# Sources of Manufacturing Productivity Growth: U.S. States 1990–1999

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**Summary.** In this paper we employ a panel of state level manufacturing data for the U.S. to estimate productivity growth and its sources during the 1990s. Following Kumar and Russell (2002), we augment the usual Malmquist decomposition of productivity growth with a capital deepening component. We find that innovation was the primary determinant of manufacturing productivity growth in all states, but that most states ended the decade further from the production possibilities frontier than they started. Capital deepening contributed to labor productivity growth in all but three states, and explains at least half of the labor productivity growth in a dozen states.

In a second stage, we investigate various policy-related variables and their relationship to productivity growth and its components. We find that a growing technology sector was a strong contributor to labor productivity growth, while a growing public sector was largely a drag. Improvements in labor force quality appear to have had little impact on the pace of technical change or the diffusion of technology, but capital deepening was significantly greater in states with a more highly educated population.

**Key words:** productivity, capital deepening, Malmquist, state manufacturing

## 1 Introduction

The literature on the impact of public capital on private productivity has a long history. Recent interest in the question, however, has been sparked by two important papers: Aschauer's provocative analysis suggesting that

* We have benefitted from comments and discussion with Donna Ginther, Steve Brown, Thijs ten Raa, Daniel Henderson and others.

public capital is grossly under provided in the United States (Aschauer 1989) and Munnell's analysis suggesting that state and local public capital is under provided in the United States (Munnell 1990). Munnell's analysis has been particularly influential because she generated a panel data set on public and private capital for the U.S. states that has been used by many subsequent researchers (e.g. Morrison and Schwartz 1994, 1996a,b, Kelejian and Robinson 1997, Holtz-Eakin 1994, Domazlicky and Weber 1998, Boisso, Grosskopf and Hayes 2000). As researchers have refined these seminal analyses, the case for significant under provision of public capital has faded. Holtz-Eakin (1994) and Garcia-Mila, McGuire and Porter (1996) find little evidence that public capital contributes to private sector productivity. Using a cost-function with quasi-fixed factors, Morrison and Schwartz (1994, 1996a,b) find evidence of positive direct productivity impacts of pubic capital but conclude that these direct effects are typically offset by indirect effects on factor accumulation. Brown, Hayes and Taylor (2003) found that not only does growth in public capital tend to discourage the accumulation of private capital and labor, it may also directly discourage output growth. In contrast, Henderson and Kumbhakar (2005) find a positive return to public capital when they use Li-Racine generalized kernal estimation.

A common characteristic of this literature has been that productivity is measured indirectly from an estimated production or cost function. A recent trend has been to use more direct measures of productivity. Domazlicky and Weber (1997, 1998) calculate Malmquist productivity indexes for each of the 48 contiguous states and use them to examine the impact of agglomeration economies and education levels on productivity. They find no relationship between public capital and private productivity. Boisso et al. (2000) also calculate Malmquist productivity indices and then examine the impact of business cycles and various measures of public capital. In contrast to Domazlicky and Weber, Boisso et al. find that the ratio of public capital to private capital has a positive impact on productivity. Boisso et al. also find evidence of spillover effects with respect to highway capital.

In this paper we add to the evidence on direct measures of productivity by augmenting the usual components of Malmquist productivity change to include capital deepening, following Kumar and Russell (2002).[4] We develop new perpetual-inventory estimates of manufacturing capital stocks for states and include those estimates in our analysis. Finally, we investigate the impacts on innovation, diffusion and capital deepening of several policy related instruments including labor quality, high tech share of manufacturing, public capital stocks and the size of state government. We find that capital deepening and technical change are the major sources of labor productivity growth in the period 1990-1999. A growing technology sector was a strong contributor to labor productivity growth, while a growing public sector was largely a drag. Growth in average educational attainment appears to have had little

[4] See also Henderson and Russell (2005) and Weber and Domazlicky (2006).

impact on the pace of technical change or the diffusion of technology, but capital deepening was significantly greater in states with a more highly educated population.

## 2 Method

We follow Kumar and Russell (2002) who augmented the standard Malmquist productivity index to allow for the identification of productivity changes due to efficiency change, technical change and capital deepening. Before turning to that decomposition, we can relate their decomposition to standard growth accounting approaches as in ten Raa and Mohnen (2002). Let Y denote output, which is a function of capital (K), labor (L) and time (t). To allow for inefficiency define $\theta$ as the factor which yields maximum potential output, i.e.,

$$\theta Y = F(L, K, t). \tag{1}$$

If we assume constant returns to scale, then we may normalize output and capital by labor, where $y = Y/L, k = K/L$ thus we may write

$$\theta y = f(k, t). \tag{2}$$

As is usual in the growth accounting literature, we express this in terms of growth rates yielding

$$\hat{y} = \hat{f}_t - \hat{\theta} + \frac{f_k}{f}\hat{k} \tag{3}$$

which states that the growth in output per unit of labor is equal to technical change plus efficiency change plus capital deepening, i.e., the change in the capital labor ratio. This would typically be 'estimated' or deduced from a parametric specification of the production or cost function. Here we replace that function with an estimation of a nonparametric best practice frontier and substitute discrete changes for the derivatives in (3) as discussed below.

