productivity by real wage per-worker, we plot this series for the United States as well as four census regions: Northeast, Midwest, South, and West.[3] While real wages per worker vary from region to region, in every region we observe a substantial and dramatic acceleration in productivity starting in 1996. These figures suggest that not only was the national productivity surge widespread over industries, but it was also widespread, to varying degrees, geographically. Moreover, these observations suggest that the determinants may very well have differing effects on productivity pre- and post-1996. It is possible, for instance, that given the rapid development and diffusion of information technology and the continuing growth of the nation's professional and service sectors, location is less important to making productive gains today than it was in the 1980s and early 1990s.

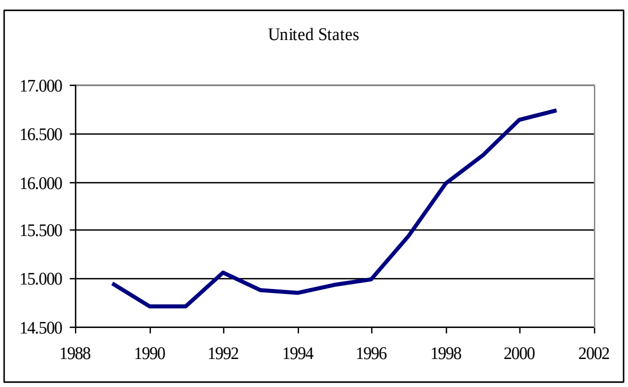


**Figure 1a.** Real wage per worker, United States

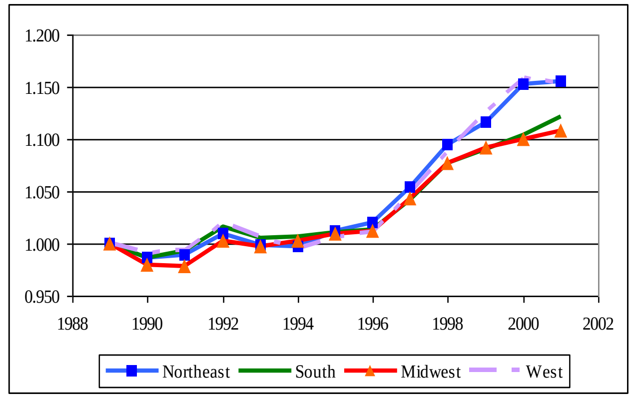


**Figure 1b.** Real wage per worker, Census Regions (indexed to 1989 value)

In what follows, we examine how commonly analyzed state economic characteristics influence productivity growth over the 1989 to 2000 period as well as the two sub-periods, 1989 to 1995 and 1996 to 2000. Following Carlino and Voith (1992), we utilize a structural model based on a CES production function to estimate which state economic and policy characteristics are contributing to productivity growth in state economies. Our contention throughout is that state economies are an appropriate lens through which to examine aggregate productivity growth. While there are some similarities, state economies can differ widely. They are not, for instance, perfectly synchronized with the national business cycle. This makes it possible to exploit state differences in productivity growth to isolate the influence of long-run structural factors that influence productivity from productivity growth trends over the business cycle. Such long-run structural factors include state economic characteristics like population density and industrial specialization and policy variables such as education levels and environmental quality. The usefulness of state-level data is also enhanced because of variation in these economic characteristics and policies between states and over time within states.

The next section contains a literature review on state productivity growth, while the structural model is presented in the third section and the data are described in the fourth section. Regression results are presented in the fifth section, and the sixth section includes a discussion and conclusion.

## 2. Literature review

Studies investigating state productivity are numerous and varied, employing different measures of productivity as well as different measures of common determinants. Below, we focus on those studies most similar in nature to our own.

[3] State classifications within these regions are as follows: Northeast: Connecticut, Massachusetts, Maine, New Hampshire, Rhode Island, Vermont, New Jersey, New York, and Pennsylvania; South: Delaware, Florida, Maryland, Georgia, North Carolina, South Carolina, Virginia, West Virginia, Alabama, Kentucky, Mississippi, Tennessee, Arkansas, Louisiana, Oklahoma, Texas; Midwest: Illinois, Indiana, Michigan, Ohio, Wisconsin, Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, South Dakota; West: Idaho, Oregon, Montana, Washington, Wyoming, Alaska, Arizona, California, Colorado, Hawaii, New Mexico, Nevada, Utah. The four-region breakdown was selected for the sake of brevity. It should be pointed out that a similar pattern arises for individual sub-regions and most states.

