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Productivity and Convergence Across U.S. States and Industries

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Abstract: We examine the sources of aggregate labor productivity movements and convergence in the U.S. states from 1963 to 1989. Productivity levels vary widely across sectors and across states, as do sectoral output and employment shares. The main finding is the diverse performance of sectors regarding convergence. Using both cross-section and time series methods, we find convergence in labor productivity for both manufacturing and mining. However, we find that convergence does not hold for all sectors over the period. Decomposing aggregate convergence into industry productivity gains and changing sectoral shares of output, we find the manufacturing sector to be responsible for the bulk of cross-state convergence.

Key Words: Economic growth, labor productivity, convergence, industry composition, panel unit roots

JEL Classification: O47, O51, C33

1 Introduction

In recent years, a large body of empirical work has developed on the question of whether regions, particularly countries, are becoming more similar in terms of their aggregate income and productivity. This research, stimulated largely by the resurgence of work on growth theory, has dealt almost exclusively with the yes-or-no question of whether countries are converging. While the debate continues, the sources of these aggregate productivity movements at the sectoral level remain largely unstudied.

In this paper, we explore the sources of aggregate labor productivity convergence in U.S. states during the period 1963–1989.[2] Using data on sectors in U.S.

[1] We thank Kevin Hetherington and Sevin Yeltekin for excellent research assistance, and the World Economy Laboratory at M.I.T. and the Center for Economic Policy Research at Stanford for financial assistance.

[2] The fact of state convergence during the period is remarkably uncontroversial relative to other samples of countries and regions. See Barro and Sala-i-Martin (1991, 1992) for cross-section analyses, Carlino and Mills (1993) and Quah (1994) for time series approaches.

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states, we examine productivity levels and growth rates across states.[3] Additionally, we ask whether individual sectors exhibit convergence and therefore contribute to aggregate convergence, and whether the changing mix of industries is an important factor.

While most work on productivity movements and convergence has concentrated on aggregate cross-country comparisons, some research has studied movements within countries, in particular across the U.S. states. In several papers, Barro and Sala-i-Martin (1991, 1992) document convergence across U.S. states in terms of income per capita and gross state product per capita. They find that convergence holds in aggregate across U.S. states using cross-section techniques with speeds of convergence to steady state around 2 percent per year. Considering productivity growth by sector from 1963–1989, Barro and Sala-i-Martin (1991) conclude that convergence was occurring in all sectors, although more rapidly in manufacturing than in other sectors. They also conclude that a lack of aggregate convergence after the early 1970s was due primarily to relative price movements in oil-related industries. In separate work, Keil and Vohra (1993) also emphasize the importance of oil and mining, arguing that convergence across states disappears once the influence of oil and other extractive industries is taken into account. In contrast, our results do not point towards mining or mining-intensive states as critical in the overall convergence, or lack thereof, of labor productivity from 1963–1989.

This paper is divided into two main sections. The first section, Section 2, discusses the state productivity data that underlies our results. We highlight interesting variation in productivity levels, employment shares, and growth rates across states and sectors. Examples include the tremendous differences in labor productivity across sectors and the enormous variation across states in manufacturing employment shares. Then we discuss the sources of state productivity growth. Here, our primary findings are twofold: productivity growth in the manufacturing sector accounts for the bulk of private non-farm productivity growth, and the shift away from highly productive sectors to sectors with lower productivity reduced productivity growth for the average state by 0.23 percentage points, or 28 percent of productivity growth.