Kumar and Russell (2002) arrive at the tripartite decomposition above by generalizing a Malmquist productivity index. The basic building block of these productivity indexes is the Shephard output distance function, which is defined as

$$D(x, y) \;=\; \inf\{\theta : y/\theta \in P(x)\}, \tag{4}$$

where $y \in \Re^M_+$ is a vector of outputs, $x \in \Re^N_+$ is a vector of inputs (in our case labor and capital), and $P(x)$ is the output set, i.e., it consists of the set of all outputs producible from a given input vector $x$. This function has the advantage of readily modeling multi-output technology without requiring data on prices, and identifies deviations from the frontier of technology. It is also easily computed using linear programming methods. For example, we can estimate the distance function for an observation $k'$ in period $t$ as the solution to the following linear programming problem

$$
\begin{aligned}
(D^t(x^t_{k'n}, y^t_{k'm}))^{-1} &= \max \theta \qquad (5)\\
\text{subject to} & \\
\sum_{k=1}^{K} z_k y^t_{km} &\geq \theta y^t_{k'm},\ m = 1, \dots, M,\\
\sum_{k=1}^{K} z_k x^t_{kn} &\leq x^t_{k'n},\ n = 1, \dots, N,\\
z_k &\geq 0,\ k = 1, \dots, K.
\end{aligned}
$$

The $z's$ are intensity variables which serve to construct the technology from the observed data. In our case, the resulting technology would be based on all the states in the sample and would identify the nonparametric best practice frontier of that meta-state technology.

Following Kumar and Russell, we use the distance functions to achieve a tripartite decomposition of labor productivity into technical change, technological catch up and capital deepening. Taking advantage of the fact that the above specified technology satisfies constant returns to scale, we can normalize output and capital by labor, i.e., let $y$ = output/labor, $x$ = capital/labor. Following Kumar and Russell, let $c$ denote the current period and $b$ the previous period, then the tripartite decomposition is defined as follows

$$y^c/y^b = D^c(x^c, y^c)/D^b(x^b, y^b)\left(\frac{D^b(x^c, y^c)}{D^c(x^c, y^c)}\frac{D^b(x^b, y^b)}{D^c(x^b, y^b)}\right)^{1/2} KACCUM \qquad (6)$$

or

$$y^c/y^b = EFF \times TECH \times KACCUM \qquad (7)$$

where EFF is efficiency change (diffusion, or catching up to the frontier), TECH is technical change (innovation or shifts in the frontier) and KACCUM is a residual term capturing the effect of capital deepening (increase in the capital labor ratio). Note that $EFF \times TECH$ yields the traditional Malmquist productivity index proposed by Caves, Christensen and Diewert (1982).

The distance functions are estimated using the programming problem described above with the appropriate substitution of time periods. Thus we will have measures of productivity change for each state for adjacent periods covering the time period 1990–1999.

## 3 Data and Estimation

We follow a multi-part strategy for evaluating the changes in manufacturing output per worker during the 1990s. In the first stage, we use data on gross state product, employment, and manufacturing capital stocks to generate annual measures of efficiency (the distance functions discussed in the previous section) for U.S. states.

In the second stage of the analysis, we use year-to-year changes in our efficiency measures to decompose changes in manufacturing output per worker into its three components—technical change, efficiency change and capital deepening. We then describe the distributions of these component factors and their relative contributions to productivity growth.

In the final stage of the analysis, we explore possible determinants of our efficiency and productivity measures. Various economists have argued that measured improvements in labor productivity reflect changes in industrial mix, increases in labor force quality, changes in the public capital stock or decreases in the size of the public sector.[5] We use our panel of labor productivity data to examine the impact of each of these factors.

## 3.1 Data

The Bureau of Economic Analysis (BEA) is the primary source of data for productivity analysis. Annual state-level data on gross state product and employment in manufacturing come directly from the BEA. Following Munnell (1990a,b,c), we estimate net manufacturing capital stocks for each state by apportioning the BEA's national estimates. However, whereas Munnell assumed that manufacturing capital stocks grew at the national rate in most years,[6] we use annual investment data for each state to construct perpetual-inventory estimates of manufacturing capital stocks. These perpetual-inventory estimates are then used to apportion the BEA's national stock estimates for manufacturing capital. See the data appendix for further details.

Data on industrial mix also come from the BEA. Our measure of industrial mix is the high-tech manufacturing sector's share of total manufacturing output. We define high-tech manufacturing as the sum of the industrial machinery (the industry that includes computers), electronics and instruments industries (SIC codes 335,336 and 338).

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[5] See, for example, Brown, Hayes and Taylor (2003); Cameron (2003); Cook (2004); Domazlicky and Weber (1997, 1998); Kahn and Lim (1998); Grosskopf, Hayes and Taylor (2003), or Taylor and Brown (forthcoming).

[6] Munnell (1990c) decomposes U.S. estimates of private capital into state-level estimates using information from industry censuses to identify each state's share of U.S. capital for that industry in census years. She then assumes that the state shares of private capital are constant for a multi-year period centered on the census year. "Data from the 1972 Census were used to apportion among the states the BEA national stock estimates for 1969 to 1974; 1977 shares were used for the 1975 to 1979 stock estimates; 1982 shares were the basis for the estimates from 1980 to 1984 and 1987 data were used to apportion national asset totals for 1985 and 1986" (Munnell 1990c, pg. 97). Thus, in 1975, 1980 and 1985, growth rates are exaggerated in each industry to "catch up" for the five-year deviations in the state's growth rate from the national average. In all other years, there is no cross-sectional variation in the growth of private manufacturing capital under the Munnell approach.