Carlino and Voith (1992) initiated a series of papers examining determinants of aggregate labor productivity at the state level. The authors developed a model of marginal labor productivity using a CES production function and data for the years 1967 to 1986. The authors considered the effects of industry mix, labor force characteristics (proxied by unionized labor), public investment in infrastructure (proxied by highway density), and agglomeration economies (proxied by population density) on state labor productivity. They find that education, public infrastructure, and percentage of urbanized population have a statistically significant positive influence in explaining differences in state labor productivity across states.

Smoluk and Andrews (2005) build upon Carlino and Voith (1992) and investigate the factors that influence labor productivity among 48 US states during the 1993 to 2000 period, again using the CES production function framework. Smoluk and Andrews (2005) focus on the influence of education and population density on state labor productivity, and also introduce a variable for state tax burden. Their results indicate that labor productivity is positively related to both the percentage of a state's population with a bachelor's degree or higher and the population density of a state, and negatively related to tax burden. Their results show that differences in population density account for the largest share of the difference in labor productivity across states.

Other research supports the basic findings of Carlino and Voith (1992) and Smoluk and Andrews (2005) regarding the importance of population density and education. Ciccone and Hall (1996) argue that high population density results in positive externalities by promoting a greater variety of intermediate products that tend to enhance the productivity of final goods and services. This phenomenon explains the observation that cities with high population density pay higher wages than less densely populated cities. Ciccone and Hall (1996) found that population density accounts for more than 50 percent of the differences in labor productivity across states. There is also a well-known positive association between productivity and population density. This linkage may be related to the scale at which producers operate. Wheeler (2006) offers some support for this conjecture.

With respect to taxes, the literature suggests that higher marginal tax rates tend to reduce labor productivity through reduced worker effort. Mullen and Williams (1994) examine the link between state economic growth and average and marginal tax rates. They find that marginal tax rates are negatively related to both gross state product growth and productivity growth.

With respect to the linkage between education and economic growth, Crihfield and Panggabean (1995) find a strong positive association between levels of initial education attainment and US metropolitan area growth. Krueger and Lindahl (2001) examine differences across countries and show that because the level of education and economic growth can differ dramatically, the relation between the average level of schooling and economic growth is a more reliable measure. Bils and Klenow (1998) investigate the causal linkage between education and economic growth. They conclude that the direction runs from economic growth to return to schooling in that economic growth drives the return to schooling rather than the reverse.

Each of these three key factors – density, education, and tax burden (as proxied by government's share of a state's economy) – are examined in our own analysis of state productivity growth utilizing the Carlino and Voith (1992) model. We examine the period from 1989 to 2000, and for two sub-periods, 1989 through 1995 and 1996 through 2000.

## 3. Theoretical development of estimated model

Following Carlino and Voith (1992), we utilize a CES production function for state economies. In the model, gross state product in a particular year t ($Q_{it}$) is a function of total factor productivity ($A_{it}$), labor ($L_{it}$), and private capital ($K_{it}$).

$$Q_{it} = A_{it}[\alpha L_{it}{}^{-\rho} + (1-\alpha)K_{it}{}^{-\rho}]^{-(\beta/\rho)} \tag{1}$$

Taking the first derivate with respect to labor yields:

$$\partial Q_{it} / \partial L_{it} = \alpha\beta L_{it}{}^{-(1+\rho)} A_{it}[\alpha L_{it}{}^{-\rho} + (1-\alpha)K_{it}{}^{-\rho}]^{-(\beta/\rho)-1} \tag{2}$$

Substituting output for capital in equation 2 yields:

$$\partial Q_{it} / \partial L_{it} = \alpha\beta L_{it}{}^{-(1+\rho)} A_{it}{}^{-(\rho/\beta)} Q^{(1-\rho/\beta)} \tag{3}$$

Carlino and Voith (1992) point out that because output is a value-added concept in Equations 1 through 3, the left-hand side of Equation 3 equals the marginal value product of labor in each state, which is theoretically equivalent to average state wages in optimality. Substituting average wages for the marginal product of labor term in (3) yields:

$$w_{it} = \alpha\beta L_{it}{}^{-(1+\rho)} A_{it}{}^{-(\rho/\beta)} Q^{(1-\rho/\beta)} \tag{4}$$

Total factor productivity is a function of factors that influence the efficiency of the economy such as the size of government ($G_{it}$), public capital ($P_{it}$), safety ($S_{it}$), the regulatory environment ($R_{it}$), agglomeration ($AG_{it}$), and industrial specialization ($IS_{it}$). Finally, there exists a rich theoretical literature that demonstrates that regional productivity, and thus wage, differentials persist due to differences in regions' human capital (see, e.g., Gallaway and Cebula, 1972). To account for this, we introduce the regions' education level ($E_{it}$) of the workforce into our total factor productivity specification.[4] Following Smoluk and Andrews (2005), we argue that total factor productivity is a multiplicative function of each of the factors that influence total factor productivity as below:

$$A_{it} = P_{it}^{\chi} G_{it}^{\delta} S_{it}^{\varepsilon} R_{it}^{\phi} AG_{it}^{\varphi} E_{it}^{\gamma} IS_{it}^{\eta} \tag{5}$$

Substituting Equation 5 into Equation 4 and taking the log of both sides, we generate an empirical equation for estimating state wages.