The second main part of the paper, Section 3, documents the evidence on sectoral convergence across the U.S. states. Employing both cross-section and time series methodologies, we consider the evidence for convergence in labor productivity across states for total private output and for individual sectors. As in other studies, we find evidence for convergence in gross state product per worker over the period 1963–1989; catch-up for total labor productivity is occuring at a rate of over 4 percent per year. However, unlike previous work, our results for individual sectors show substantial variation. There is strong evidence of convergence for manufacturing and mining using both cross-section

[3] Throughout the paper, the term "productivity" will often be used without a modifier to refer to labor productivity.

and time series techniques. On the other hand, the construction and wholesale/retail trade sectors show no evidence of convergence over the period, while the results are mixed to negative for transportation and other services. The disparity of outcomes suggests that sectoral composition plays an important role in convergence of aggregate labor productivity. Decomposing convergence in total labor productivity, we find that increases in within-sector productivity account for 73 percent of the total, with changing sectoral composition making up the balance. Manufacturing productivity increases were the most important industry contribution. A final section contrasts these results to those from work on sectoral convergence in the OECD and concludes.

2 State Productivity

2.1 Productivity Levels and Growth Rates

This paper is fundamentally concerned with the movements of labor productivity across states and industries over the last thirty years. Labor productivity is constructed as the ratio of gross state product (GSP) to state employment for the period 1963 to 1989.[4] The industries analyzed here are mining; construction; manufacturing; transportation and public utilities; wholesale and retail trade; finance, insurance, and real estate (F.I.R.E.); and other services.[5] Our "total" sector reflects the sum of these sectors, i.e. it represents the total private nonfarm part of the economy.

Table 1 summarizes our data by reporting productivity levels and variation averaged across the fifty states and the District of Columbia.[6] Several interest-

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[4] Gross state product data is obtained from the Bureau of Economic Analysis for the fifty states plus the District of Columbia. Data was provided for 1963–1977 and for 1977–1989 in constant 1982 prices. The two sets of data were merged using the 1977 data in each data set. State employment data represents annual averages and is from the Bureau of Labor Statistics for the period 1950–1993, although only the 1963–1989 data is used in this project. Our results differ from those in Barro and Sala-i-Martin (1991) in part because we employ more recent revisions of Gross State Product data covering a longer time span. These revisions shift as much as 0.6 percent of U.S. GDP between regions over a 10-year period (see Trott, Dunbar and Friedenberg, 1991).

[5] Because of missing data early in the sample (typically employment data), a few states are omitted from our calculations for certain sectors. The following states are omitted from the mining sector and the other services sector for this reason: Delaware, Hawaii, Maine, Maryland, Massachusetts, Michigan, and Rhode Island. Connecticut is also dropped from the mining and construction sectors because of missing data.

[6] Averaging across states gives each state equal weight, while the U.S. level effectively weights states by their size. With the exception of the mining sector (where the U.S. productivity level is much higher than the productivity level for the average state), the results are very similar for these two summary measures.

Table 1. Productivity levels and variation across states

Sector	Average 1963	Coefficient of Variation 1963	Average 1989	Coefficient of Variation 1989
Mining	124274	104.6	130029	110.1
Construction	56230	24.2	38122	49.9
Manufacturing	23393	25.9	46459	16.3
Trans/PubUtilities	37129	8.8	71718	12.1
Wholesale/Retail	20577	12.6	25897	12.6
F.I.R.E.	91094	22.8	92047	19.9
Other Services	26739	14.6	22398	15.3
Total	34023	30.7	40146	29.3

Note: Numbers are calculated by averaging (or computing standard deviation) across states.

ing results are apparent. First, there is remarkably wide variation in productivity levels, both across sectors and across states. The mining sector is by far the most productive sector according to the labor productivity measure, at \$130,029 per worker in 1989 as compared to \$40,146 per worker for our private non-farm total. In 1989, the manufacturing sector ranks in the middle in terms of productivity at \$46,459 per worker, exceeding construction (\$38,122), wholesale/retail trade (\$25,897) and the other services (\$22,398) sectors. Interestingly, the notion that manufacturing is an especially productive sector is not readily apparent in the table, particularly at the beginning of the sample. In 1963, the manufacturing sector was second from the bottom in terms of productivity, exceeding only the wholesale/retail trade sector but below the other services sector.