Data on labor force quality—which we measure as the average educational attainment of the adult population—come from the U.S. Censuses of Population for 1990 and 2000 and the National Center for Education Statistics (NCES). To construct annual estimates of average educational attainment, we first calculate average educational attainment in the two census years.[7] We then use NCES data on degrees conferred (high school diplomas, associates degrees, bachelors' degrees, masters' degrees, first professional degrees and Ph.D. degrees) to generate annual estimates of human capital production in each state. Finally, we use the production data to impute annual changes in average educational attainment for th e state.

Data on public capital stocks come from Brown, Hayes and Taylor (2003). We use their measure of total public capital, divided by the BEA's annual population estimates, as our measure of the public capital per capita.

Finally, we use state and local government noncapital expenditures (net of tuition and health care charges and relative to gross state product) as our measure of government size. The expenditures data come from the annual Censuses and Surveys of Governments.

## 4 Results

As figure 1 illustrates, there were substantial differences across U.S. states in labor productivity growth in manufacturing during the 1990s. Two states—Louisiana and Delaware—saw declines in output per manufacturing worker, while a handful of states saw labor productivity increase by more than 6 percent per year, on average. New Mexico posted by far the highest gains in labor productivity. At 24 percent per year, New Mexico's increase in output per worker was more than double that of any other state, and nearly six times the national average increase.

Figure 2 illustrates the year-by-year distribution of productivity growth during the 1990s, for the contiguous U.S. states, excluding New Mexico.[8] The markers represent the (output-weighted[9]) average productivity change for each year, while the bars indicate the 5th percentile to 95th percentile ranges.

As the figure demonstrates, productivity growth generally accelerated during the 1990s. For the output-weighted average state, the average rate of productivity growth in the second half of the 1990s (4.7 percent per year) is two

[7] Average educational attainment is a weighted average of the share of the adult population in each educational attainment category (less than high school, high school drop-out, high-school graduate, etcetera) where the weights represent average years of schooling associated with the attainment level.

[8] Given its rate of productivity growth, we consider New Mexico an outlier and exclude it from our analysis.

[9] We follow Zelenyuk (forthcoming) and compute the output weighted harmonic mean to estimate average labor productivity and its components.

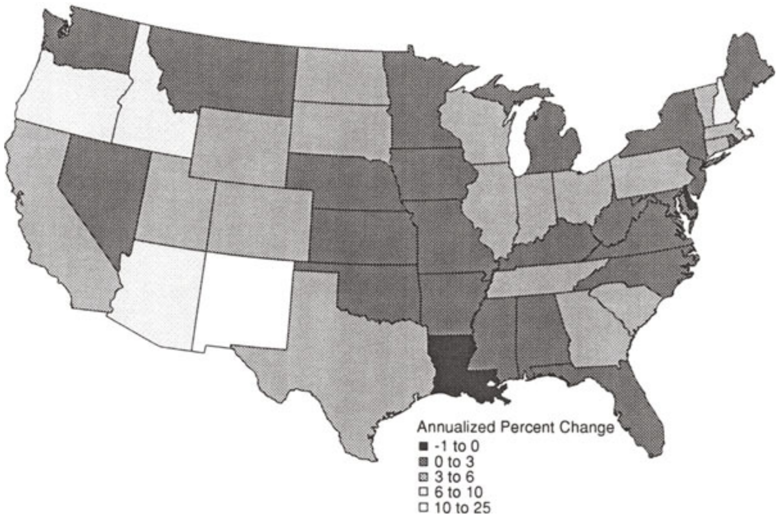
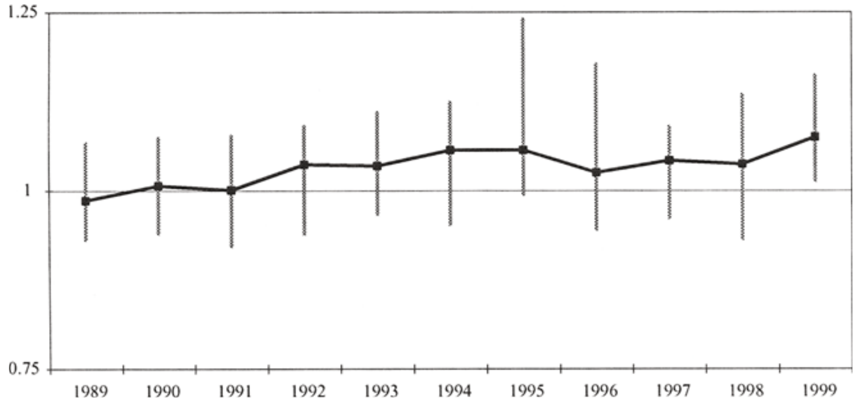