As indicated below, we have a panel data set covering 48 states over the period 1989 to 2000.[5] To empirically estimate our productivity equation, we follow the existing literature by conducting three separate estimations. First, following Smoluk and Andrews (2005), we estimate a full pooled panel model. In addition, there may be a number of state geographic and year-specific idiosyncrasies that impact labor productivity which are not captured by the items comprising $A_{it}$ above. To address this we also utilize a fixed effects regression framework in our econometric analysis (following Carlino and Voith (1992) as well as Smoluk and Andrews (2005)). Hence, unchanging household, business and state amenity variables in both geographic space and time would be controlled for in such analysis. Therefore, the full two-way fixed effects model estimated becomes:

$$\begin{aligned} \ln(w_{i,t}) = {} & \alpha + b_1 \ln(G_{it}) + b_2 \ln(S_{it}) + b_3 \ln(R_{it}) + b_4 \ln(AG_{it}) \\ & + b_5 \ln(E_{it}) + b_6 \ln(IS_{it}) + b_7 \ln(P_{it}) + b_8 \ln(L_{it}) \\ & + b_9 \ln(Q_{it}) + \sum_{t=2}^{T} \delta_t year_t + \sum_{i=2}^{N} \gamma_i state_i + \varepsilon_{i,t} \end{aligned} \tag{6}$$

where $w_{it}$ is the average real per worker wages and $year_t$ and $state_i$ are dummy variable indicators for given years and states in the fixed effects model (note, in the full pooled model, $\gamma_i$ and $\delta_t = 0$ for all i and t). Finally, we also test whether or not a random effects specification is favorable over a fixed effects specification since it might be that corresponding effects $\gamma_i$ and $\delta_t$ are realizations of independent random variables with mean zero and finite variance and that these effects are uncorrelated with the residual $\varepsilon_{i,t}$.

To determine which of these three specifications is preferable given our data, we conduct a redundant fixed effects likelihood ratio F-test which tests the null hypothesis that the cross section and period effects are jointly statistically insignificant. That is, the test determines if the cross section and time period identifiers are beneficial to the model. Next, we conduct a standard Hausman test to determine if the fixed effects model is desirable relative to the random effects specification.[6] These results are discussed in Section 5 below.

## 4. Data description

We empirically examine real wages per worker utilizing data for the lower 48 states for the period 1989 to 2000. Analysis begins in 1989 given certain historical limitations on our data (notably the TRI data discussed below) and ends in 2000 as changes in the industrial coding system will not allow us to calculate our industrial specialization measure (IS) after this year. We describe our data briefly here but more complete information on data sources is provided in Table 1. Our model requires a value-added measure of Q. We utilize Gross State Product (GSP - measured in real 2000 dollars) for each state from 1989 through 2000. The data is taken from the *Regional Economic Information System* (REIS) data base of the US Bureau of Economic Analysis. Our measure of labor is a state's total full- and part-time employment, also from the REIS. Data on the number of jobs are used since data are not available on aggregate hours worked each year at the state level. Annual average wages per job also come from the *Regional Economic Information System*.[7]

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[4] Some theoretical models such as the one developed by Gallaway and Cebula (1972) explicitly incorporate human capital into the production function. In our case, since our theoretical model is presented largely to motivate and extend empirical analysis, we subsume it within total factor productivity. That said, there may be benefits to explicit incorporation in future research.

[5] Following convention in the literature, Alaska and Hawaii are not included in our dataset.

[6] See Hausman (1978) and Johnston and DiNardo (1997, 403-404) for details on the implementation of this test for models using panel data.

[7] We follow convention in the existing literature by defining wages on a per-employee basis rather than on a per-hour basis. Data on hours worked by industry is severely limited at the state level and the distinction between part-time and full-time employees is not available. To be sure, this common means of defining productivity has its limitations. A wage per hour measure, for instance, better captures labor productivity than wage per employee since hours worked differs across industries and states. Moreover, computing the annual wage per full-time worker may be preferred as it circumvents problems that might arise due to differences in the relative number of workers that exist across states, differences that are likely to be more dramatic over a given business cycle. While current data limitations prevent the adoption of these approaches, this may be a valuable avenue for future research.