This observation leads one immediately to wonder about measurement error, and there is ample evidence in Table 1 of the kind of problems in measuring productivity that have been documented by Baily and Gordon (1988), Griliches (1994), and others. As one striking example, notice that according to this data, average productivity in the construction sector has fallen by 32 percent percent, from \$56,230 in 1963 to \$38,122 in 1989. Labor productivity also appears to fall in the other services sector and to remain relatively unchanged in the finance, insurance, and real estate (F.I.R.E.) sector.

The variation in productivity levels across sectors is matched by a large amount of variation in productivity levels across states. The standard deviation of productivity levels for the total private non-farm sector is 30.7 percent of the average productivity level in 1963 and falls only slightly to 29.3 percent by 1989, as shown by the coefficients of variation in Table 1. The coefficient of variation in the manufacturing sector displays a standard pattern of convergence, beginning at 25.9 percent in 1963 and falling to 16.3 percent in 1989, while other sectors show very different behavior. The mining sector shows extremely large variation, with a coefficient of variation of 104.6 percent in 1963 and 110.1 percent in 1989. On the other hand, the transportation/public utilities sector

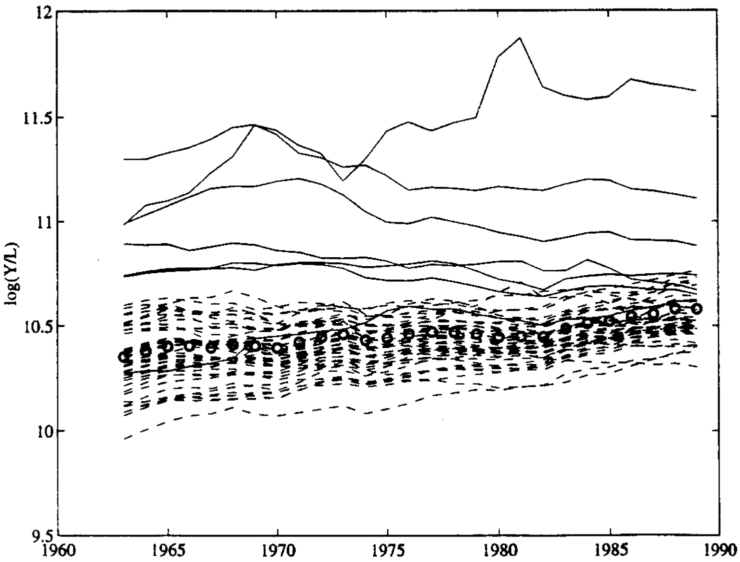

Fig. 1. Private non-farm productivity. The U.S. is indicated by circles. Mining states are solid, and non-mining states are dashed

shows relatively little variation across states, at 8.8 percent in 1963 and 12.1 percent in 1989.

Figure 1 displays labor productivity data for the total private non-farm sector. In the figure, the "mining" states are displayed with solid lines, while the remaining states are displayed with broken lines.[7] Labor productivity for the U.S. is indicated by circles. Perhaps the most striking result in the figure is the difference between the mining and non-mining states. The mining states are much more productive in aggregate than the remaining states. In part, this results from the large labor productivity in the mining sector, combined with the large share of mining in non-farm private output for these states. However, it turns out that the mining states are typically the most productive states in the other sectors as well. For example, Alaska is the most productive state in construction, wholesale/retail trade, F.I.R.E., and other services in 1963. Although we find it plausible that the mining states are the most productive states in mining, it is much more difficult to believe this productivity advantage carries over into other sectors of the economy. In fact, much of this apparent higher productivity may reflect problems in adjusting for relative

[7] The "mining" states are defined as those that average more than 20 percent of output in the mining sector. These states, together with their average mining shares, are Alaska (30.7%), Louisiana (39.8%), New Mexico (29.3%), Oklahoma (25.6%), Texas (23.9%), and Wyoming (46.1%).

prices. For this reason, we will often exclude the mining states from our analysis.[8]