**Fig. 1.** Changes in the productivity of manufacturing labor 1990–1999

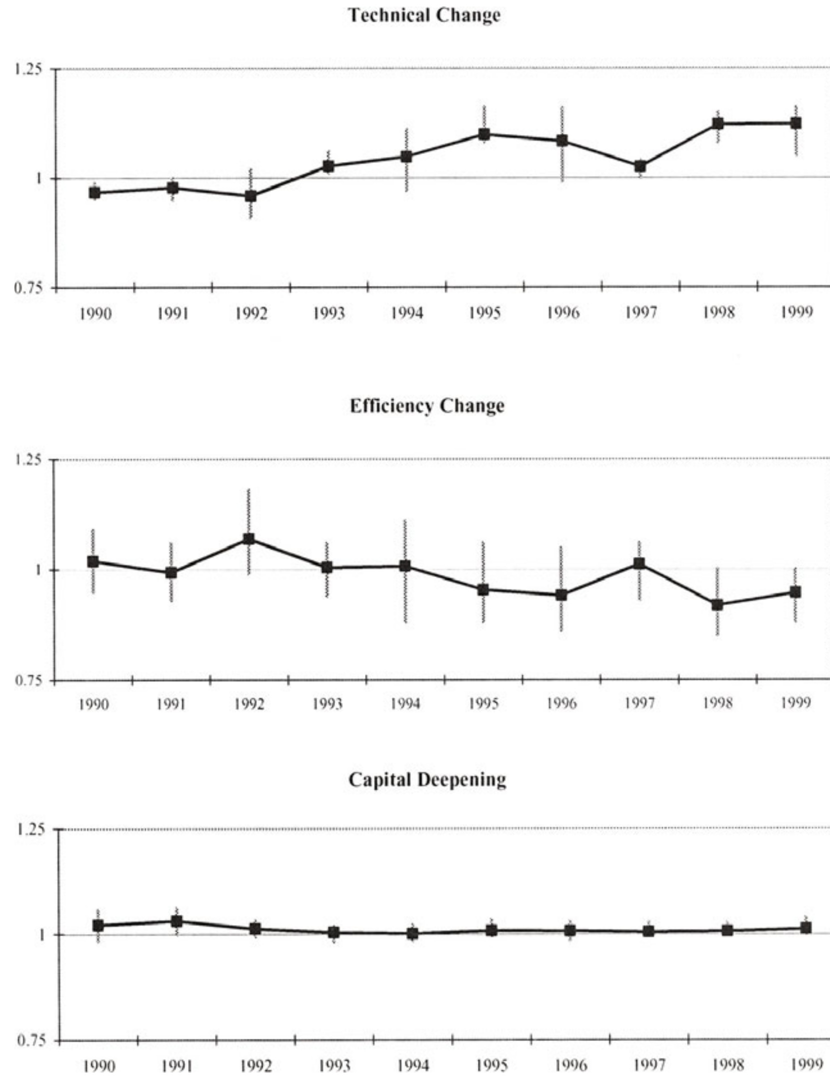



Note: The markers indicate the output-weighted average change in output per worker for 47 U.S. states. (Alaska, Hawaii and New Mexico are excluded.) The bars indicate the 5th and 95th percentile ranges.

**Fig. 2.** Labor productivity in manufacturing generally accelerated during the 1990s (year over year changes in output per worker)

percentage points higher than the average rate of productivity growth in the first half of the decade. Thirty-five of the 47 states under analysis experienced more rapid productivity growth after 1994.

Figure 3 illustrates the distributions of technical change, efficiency change and capital deepening. As the figure illustrates, any acceleration in manufacturing productivity during the 1990s is wholly attributable to an acceleration




Note: The markers indicate the output-weighted averages for 47 U.S. states. (Alaska, Hawaii and New Mexico are excluded.) The bars indicate the 5th and 95th percentile ranges.

**Fig. 3.** Sources of Labor Productivity Growth in Manufacturing

in technical change. Capital deepening held steady for most of the decade while efficiency change exhibited a significant downward trend. Average efficiency change was below one during much of the latter half of the 1990s. Apparently the pace of technical change was so rapid that many states had trouble keeping up.

The cumulative impact of a decade of change is striking. (See Table 1.) Technical change was the primary determinant of labor productivity growth