**Table 1.** Data sources and descriptive statistics

| Variable | Description | Source | Mean* | Std. Dev.* |
|---|---|---|---|---|
| w | Real wage and salary disbursements per worker ($ thousands) | US Bureau of Economic Analysis at http://www.bea.gov/bea/regional/gsp.htm and Regional Economic Information Services (REIS), US Bureau of Economic Analysis, US Department of Commerce at http://www.bea.gov/bea/regional/reis/ | 13.97 | 2.44 |
| Q | Real (2000 base year) gross state product by state ($ thousands) | US Bureau of Economic Analysis at http://www.bea.gov/bea/regional/gsp.htm | 163,205 | 188,272 |
| L | Total Employment by state | Regional Economic Information Services (REIS), US Bureau of Economic Analysis, US Department of Commerce at http://www.bea.gov/bea/regional/reis/ | 3,064,497 | 3,178,272 |
| IS | Industry specialization defined as the sum of the squared GSP share originating in: agricultural services, mining, construction, manufacturing, transportation and utilities, wholesale and retail trade, finance insurance and real estate services | Garrett, Wagner and Wheelock (2005) | 1,420.67 | 233.67 |
| ED | Share of state's population age 25 and older with at least a bachelor's degree (share * 100) | Garrett, Wagner and Wheelock (2005) | 22.25 | 4.55 |
| G | Government (all levels) share of GSP (share * 100) | Garrett, Wagner and Wheelock (2005) | 13.41 | 2.79 |
| S | Violent crime activity per 100,000 state residents; includes murder, rape and sexual assault, robbery, and assault | FBI's Uniform crime reports at http://bjsdata.ojp.usdoj.gov/dataonline/ | 512.47 | 263.18 |
| AG | Agglomeration measured as the share of metropolitan population to total population by state | Regional Economic Information Services (REIS), US Bureau of Economic Analysis, US Department of Commerce at http://www.bea.gov/bea/regional/reis/ | 0.72 | 0.19 |
| R | Total on and off site releases (in pounds released) of the US EPA's 1988 core toxic chemicals (248 chemicals and chemical compounds) as a proportion of Gross State Product, Q | US Environmental Protection Agency's Toxic Release Inventory at http://www.epa.gov/triexplorer/geography.htm and US Bureau of Economic Analysis at http://www.bea.gov/bea/regional/gsp.htm | 389.81 | 465.06 |
| P | Real public infrastructure capital stock by state ($ millions) | Brown, Hayes and Taylor (2003) | 66,973 | 72,678 |

Notes: * Figures based on a consistent data period, 1989-2000

To test whether or not urbanization matters, we use the same measure employed by Carlino and Voith (1992) and utilize an urban population density measure. To this end, we collected data from the REIS on the number of state residents living in a metropolitan area as well as total state population. If urbanization matters, we would expect states with a higher proportion of metropolitan dwellers (AG) to have higher productivity measures.[8]

Our measure of a state's industrial specialization, (IS) was compiled and provided to us by Garrett, Wagner and Wheelock (2005).[9] The variable IS is a Herfindahl index constructed by calculating the squared shares of each of the eight broadly classified industries comprising a state's GSP (see Table 1), summing, and then multiplying by 10,000. The larger is the resulting IS value, the more specialized (and less diverse) is a state's economy. To the extent that specialization matters, one might expect a positive coefficient.

As indicated above, our measure of human capital within a state is captured by ED, again supplied by Garrett, Wagner and Wheelock (2005), which measures the proportion of a state's adult population (aged 25 or over) that has obtained at least a bachelor's degree. Our hypothesis is that a more educated workforce will produce more efficiently, thus boosting productivity.

G measures the share of a state's GSP that national, state, and local government accounts for. This measure also should account for state tax rates since states with higher shares of government activity would tend to require higher tax rates. The higher is this measure, the more of a drag government places on private industry within a state, thus depressing productivity.

We obtained data on public capital stock (P) as constructed by and described in Brown, Hayes and Taylor (2003).[10] This data captures the dollar value of public capital stock by state over time. Based on Holtz-Eakin (1994) and Brown, Hayes and Taylor (2003), our expectation is that public capital would not increase productivity.