Productivity levels by sector for the non-mining states are displayed graphically in Figure 2. In this and subsequent figures, the data for the United States is plotted with circles, while the data for California is highlighted as a thick solid line. This figure reinforces the results discussed in Table 1. Productivity in manufacturing, transportation, wholesale/retail trade, and in the private non-farm sector as a whole shows substantial growth. Measurement problems in construction and other services are apparent in the declining productivity levels and in the substantial increase in variation for construction in the late 1970s. In general, productivity levels differ substantially across states within a sector. In wholesale/retail trade, for example, where the coefficient of variation in 1989 from Table 1 was only 12.6 percent, productivity levels still vary substantially, from $34,026 per worker in Connecticut to only $20,661 in Montana. As a prelude to the results on convergence, one sees distinct evidence of convergence in manufacturing and mining, some evidence for the total, and little or no evidence of a narrowing in cross-section dispersion for the other sectors. This evidence will be considered more formally in the next section.

Growth rates for both the full sample and the non-mining sample are displayed in Table 2 for comparison.[9] Labor productivity grew at an annual rate of 0.53 percent for the average state in our full sample during 1963–1989, and slightly faster at 0.62 percent for the non-mining sample. However, this summary statistic masks substantial variation across sectors and states. Measured

Table 2. Growth rates – percent

				Nonmining		
Sector	U.S.	Average	StdDev	U.S.	Average	StdDev
Mining	−1.79	0.28	3.15	−0.28	0.65	2.95
Construction	−1.99	−1.83	1.65	−2.16	−2.17	1.20
Manufacturing	2.37	2.51	0.95	2.32	2.48	0.95
Trans/PubUtilities	2.30	2.24	0.46	2.27	2.19	0.46
Wholesale/Retail	0.93	0.78	0.40	0.89	0.77	0.36
F.I.R.E.	0.11	0.03	0.79	0.05	−0.08	0.74
Other Services	−0.59	−0.76	0.40	−0.64	−0.76	0.33
Total	0.61	0.53	0.67	0.69	0.62	0.48

8 The District of Columbia, in which the government sector accounts for 45.3 percent of gross state product and in which productivity in the construction sector in 1989 at $135,901 was more than twice its closest rival, will also be excluded whenever the mining states are excluded. The next mining state in line to be excluded was West Virginia, with 18.5 percent of its output in mining. However, it did not seem to be an outlier in terms of productivity in the other sectors.

9 The growth rates are constructed by regressing the natural log of productivity on a constant and a time trend. The coefficient on the time trend is reported as the average growth rate.