Table 1. Cumulative Changes in State Manf. Productivity: 1990s

| State | PROD | EFF | TECH | KACCUM | State | PROD | EFF | TECH | KACCUM |
|---|---|---|---|---|---|---|---|---|---|
| AL | 1.249 | 0.789 | 1.508 | 1.051 | NC | 1.260 | 0.701 | 1.542 | 1.166 |
| AR | 1.266 | 0.761 | 1.567 | 1.061 | ND | 1.414 | 1.010 | 1.440 | 0.972 |
| AZ | 2.500 | 1.348 | 1.514 | 1.225 | NE | 1.268 | 0.773 | 1.554 | 1.056 |
| CA | 1.769 | 0.964 | 1.516 | 1.209 | NH | 2.178 | 1.077 | 1.642 | 1.232 |
| CO | 1.416 | 0.853 | 1.460 | 1.138 | NJ | 1.277 | 0.730 | 1.425 | 1.226 |
| CT | 1.666 | 0.894 | 1.503 | 1.240 | NV | 1.241 | 0.801 | 1.448 | 1.070 |
| DE | 0.991 | 0.616 | 1.474 | 1.092 | NY | 1.291 | 0.746 | 1.471 | 1.177 |
| FL | 1.308 | 0.750 | 1.540 | 1.133 | OH | 1.406 | 0.876 | 1.461 | 1.098 |
| GA | 1.412 | 0.840 | 1.471 | 1.142 | OK | 1.308 | 0.909 | 1.413 | 1.018 |
| IA | 1.327 | 0.879 | 1.427 | 1.058 | OR | 2.418 | 1.282 | 1.567 | 1.204 |
| ID | 2.111 | 1.141 | 1.438 | 1.286 | PA | 1.576 | 1.004 | 1.440 | 1.090 |
| IL | 1.423 | 0.929 | 1.495 | 1.024 | RI | 1.253 | 0.535 | 1.720 | 1.362 |
| IN | 1.463 | 0.929 | 1.550 | 1.016 | SC | 1.439 | 0.909 | 1.489 | 1.064 |
| KS | 1.115 | 0.738 | 1.429 | 1.056 | SD | 1.664 | 0.858 | 1.556 | 1.246 |
| KY | 1.247 | 0.776 | 1.475 | 1.090 | TN | 1.368 | 0.783 | 1.484 | 1.177 |
| LA | 0.987 | 0.800 | 1.232 | 1.001 | TX | 1.501 | 1.015 | 1.468 | 1.008 |
| MA | 1.542 | 0.829 | 1.515 | 1.228 | UT | 1.393 | 0.829 | 1.515 | 1.109 |
| MD | 1.302 | 0.850 | 1.536 | 0.997 | VA | 1.145 | 0.693 | 1.486 | 1.112 |
| ME | 1.222 | 0.773 | 1.545 | 1.024 | VT | 1.407 | 0.895 | 1.517 | 1.036 |
| MI | 1.231 | 0.782 | 1.562 | 1.007 | WA | 1.114 | 0.679 | 1.402 | 1.171 |
| MN | 1.213 | 0.676 | 1.527 | 1.175 | WI | 1.377 | 0.822 | 1.528 | 1.096 |
| MO | 1.263 | 0.687 | 1.529 | 1.201 | WV | 1.148 | 0.794 | 1.422 | 1.018 |
| MS | 1.293 | 0.766 | 1.540 | 1.096 | WY | 1.557 | 1.068 | 1.448 | 1.007 |
| MT | 1.045 | 0.744 | 1.471 | 0.955 | | | | | |

PROD is change in labor productivity, EFF is efficiency change, TECH is technical change and KACCUM is change in the capital labor ratio or capital deepening.

in all states, but most states ended the decade further from the production possibilities frontier than they started. Capital deepening contributed to labor productivity growth in all but three states, and explains at least half of the labor productivity growth in a dozen states. In four states—Delaware, Louisiana, Rhode Island and Washington—capital deepening can more than explain growth in output per worker.

### 4.1 The Usual Suspects

Further analysis can shed additional light on the pattern of productivity gain. In this final stage, we examine the relationship between the rate of productivity change (and its components) and factors frequently used to explain it: changes in industrial mix, increases in labor force quality, increases in the public capital stock or decreases in the size of the public sector.

Our estimation is based on a nine-year panel covering the period 1991-1999 for 47 states.[10] Productivity change and its components are each modeled as a function of the average educational attainment in the state, public capital per capita, the size of the public sector, the share of the manufacturing sector that is high tech manufacturing (all lagged one year) and the changes in each of these factors. Because states that are not on the productivity frontier may have more "room for improvement," the model also includes the state's relative efficiency in the prior year. Fixed effects for time capture national business cycles and other time trends.

Arguably, the initial efficiency level is endogenous. Furthermore, there may be a correlation among the residuals for any given state. Therefore, table 2 presents four variations on a theme. Our first model estimates the relationship between productivity growth and the policy factors using fixed effects for states. The second model incorporates random effects for states. The third model is an instrumental variables regression with state fixed effects. The manufacturing sector's share of gross state product is used as an instrument for the potentially endogenous initial efficiency. Model four incorporates random effects for states into an instrumental variables analysis, using the same instrument as in model three.

As table 2 illustrates, except for the estimated effect of initial efficiency, the estimation is generally insensitive to modeling strategy. Specification tests reject the fixed and random effects models in favor of their IV counterparts.[11]

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[10] Alaska, Hawaii and New Mexico are excluded.

[11] A Hausman specification test rejects the random effects model in favor of the IV random effects model, but does not reject the fixed effects model in favor of its IV counterpart. (The probabilities of a greater chi-squared test statistic are 0.0538 and 0.9620, respectively.) However, a Durbin-Wu-Hausman test easily rejects the fixed effects model in favor of the fixed effects IV specification. (The probability of a greater F-statistic is 0.0030.)