Finally, we include two "business amenity" variables not considered by Carlino and Voith (1992) or Smoluk and Andrews (2005). These address safety and the level of regulation. Our first measure is S, obtained from the Federal Bureau of Investigation's (FBI) Uniform Crime Statistics. This variable captures the number of violent crimes committed per 100,000 residents by state over time. Increased criminal activity can put life and property at risk. There is a substantial literature linking secure enforceable property rights to increased incentives to make capital investments (see, e.g. Besley, 1995). It is plausible then that increased criminal activity would deter productivity-enhancing investment. Our expectation is that a higher crime rate should depress productivity.

Also, we attempt to measure the potential benefits of a cleaner environment by including a variable that captures the environmental conditions of a given state, making that state more susceptible to tighter environmental regulations. There has been much debate in the literature, dating from the 1970s, as to the impact of environmental regulation and productivity. For instance, Haveman and Christiansen (1981) and Barbera and McConnell (1990) find significant declines in manufacturing productivity due to environmental regulation. By contrast, Telle and Larsson (2007) find regulatory stringency has no statistical impact on productivity. In deference to this debate, we attempt to address this issue within the context of our model and database to see if the experience in the 1990s supports productivity declines or not. Specifically, this variable measures toxic releases of some 600 different chemicals by certain manufacturing industries into a variety of environmental media (air, water, etc.). This data is commonly called the "toxic release inventory" (TRI). The TRI was collected from the US Environmental Protection Agency and measures the total amount of toxic chemical pollutants emitted into the air and water or stored underground by state over time. As part of the US's Emergency Planning and

[8] It should be noted that there are other measures of density that have been used to capture the type of agglomeration effects we are investigating here. For instance, Smoluk and Andrews (2005) use state population to state area (measured in square footage) as a measure of agglomeration. While this is a reasonable measure, we follow Carlino and Voith (1992), favoring the urban to total population measure in our analysis. Given our particular focus on whether or not person-to-person connectivity matters for stimulating productivity, the population-to-area measure seems to generate a number of notable anomalies. For instance, in Arizona 88 percent of the population lives in metropolitan areas (much higher than the national average of 72 percent). While it would appear then that Arizona is largely an urban type economy, the population to area ratio is one of the lowest in the United States, largely due to the state's sizable land area. A population-to-area ratio might then reasonably mis-characterize this state as not possessing the potential agglomeration effects that a more reliable figure (metropolitan to total population) would. A similar story exists for states like Nevada, Washington, Oregon, and Utah, all of which have metropolitan to total population figures in excess of the national average but also have some of the lowest population to area ratios in the nation due simply to the fact that these are very large states. Hence, we will follow Carlino and Voith (1992). That said, it is worth noting we did attempt to replicate Smoluk and Andrews (2005) by using the population to area measure of agglomeration over the period they estimated (1993 to 2000) and got results from our pooled regression which were very similar to theirs.

[9] We thank Gary Wheelock for supplying us with this and other data.

[10] We thank Kathy Hayes for supplying us with this data.

Community Right-to-Know Act of 1986, facilities (primarily industrial plants) emitting any amount of an EPA-listed chemical are required to report on an annual bases these emissions. These emissions are then made available to the public. While the accuracy of such self-reported data is always of concern, the data has been used extensively by researchers as it tends to be a very rich and comprehensive measure of pollution releases.[11] With respect to the present study, our expectation would be that more TRI releases *per dollar of GSP* (which we label R) would likely mean that the region is more likely to be affected by state and/or federal regulation of local pollution.[12]

## 5. Estimation results

Table 2 summarizes the likelihood ratio and Hausman tests for model specification. The likelihood ratio test indicates that we can reject the null hypothesis that both the cross section and period effects are redundant (i.e., $\gamma_i$ and $\delta_t = 0$ for all i and t), indicating that pooled regression restrictions are not justified. Therefore, our results suggest either a fixed or random effects specification. The Hausman test indicates that we can reject the null hypothesis that the random cross section and period effects are uncorrelated with the model's explanatory variables, thus the data favors the fixed effects specification. Given these results, we proceed with a fixed effects model.[13]

Table 3 illustrates the regression results for Equation 6 for the full 1989 to 2000 period. Most of the results are in line with the findings of previous research. The coefficient on the labor variable is negative and statistically significant and coefficient on the output variable is positive and significant. As in Smoluk and Andrews (2005) and Carlino and Voith (1992), the coefficient on the agglomeration variable (AG) was positive and statistically significant.