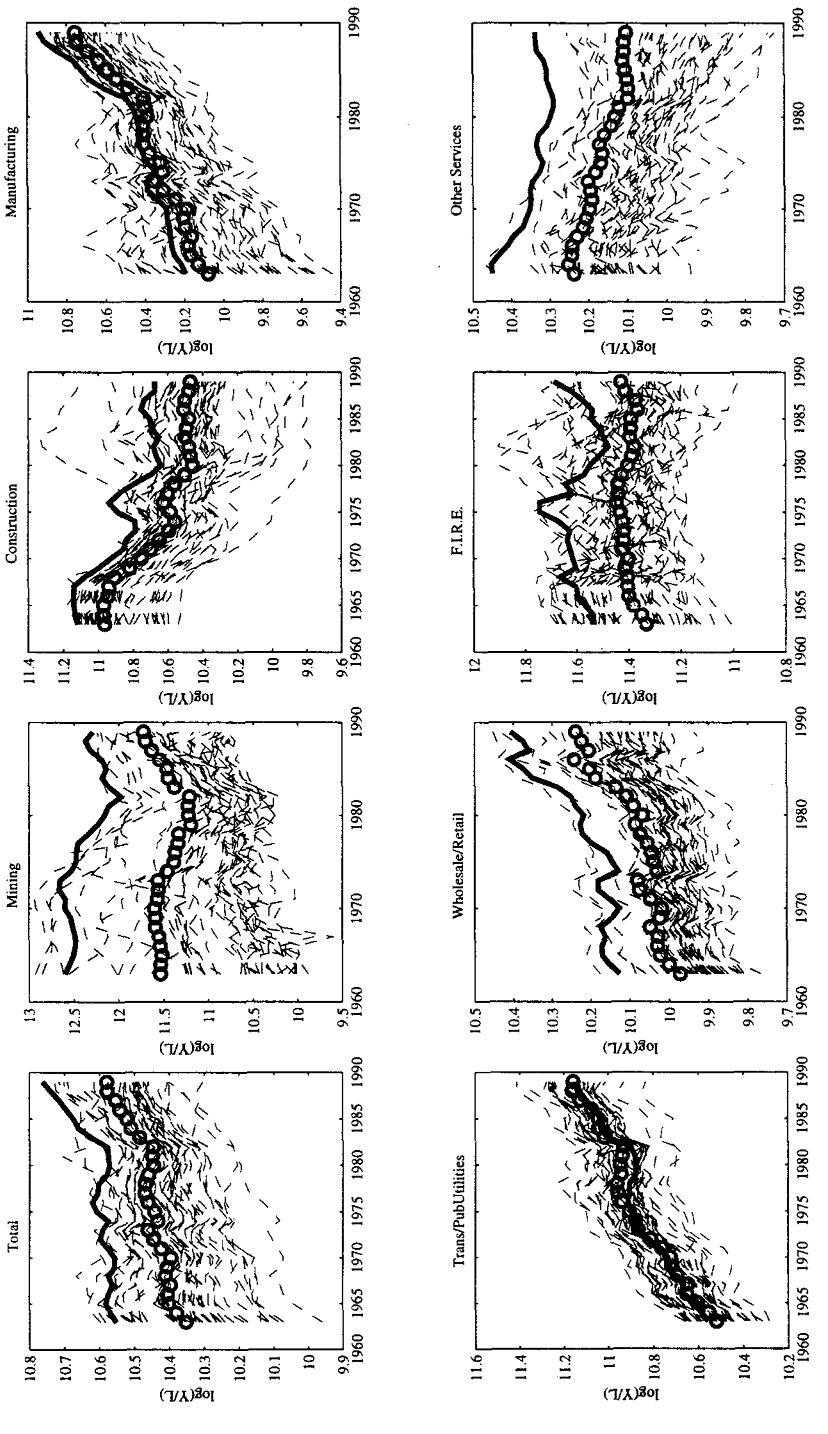

Fig. 2. Productivity levels by state (non-mining sample). The U.S. is indicated by circles and California is indicated by a solid line

productivity actually declined for the average non-mining state for construction, F.I.R.E., and other services, while it rose at 2.48 percent in the manufacturing sector.

Table 3 reports average employment and output shares across states for 1963 and 1989. Manufacturing, wholesale/retail trade, and other services are the most important sectors in the economy in terms of employment and output shares. The well-known shift away from manufacturing and toward trade and services is documented by the employment shares. Interestingly, for the average state we do not see a marked decline in the manufacturing output share despite the decline in employment. The maintenance of output shares is a mark of the relatively strong performance in terms of productivity growth that has occurred in manufacturing.[10] The variation across states in employment shares is marked, as shown in Figure 3. For example, in 1963 the variation in manufacturing employment shares of private non-farm employment ranges from less than 10 percent to more than 50 percent. Moreover, although employment shares in manufacturing have declined over time, the variation in employment shares remains substantial. This wide variation is consistent with a theory that emphasizes the specialization across states in different activities. Much of the Midwest has more than 40 percent of its employment in manufacturing; Florida and Texas have manufacturing shares of only 16.3 percent and 21.8 percent, respectively. Nevada specializes in producing entertainment, and this is reflected in our data by an employment share in "other services" that begins at about 30 percent in 1963 and rises to around 50 percent by the late 1980s.