Table 2. Influences on Manufacturing Productivity Growth During the 1990s

| | State Fixed Eff | | State Rand Eff | | IV Fixed Eff | | IV Rand Eff | |
|---|---|---|---|---|---|---|---|---|
| | $\hat{\beta}$ | $\hat{\sigma}$ | $\hat{\beta}$ | $\hat{\sigma}$ | $\hat{\beta}$ | $\hat{\sigma}$ | $\hat{\beta}$ | $\hat{\sigma}$ |
| Intercept | 2.882 | 1.296** | 1.258 | 0.120*** | 3.454 | 1.338*** | 2.532 | 0.709*** |
| Init effic | −0.223 | 0.053*** | −0.047 | 0.023** | −0.433 | 0.090*** | −0.384 | 0.095*** |
| High Tech | 0.004 | 0.001*** | 0.002 | 0.0002*** | 0.006 | 0.001*** | 0.005 | 0.001*** |
| Avg H Cap | −0.105 | 0.101 | −0.016 | 0.009* | −0.116 | 0.104 | −0.082 | 0.054 |
| Pub Cap | −0.207 | 0.114* | 0.001 | 0.008 | −0.357 | 0.128*** | −0.057 | 0.056 |
| Govt Size | −0.013 | 0.006** | −0.003 | 0.002 | −0.016 | 0.007** | −0.016 | 0.006*** |
| Change in: | | | | | | | | |
| Hi Tech | 0.010 | 0.001*** | 0.010 | 0.001*** | 0.010 | 0.001*** | 0.010 | 0.001*** |
| Avg H Cap | −1.517 | 1.776 | −0.189 | 0.283 | −3.328 | 1.919* | −1.341 | 1.403 |
| Pub Cap | 0.272 | 0.309 | 0.030 | 0.220 | 0.377 | 0.317 | 0.581 | 0.301* |
| Govt Size | −0.024 | 0.006*** | −0.020 | 0.005*** | −0.024 | 0.006*** | −0.023 | 0.006*** |
| y92 | 0.036 | 0.011*** | 0.024 | 0.010** | 0.041 | 0.011*** | 0.036 | 0.010*** |
| y93 | 0.050 | 0.015*** | 0.020 | 0.011* | 0.068 | 0.016*** | 0.056 | 0.014*** |
| y94 | 0.069 | 0.017*** | 0.035 | 0.011*** | 0.087 | 0.019*** | 0.073 | 0.015*** |
| y95 | 0.103 | 0.021*** | 0.062 | 0.011*** | 0.125 | 0.023*** | 0.105 | 0.016*** |
| y96 | 0.053 | 0.025** | 0.014 | 0.011 | 0.070 | 0.026*** | 0.046 | 0.017*** |
| y97 | 0.050 | 0.029* | 0.015 | 0.011 | 0.060 | 0.030** | 0.031 | 0.018* |
| y98 | 0.058 | 0.034* | 0.015 | 0.011 | 0.073 | 0.035** | 0.035 | 0.020* |
| y99 | 0.100 | 0.039*** | 0.060 | 0.011*** | 0.104 | 0.039*** | 0.061 | 0.022*** |
| R-square | 0.454 | | 0.368 | | 0.431 | | 0.209 | |
| Num of Obs | 423 | | 423 | | 423 | | 423 | |

Note: Initial efficiency is endogenous in the IV models. The instrument is manufacturing's share of GSP. The asterisks indicate that the coefficient is significantly different from zero at the 1-percent (***), 5-percent (**), or the 10-percent (*) level.

A Hausman test also indicates that the random effects IV model is both efficient and consistent, making it our preferred model.[12]

Our analysis reveals a number of interesting patterns. First, the estimation suggests that initial efficiency has a significant influence on productivity growth. States that start the year far from the production possibilities frontier show more productivity growth than states that start the year on the frontier. The pattern suggests that diffusion or catching up is a significant determinant of regional variations in labor productivity growth.

States with a large or growing high tech share are also much more likely than other states to experience rapid growth in output per worker. Such a pattern is not surprising given other work indicating that the productivity gains in high tech manufacturing are substantially greater than the gains in manufacturing as a whole (e.g. Grosskopf et al. 2002).

On the other hand, states with a large or growing public sector register less productivity growth than other states. One possible interpretation is that a growing public sector crowds out private manufacturing (e.g., as found in Brown et al. 2003). Alternatively, given that budget balance is generally required at the state level, the negative relationship between productivity growth and government growth may simply indicate that taxes discourage private manufacturing activity.

The fixed-effects specifications indicate that public capital is a drag on labor productivity growth, but the fixed effects themselves are highly and positively correlated with public capital per capita.[13] Meanwhile, the random effects specifications indicate that states where public capital stocks per capita are growing experience faster productivity growth than other states. However, the effect is only significant at the 10 percent level and completely disappears when Wyoming data are excluded from the analysis.[14] We can only conclude that the evidence on the impact of public capital deepening is weak and inconclusive.

Intriguingly, there also is no apparent relationship between gains in average educational attainment and labor productivity growth in manufacturing. States where average educational attainment was rising rapidly experienced no greater gains in manufacturing productivity than did other states. In none of the specifications can we reject the hypothesis that both human capital measures are jointly insignificant. In general, the evidence indicates that average educational attainment has no relationship with manufacturing productivity growth. One possible interpretation for this finding is that the educational attainment of the general population is a poor proxy for the educational attainment of manufacturing workers.

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[12] The chi-squared test statistic is 6.96. The probability of a greater chi-squared is 0.9840.

[13] The Pearson correlation between public capital per capita at the start of the decade and the state fixed effects from the IV model is 0.8875.

[14] Wyoming has significantly more public capital per capita than any other state.

Table 3. The Determinants of Initial Efficiency

State Random Effects

| | $\hat{\beta}$ | $\hat{\sigma}$ |
|---|---|---|
| Intercept | −0.6320 | 0.5709 |
| Manufacturing Share | 0.0207 | 0.0020*** |
| High Tech Share | 0.0034 | 0.0006*** |
| Avg Human Capital | 0.0804 | 0.0448* |
| Public Capital | 0.0524 | 0.0498 |
| Government Size | −0.0122 | 0.0045*** |
| y92 | 0.0124 | 0.0097 |
| y93 | 0.0633 | 0.0107*** |
| y94 | 0.0583 | 0.0113*** |
| y95 | 0.0562 | 0.0122*** |
| y96 | 0.0099 | 0.0135 |
| y97 | −0.0279 | 0.0143* |
| y98 | −0.0258 | 0.0156* |
| y99 | −0.0874 | 0.0171*** |
| R-square | | 0.1366 |
| Number of Observations | | 423 |

Note: The asterisks indicate that the coefficient is significantly different from zero at the 1-percent (***), 5-percent (**), or the 10-percent (*) level.