**Table 2.** Model specification tests

| *Test* | *Statistic* | *p-value* |
|---|---|---|
| Redundant Fixed Effects Likelihood Ratio Test | | |
| *cross-section F-statistic (df: 47,508)* | 110.00 | 0.000 |
| *period F-statistic (df: 11, 508)* | 34.40 | 0.000 |
| Hausman Test | | |
| *cross-section random Chi-square (df: 9)* | 48.11 | 0.000 |
| *period random Chi-square (df: 9)* | 78.09 | 0.000 |

**Table 3.** Factors influencing average wages (labor productivity), 1989-2000

| Variable | Coefficient | Standard Error | Sig. |
|---|---|---|---|
| Constant | 4.2215 | 0.7258 | *** |
| ln(ED) (% College) | -0.0157 | 0.0108 | |
| ln(IS) (Industrial Specialization) | 0.0126 | 0.0060 | ** |
| ln(R) (Pollution) | 0.0008 | 0.0027 | |
| ln(S) (Violent Crime) | -0.0233 | 0.0060 | *** |
| ln(G) (Government Share) | -0.0711 | 0.0317 | ** |
| ln(P) (Public Capital) | 0.0279 | 0.0204 | |
| ln(L) (Employment) | -0.3581 | 0.0612 | *** |
| ln(Q) (GSP) | 0.3175 | 0.0421 | *** |
| ln(AG) (Agglomeration) | 0.1990 | 0.0544 | *** |
| N | 576 | | |
| Adj R-squared | 0.993 | | |

Notes: Estimated with White's cross-section standard errors and covariance.
* - Significant at the 10% level.
** - Significant at the 5% level.
*** - Significant at the 1% level.

Moreover, the share of gross state product accounted for by government (G) was negative and significant. This is consistent with the earlier finding by Smoluk and Andrews (2005) that higher taxes were negatively related to average wages (and labor productivity). Public capital (P) was not related to average wages. Among business disamenities, pollution (R) also had no effect on average annual wages, a result consistent with Telle and Larsonn (2007), but the coefficient on the crime variable was negative and statistically significant. This result suggests that higher crime rates do reduce labor productivity. Finally, the coefficient on the industrial specialization variable (IS) is

[11] The TRI data can be obtained as far back as 1987 but for a number of reasons, many researchers feel as though the first year of reliable data is 1989. It should be noted that with respect to the TRI, year-to-year comparisons should be made with great care as periodically the EPA will either de-list or add to the list chemicals or compounds for which reporting is required. Hence, if a number of new chemicals were required reporting in, say, 1995 but not 1994, then causes of increases in TRI releases will be difficult at best to ascertain. To address this, our TRI releases reflect a consistent chemical list and, since our desire was to obtain as much historical data as possible, we chose to extract data from the original set of core chemicals as determined by the EPA in 1987.

[12] This is not the first study to employ the TRI data to address productivity issues (see, e.g. Weber and Domazlicky, 2001). Moreover, there is evidence that regulators do indeed consider TRI releases in enforcement activities (see, e.g. Decker, 2005).

[13] Given that the statistical evidence supports the fixed effects model, to conserve on space, these are the results presented here. However, if interested, both the pooled and random effects specifications are available from the authors upon request.

positive, indicating that a *more specialized* economy also has greater labor productivity.[14]

While our findings (for 1989 to 2000) were consistent with Smoluk and Andrews (2005) for a similar period (1993 to 2000) and Carlino and Voith (1992) for an earlier period (1967 to 1986), for reasons offered earlier we next examine whether or not estimation results on the determinants of labor productivity had consistent effects during the sub-periods 1989 to 1995 and 1996 to 2000. To address these sub-periods, we tested the validity of the fixed effects model over the pooled and random effects specification. As with the full sample model, we found that the pooled regression model can be improved upon by including cross section and period effects and that the fixed effects model is favored over the random effects model. Thus, we use the fixed effects model.

Table 4 contains results for the 1989 to 1995 period, i.e., before the rapid productivity growth of the late 1990s. These results are consistent with our full-period results as well as the previous literature. Notably, density was positively related to average wages (i.e. labor productivity) during the period, as was industrial specialization.[15] Education also was positively related to productivity, as in most previous literature. The only major differences with the literature and full-period results occurred for the crime and government spending variables. Both government spending and crime rates positively affected productivity over the period 1989 to 1995.

From Table 4 and Table 5, we see that model results were quite different during the 1996 to 2000 period. A number of key results differ from our full-period results, our 1989 to 1995 results, and results of Carlino and Voith (1992) and Smoluk and Andrews (2005). In short, the determinants of productivity are much different today than they were prior to 1996. During the latter 1990s greater industrial specialization (IS) appeared to have reduced labor productivity, whereas the earlier period specialization promoted productivity (see both Tables 3 and 4).[16] This result is consistent with Stiroh's (2002) results suggesting that the productivity surge of the late 1990s was widespread industrially as IT impacted a variety of economic sectors.