Table 3. Employment and output shares for average state (percent)

Sector	Employment shares		Output shares	
	1963	1989	1963	1989
Mining	2.8	1.4	8.9	5.7
Construction	7.5	5.7	12.4	5.3
Manufacturing	31.2	20.2	22.6	24.2
Trans/PubUtilities	9.0	6.7	9.9	12.0
Wholesale/Retail	26.4	29.1	16.6	19.4
F.I.R.E.	5.7	6.9	15.4	15.8
Other Services	17.9	30.0	14.7	17.5
Total	100.0	100.0	100.0	100.0

[10] For manufacturing, the output shares for the average state differ somewhat from the output shares for the United States. The manufacturing employment share in the U.S. declined from 36.0 percent in 1963 to 21.6 percent in 1989, while the output share was relatively steady at 26.5 percent in 1963 and 25.7 percent in 1989.

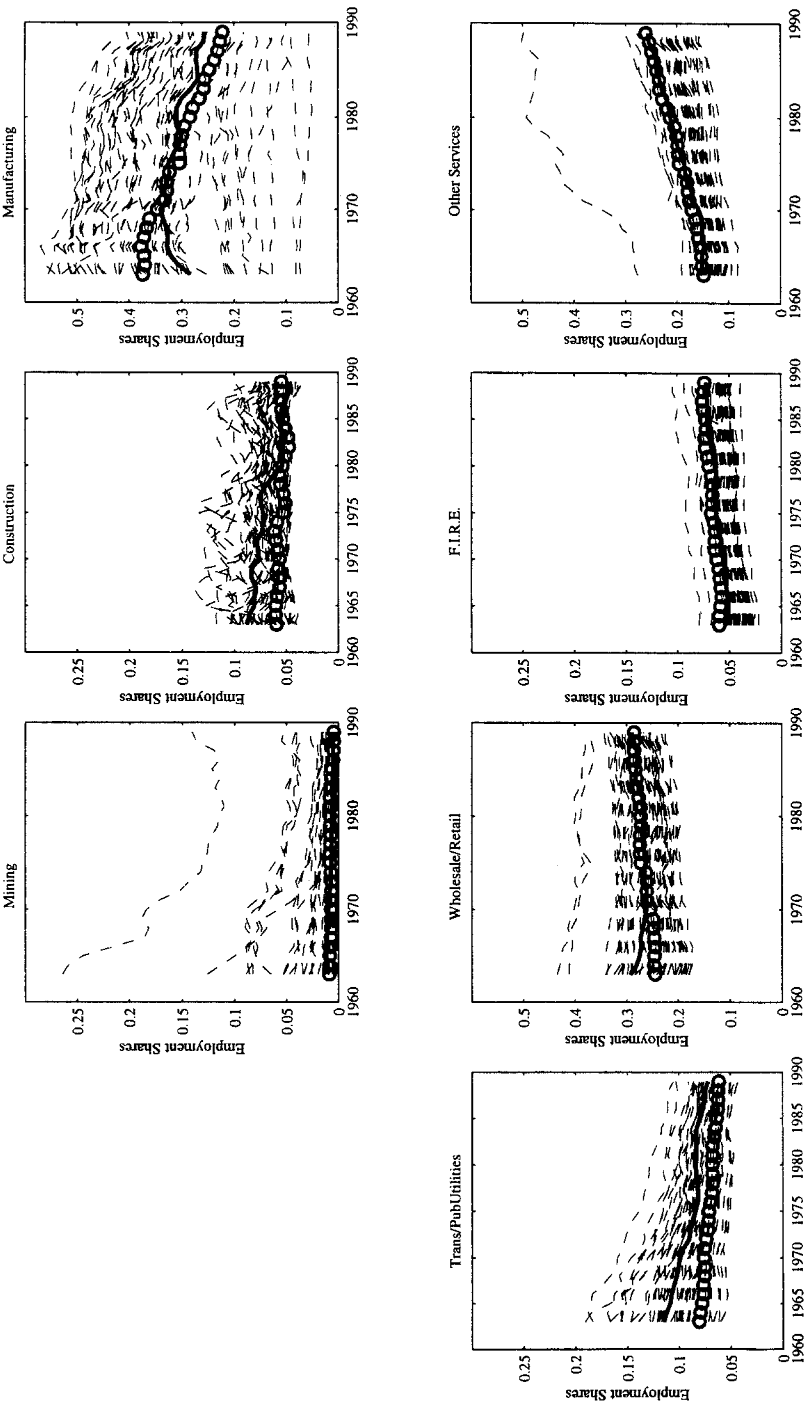

Fig. 3. Employment shares by state. The U.S. is indicated by circles

2.2 *Sources of State Productivity Growth*

Where does the growth in private non-farm productivity come from? The answer certainly varies across states and involves a combination of productivity growth within the various sectors and a shifting of employment from some sectors to others. In this section, we formalize this intuition and construct a decomposition of state productivity growth.

We can write private non-farm labor productivity in a state as a weighted sum of sectoral labor productivity, where the weights are the sectoral employment shares. Letting $y \equiv Y/L$ represent labor productivity,

$$y = \sum_i \frac{Y_i}{L_i} \cdot \frac{L_i}{L} \equiv \sum_i y_i \cdot w_i \ . \tag{1}$$

Using this accounting framework, we can decompose the change in aggregate labor productivity in each state into between and within sector components as follows:

$$\Delta y = \sum_j \Delta y_j \cdot \overline{w_j} + \sum_j \Delta w_j \cdot \overline{y_j} \ . \tag{2}$$

Here, the change is calculated between two periods, 0 and T, and $\bar{x}$ represents the average value of x across the two periods. Rewriting this decomposition in terms of percentage changes we get

$$\% \Delta y = \sum_j \underbrace{\% \Delta(y_j) \left(\frac{y_{j,0}}{y_0} \right) \overline{(w_j)}}_{\text{Productivity Growth Effect (PGE)}} + \sum_j \underbrace{\Delta(w_j) \frac{\overline{(y_j)}}{y_0}}_{\text{Share Effect (SE)}} \ . \tag{3}$$

Finally, these percentage changes can be annualized by dividing by T.