Exploring further, table 3 illustrates the relationship between initial efficiency and the levels of the other explanatory variables. As the table illustrates, states with a relatively large manufacturing sector or a relatively large high tech share tend to be more technically efficient than other states. Manufacturing efficiency also appears to be higher in states where the public sector is smaller or the labor force is more highly educated, all other things being equal. Public capital per capita has no apparent influence on initial efficiency.

Table 4 decomposes the change in output per worker into its three component pieces: technical change, efficiency change and capital deepening.

Table 4. Decomposing Manufacturing Productivity Growth: 1990s

State Random Effects IV Models

| | Effic Change | | Tech Change | | Capital Deep | |
|---|---|---|---|---|---|---|
| | $\hat{\beta}$ | $\hat{\sigma}$ | $\hat{\beta}$ | $\hat{\sigma}$ | $\hat{\beta}$ | $\hat{\sigma}$ |
| Intercept | 2.727 | 0.732*** | 0.959 | 0.186*** | 0.590 | 0.161*** |
| Initial Eff | −0.349 | 0.087*** | −0.008 | 0.101 | 0.066 | 0.030** |
| High Tech Share | 0.004 | 0.001*** | 0.000 | 0.000 | 0.000 | 0.000 |
| Avg Human Cap | −0.105 | 0.056* | 0.002 | 0.008 | 0.032 | 0.012*** |
| Public Capital | −0.011 | 0.060 | −0.005 | 0.006 | −0.016 | 0.012 |
| Govt Size | −0.018 | 0.005*** | 0.000 | 0.003 | −0.002 | 0.002 |
| Change in: | | | | | | |
| High Tech Share | 0.004 | 0.001*** | 0.004 | 0.001*** | 0.001 | 0.0003** |
| Avg Human Cap | −0.040 | 1.395 | 0.075 | 0.251 | 0.530 | 0.336 |
| Public Capital | 0.253 | 0.283 | 0.109 | 0.283 | 0.137 | 0.087 |
| Govt Size | −0.024 | 0.006*** | −0.003 | 0.004 | 0.001 | 0.002 |
| YR92 | 0.073 | 0.010*** | −0.016 | 0.008** | −0.018 | 0.003*** |
| YR93 | 0.032 | 0.013** | 0.050 | 0.011*** | −0.030 | 0.004*** |
| YR94 | 0.039 | 0.014*** | 0.061 | 0.011*** | −0.032 | 0.004*** |
| YR95 | −0.002 | 0.016 | 0.123 | 0.011*** | −0.024 | 0.004*** |
| YR96 | −0.025 | 0.017 | 0.100 | 0.009*** | −0.028 | 0.004*** |
| YR97 | 0.013 | 0.018 | 0.040 | 0.009*** | −0.027 | 0.004*** |
| YR98 | −0.072 | 0.021*** | 0.136 | 0.009*** | −0.028 | 0.005*** |
| YR99 | −0.056 | 0.023** | 0.137 | 0.013*** | −0.018 | 0.006*** |
| R-square | | 0.311 | | 0.716 | | 0.195 |
| Number of Obs | | 423 | | 423 | | 423 |

Note: All models are instrumental variables with random effects for states. Initial efficiency is treated as endogenous. The instrument is manufacturing's share of GSP. Asterisks indicate that the coefficient is significantly different from zero at the 1-percent (***), 5-percent (**), or the 10-percent (*) level.

All three models are estimated using an instrumental variables, random effects by state specification. In all cases, Hausman tests indicate that the random effects model is both efficient and consistent.[15]

The decomposition reveals additional information about productivity growth. First, as expected, the evidence suggests that starting the period farther from the production possibilities frontier leads to significantly more growth through diffusion. The coefficient on initial efficiency is significantly negative in the efficiency change equation. Somewhat surprisingly, the estimation also reveals that initial efficiency affects capital deepening. States where the manufacturing sector is initially inefficient appear to draw less capital investment (relative to labor growth) than other states. Capital deepening is significantly greater in states that are on or near the production possibilities frontier.

Strikingly, the positive relationship between productivity growth and the high tech sector is found in all three components of productivity growth. An increasing concentration in high tech manufacturing appears to enhance manufacturing productivity not only by inducing technological change, but also by attracting capital investment. Furthermore, states with a large share of manufacturing in high tech industries did a better job of keeping up with technological change (i.e. moving closer to the production possibilities frontier) than did states with a relatively small high tech sector.

On the other hand, changes in government spending appear to affect labor productivity only through their effect on diffusion. States where the public sector is growing are less likely to catch up to the production possibilities frontier (as evidenced by the negative coefficient on the change in government size) but no more likely to grow through innovation or capital deepening.

There is little evidence that labor force quality can explain innovation or the diffusion of technology (efficiency change). The indicators of labor force quality are jointly insignificant in the equations for both components of the standard Malmquist index. However, capital appears drawn to states with a relatively well educated population. States with a high degree of human capital deepening also experience a high degree of physical capital deepening, suggesting that human and physical capital are complements rather than substitutes.

There is no evidence that a lack of public capital affects, innovation, diffusion or capital deepening. Both indicators of public capital are jointly insignificant in all three equations. This finding is generally consistent with Brown, et al. (2003) who found that the growth of public capital tended to discourage the growth of both private capital and private sector labor. Our analysis of labor productivity in manufacturing would not detect influences on factor accumulation that impacted both capital and labor in comparable ways.