**Table 4.** Factors influencing average wages (labor productivity), 1989-1995

| Variable | Coefficient | Standard Error | Sig. |
|---|---|---|---|
| Constant | 1.3608 | 0.4636 | *** |
| ln(ED) (% College) | 0.0196 | 0.0080 | ** |
| ln(IS) (Industrial Specialization) | 0.0396 | 0.0187 | ** |
| ln(R) (Pollution) | -0.0002 | 0.0028 | |
| ln(S) (Violent Crime) | 0.0083 | 0.0049 | * |
| ln(G) (Government Share) | 0.0864 | 0.0365 | ** |
| ln(P) (Public Capital) | 0.0576 | 0.0107 | *** |
| ln(L) (Employment) | -0.2221 | 0.0538 | *** |
| ln(Q) (GSP) | 0.2889 | 0.0425 | *** |
| ln(AG) (Agglomeration) | 0.2064 | 0.0783 | *** |
| N | 336 | | |
| Adj R-squared | 0.997 | | |

Notes: Estimated with White's cross-section standard errors and covariance.
* - Significant at the 10% level.
** - Significant at the 5% level.
*** - Significant at the 1% level.

**Table 5.** Factors influencing average wages (labor productivity), 1996-2000

| Variable | Coefficient | Standard Error | Sig. |
|---|---|---|---|
| Constant | 3.1985 | 1.0615 | *** |
| ln(ED) (% College) | -0.0213 | 0.0090 | ** |
| ln(IS) (Industrial Specialization) | -0.0739 | 0.0412 | * |
| ln(R) (Pollution) | 0.0011 | 0.0037 | |
| ln(S) (Violent Crime) | -0.0216 | 0.0124 | * |
| ln(G) (Government Share) | -0.1385 | 0.0549 | ** |
| ln(P) (Public Capital) | -0.1656 | 0.0580 | *** |
| ln(L) (Employment) | -0.1079 | 0.0352 | *** |
| ln(Q) (GSP) | 0.3397 | 0.0855 | *** |
| ln(AG) (Agglomeration) | 0.1538 | 0.2115 | |
| N | 240 | | |
| Adj R-squared | 0.996 | | |

Notes: Estimated with White's cross-section standard errors and covariance.
* - Significant at the 10% level.
** - Significant at the 5% level.
*** - Significant at the 1% level.

[14] Interestingly, education (ED) was not found to be related to real average per worker wages, a result that is at odds with the earlier findings of Smoluk and Andrews (2005) and Carlino and Voith (1992). The reason for this result may be that annual data for education had to be interpolated from decennial Census values, particularly because our fixed effects model included year dummy variables.

[15] Unlike during the full period, however, there was a positive and statistically significant relationship between education and labor productivity from 1989 to 1995 as was true with public capital. Also, during the period, both crime and government share of the economy were positive, in contrast with previous results.

[16] Also, ED appeared to impact productivity negatively during the late 1990s, unlike the earlier period. This is a peculiar result but, again, may be linked to how this data was interpolated.

While population density (agglomeration) contributed to real per worker wages during the earlier period, 1989 to 1995, population density proved *not* to be a statistically significant determinant of real per worker wages during the period 1996 to 2000. An implication of this result may very well rest, then, on the degree to which rapid advance and diffusion of information-related technologies changed during the mid to late 1990s. It seems reasonable to suggest that urbanization and the associated agglomeration economies that historically exerted significant influence on labor productivity are no longer necessary.

This result on population density may partially explain the changing impact of public infrastructure capital stocks (P) on state productivity as well. In the late 1990s, P appeared to exert a negative influence on productivity, quite different from the earlier period. Since most of this public stock (roads, water and sewer networks, power plants) tends to be concentrated near larger cities to support urban growth, one might then speculate that the rapid diffusion of IT that is believed to be spurring productivity growth is making spatial agglomeration (i.e., location in or near large cities) less important. Hence, the existing public infrastructure that largely supports city growth is having a detrimental impact on overall state productivity growth. As a matter of policy, public infrastructure projects may be better directed toward rural areas.