The first component, which we call the productivity growth effect, captures the contribution of within sector labor productivity growth for the state, using the average sectoral labor shares over the period in question as weights. If the employment shares had remained constant over the period in question, this would be the only term present. The second term, the share effect, shows the contribution of changing sectoral composition to aggregate labor productivity growth, where the share changes are weighted by average relative labor productivity for the sector over the period. Sectors with declining employment shares will have negative share effects.

Table 4 reports the average of the productivity growth effects and share effects for the states in our sample.[11] The average annual percentage change in labor productivity for this sample was 0.82 percent. The most important sector in generating this productivity growth was the manufacturing sector: had

[11] Our sample includes the non-mining states with complete data for 1963–1989.

Table 4. Sources of productivity growth

Sector	Growth effect	%	Share effect	%	Total effect	%
Mining	0.04	5	−0.10	−12	−0.06	−7
Construction	−0.17	−21	−0.08	−10	−0.25	−31
Manufacturing	0.81	99	−0.47	−57	0.34	41
Trans/PubUtilities	0.31	38	−0.14	−17	0.17	21
Wholesale/Retail	0.18	22	0.09	11	0.27	33
F.I.R.E.	0.00	0	0.13	16	0.13	16
Other Services	−0.12	−15	0.34	41	0.22	26
Total	1.05	128	−0.23	−28	0.82	100

Note: This table reports the average of the productivity growth decompositions for the non-mining states. Several other states are excluded because of missing data. See text for discussion. Rows and columns may not sum exactly because of rounding.

productivity not grown in that sector, aggregate productivity growth would (on average) have been lower by 0.81 percentage points, or 99 percent of the total. In other words, without productivity growth in the manufacturing sector, private non-farm productivity would essentially have been unchanged between 1963 and 1989. Share effects, though, were also important. The shift in employment for the average state was away from manufacturing, mining, construction, and transportation/public utilities, and toward the various service sectors, which on average had lower productivity. Shifting sectoral decomposition reduced productivity growth by 0.23 percentage points, or 28 percent of total productivity growth.