[15] The probability of a greater chi-squared test statistic is 0.9999, 0.7721 and 0.7868 for efficiency change, technical change and capital deepening, respectively.

## 5 Conclusions

Careful analysis of recent manufacturing productivity change in the United States provides interesting insights into an important component of economic growth.[16] The analysis reveals that labor productivity in manufacturing accelerated during the 1990s. The pace of technical change picked up sharply, leaving most states further behind the production possibilities frontier. The capital-labor ratio continued to grow, and capital deepening was an important factor in productivity growth for most states.

The growth of the high tech sector was a major contributor to productivity growth in manufacturing during the 1990s. Growth of government, on the other hand, was largely a drag on productivity growth. States with a growing public sector were less likely to catch up to the production possibilities frontier than other states, and there is no evidence that a lack of public capital slowed diffusion, innovation or capital deepening. Growth in average educational attainment appears to have had little impact on the pace technical change or the diffusion of technology, but capital deepening was significantly greater in states with a more highly educated population.

Much remains to be done. A similar analysis for the high tech manufacturing sub-sector is a natural extension, as is that of the services sector both of which experienced even faster productivity growth than manufacturing as a whole (see Anderson and Kliesen (2006)). An extended decomposition to include change in human capital as a component of productivity change following Henderson and Russell (2005) would also be useful. We have not addressed the issue of convergence of labor productivity growth here, but results by Weber and Domazlicky (2006), who also use state data applied to the Kumar and Russell decomposition find that capital deepening and efficiency change have contriuted to $\beta$-convergence in labor productivity in manufacturing over the 1977–1996 period. Technical change was divergent, and there was no evidence of $\sigma$-convergence over that time period. Since our capital data and time frame differs from theirs, a comparison may prove interesting.

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[16] As discussed in Anderson and Kliesen (2006), labor productivity increased even more in the services-producing sectors. They attribute much of the difference to the impact of falling prices of information and communications technology products.

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# 6 Data Appendix

Following Munnell (1990a,b,c), we estimate net manufacturing capital stocks for each state by apportioning the BEA's national estimates. We differ from Munnell in a number of key ways, however. Most obviously, we have extended the data set to cover the period 1977–1999. More importantly, we have based our allocation of the national capital stock estimates on new, perpetual inventory estimates of state level capital stocks.

Munnell(1990c) decomposed U.S. estimates of manufacturing capital into state-level estimates using information from the census of manufacturing to identify each state's share of U.S. capital stocks. She then assumed that the state shares of manufacturing capital were constant for a multi-year period centered on the census year. "Data from the 1972 Census were used to apportion among the states the BEA national stock estimates for 1969 to 1974; 1977 shares were used for the 1975 to 1979 stock estimates; 1982 shares were the basis for the estimates from 1980 to 1984 and 1987 data were used to apportion national asset totals for 1985 and 1986" (Munnell 1990c, pg. 97).

Munnell's approach meant that growth rates in 1975, 1980 and 1985, were exaggerated to "catch up" for the five-year deviations in the state's growth rate from the national average. In all other years, there was no cross-sectional variation in the growth of private manufacturing capital under the Munnell approach.

Because the time series properties of Munnell's capital stock series are problematic, we have adopted a different strategy for apportioning the U.S. capital stocks. We apportioned the U.S. capital stocks in manufacturing using perpetual-inventory estimates of state-level capital stocks that we developed. We have also incorporated improved estimates of national public capital stocks that were not available to Munnell.

BEA now uses a geometric depreciation strategy to generate its capital stock estimates.[17] Following BEA, we calculated our perpetual-inventory estimates of net capital stocks in each state for period $t$ as

$$N_t = \sum_{i=1}^{t} I_i(1 - \delta_T/2)(1 - \delta_t)^{t-1}$$

where $t \geq i, N_t$ is the net capital stock, $I_i$ is investment in year $i$, and $\delta_t$ is the annual geometric rate of depreciation. We assume that the geometric rate of depreciation for each state equals the implicit national rate of depreciation for the manufacturing sector in that year.

Our annual estimates of manufacturing investment by state were based on each state's share of new capital expenditures in the United States. For each year from 1970 forward, we used those shares to apportion real U.S. investment in manufacturing, thereby generating a gross investment series

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[17] For more on the construction of the national capital stock series, see U.S. Department of Commerce (1999).

for each state. For the period 1979-81, there are no data on manufacturing investment at the state level, although there are state-level estimates of gross capital stocks for total manufacturing in 1978 and 1981. We used the change in gross stocks between 1978 and 1981 to calculate investment shares for total manufacturing for 1979, 1980 and 1981.

We imputed gross stocks in 1969 by adjusting the estimates of gross capital stocks by industry for each state in 1977 to reflect cumulative real, gross investment over the 1970–77 period. State level estimate of gross capital stocks by industry are only available for 1977 and 1978, and estimates of net capital stocks are not available.

We used our estimates of gross capital stocks in 1969 and gross annual investments from 1970 through 1999 to generate perpetual inventory estimates for each state for the period 1969 through 1999. We then used them to apportion the national estimates of manufacturing capital stocks. Each year, we summed the perpetual-inventory estimates across the states and assigned each state a share of the national manufacturing capital stock according to its share of the sum-of-states estimate.