A final consideration worth noting here is whether or not the data and results represent a cycle or a long-term trend. While this is a difficult question to address here, it is worth noting that evidence presented by Stiroh (2002) supports a long-term view of this productivity surge. Indeed, Stiroh's research "supports the idea that the acceleration of aggregate productivity is a real phenomenon and not just a cyclical one" (p. 1574), lending some support that our 1996 to 2000 period results are most likely indicative of a long term trend.[17]

## 6. Conclusions and policy implications

This paper utilized Carlino and Voith's (1992) model of state labor productivity, which proxies labor productivity using real per worker wages, to examine data from the 1989 to 2000 period, with particular emphasis on the late 1990s, a period when labor productivity boomed throughout the nation. While we utilized similar variables included in previous research, we also examined the productivity impact of several business amenity variables, such as crime rates and industrial pollution. Our results for 1989 to 2000 were consistent with previous research.

However, results change when we examine our two sub samples. The determinants of labor productivity appeared to change during the productivity boom of the late 1990s. During the period 1996 to 2000, greater industrial diversity appeared to have stimulated labor productivity whereas in the earlier period, 1989 to 1995, specialization promoted productivity. Moreover, while population density contributed to real wages (labor productivity) during the earlier period, 1989 to 1995, population density proved *not* to be a statistically significant determinant of real per worker wages during the period 1996 to 2000. This finding suggests that agglomeration is no longer central to labor productivity in states as found in previous research (see, e.g., Smoluk and Andrews, 2005).

[17] Testing this notion would require substantial data construction and extension, particularly with respect to public capital stock, and is beyond the scope of this paper. We leave this to future research.

## References

Barbera, A.J. and V.D. McConnell. 1990. The impact of environmental regulations on industry productivity: Direct and indirect effects. *Journal of Environmental Economics and Management* 18:50-65.

Besley, T. 1995. Property rights and investment incentives: Theory and evidence from Ghana. *Journal of Political Economy* 103: 903-937.

Bils, M. and J.P. Klenow. 1998. Does schooling cause growth or the other way around? Working paper no. 6363, NBER.

Brown, S.P.A., K.J. Hayes, and L.L. Taylor. 2003. State and local policy, factor markets, and regional growth. *The Review of Regional Studies* 33:40-60.

Carlino, G.A. and R. Voith. 1992. Accounting for differences in aggregate state productivity. *Regional Science and Urban Economics* 22:597-617.

Ciccone, A. and R. Hall. 1996. Productivity and the density of economic activity. *American Economic Review* 86: 54-70.

Crihfield, J.G. and M.P.H. Panggabean. 1995. Growth and convergence in U.S. cities. *Journal of Urban Economics* 38:138-165.

Decker, C.S. 2005. Do regulators respond to voluntary pollution control efforts? A count data analysis. *Contemporary Economic Policy* 23:180-194.

Gallaway, L.E. and J. Cebula. 1972. Impact of property rights in human capital and regional factor proportions. *Zeitschrift fur Nationalokonomie* 32:501-503.

Garrett, T.A., G.A. Wagner, and D.C. Wheelock. 2005. Regional disparities in the spatial correlation of state income growth. Working paper series, Federal Reserve Bank of St. Louis. http://research.stlouisfed.org/wp/2005/2005-061.pdf.

Hausman, J.A. 1978. Specification tests in econometrics. *Econometrica* 46(6):1251-1271.

Haveman, E.F. and C.B. Christiansen. 1981. Environmental regulations and productivity growth. In: H.M. Peskin, P.R. Portney, and A.V. Kneese (eds.) *Environmental Regulation and the US Economy*. Washington: Resources for the Future.

Holtz-Eakin, D. 1994. Public sector capital and the productivity puzzle. *The Review of Economics and Statistics* 76:12-21.

Johnston, J. and J. DiNardo. 1997. *Econometric Methods,* Fourth Edition. New York, NY: McGraw-Hill Companies, Inc.

Krueger, A.B. and M. Lindahl. 2001. Education for growth: why and for whom. *Journal of Economic Literature* 39:1101-1136.

Mullen, J.K. and M. Williams. 1994. Marginal tax rates and state economic growth. *Regional Science and Urban Economics* 24:687-705.

Smoluk, H.J. and B.H. Andrews. 2005. A prerequisite for meaningful state economic performance comparisons: Adjusting for population density. *Annals of Regional Science* 39:253-272.

Stiroh, K.J. 2002. Information technology and the US productivity revival: What do the industry data say? *American Economic Review* 92:1559-1576.

Telle, K. and L. Larsson. 2007. Do environmental regulations hamper productivity growth? How accounting for improvements of plants' environmental performance can change the conclusion. *Ecological Economics* 61:438-445.

Weber, W. and B. Domazlicky. 2001. Productivity growth and pollution in state manufacturing. *Review of Economics and Statistics* 83:195-199.

Wheeler, C.H. 2006. Productivity and the geographic concentration of industry: The role of plant size. *Regional Science and Urban Economics* 36:313-330.