In this section, we have documented the substantial heterogeneity in productivity levels and growth rates over both industries and states. We now turn to an analysis of convergence in labor productivity across states and sectors.

3 Convergence in Labor Productivity

To understand the roles of sectors in the convergence of total labor productivity across states, we outline a simple model of catch-up and test its cross-section and time series implications. In addition we decompose catch-up in the average state into its within- and between-sector components.

3.1 A Basic Model of Productivity Convergence

The neoclassical growth model without technology predicts convergence in output per worker for similar, closed economies based on the accumulation of capital. However, even in the absence of catch-up due to capital accumulation, the narrowing of technology differentials can contribute to the convergence in labor productivity. To capture these effects, we construct a simple model of productivity catch-up.

We assume that labor productivity, y_{ijt}, evolves according to

$$\ln y_{ijt} = \gamma_{ij} + \lambda \ln D_{ijt} + \ln y_{ijt-1} + \ln \varepsilon_{ijt} \tag{4}$$

with γ_{ij} being the asymptotic rate of growth of sector j in state i, λ parameterizing the speed of catch-up denoted by D_{ijt}, and ε_{ijt} representing an industry and state-specific productivity shock. We allow D_{ijt}, the catch-up variable, to be a function of the productivity differential within sector j in state i from that in state 1, the most productive state,

$$\ln D_{ijt} = -\ln \hat{y}_{ijt-1} \tag{5}$$

where a hat indicates a ratio of a variable in state i to the same variable in state 1, i.e.

$$\hat{y}_{ijt} = \frac{y_{ijt}}{y_{1jt}} . \tag{6}$$

This formulation of productivity catch-up implies that productivity gaps between states are a function of the lagged gap in the same productivity measure.[12] For example, if labor productivity is the measure of productivity, then lagged gaps in labor productivity determine the degree of catch-up.

This formulation of output leads to a natural path for productivity:

$$\ln \hat{y}_{ijt} = (\gamma_{ij} - \gamma_{1j}) + (1 - \lambda) \ln \hat{y}_{ijt-1} + \ln \hat{\varepsilon}_{ijt} . \tag{7}$$

In this framework, values of $\lambda > 0$ provide an impetus for "catch up": productivity differentials between two states increase the relative growth rate of the state with lower productivity. However, only if $\lambda > 0$ and if $\gamma_i = \gamma_1$ (i.e. if the asymptotic growth rates of productivity are the same) will states exhibit a tendency to converge. Alternatively, if $\lambda = 0$, productivity levels will grow at different rates permanently and show no tendency to converge asymptotically.[13] Considering the relationship between long-run growth rates across states, we can rewrite the difference equation in equation (7) to yield

$$\bar{g}_i = -\frac{(1 - (1 - \lambda)^T)}{T} \ln \hat{y}_{io} + \frac{1}{T} \sum_{j=0}^{T} (1 - \lambda)^{T-j} (\gamma_i - \gamma_1 + \ln \hat{\varepsilon}_{ij}) \tag{8}$$

[12] This specification can be easily derived from a log linear approximation to a continuous time growth model with a Cobb-Douglas production technology: see Barro and Sala-i-Martin (1992) and Mankiw, Romer, and Weil (1992). Dowrick and Nguyen (1989) use a similar specification to test for catch-up in TFP in OECD countries.

[13] Of course, if the state with the lower initial level has a higher long run growth rate, γ_i, the states may appear to be converging in small samples.

where $\bar{g}_i$ denotes the average growth rate relative to state 1 between time 0 and time T. This is the familiar regression of long-run average growth rates on the initial level, where catch-up is denoted by a negative coefficient on the level.[14]

Another testing approach is to estimate equation (7) directly. If $\lambda > 0$, then the difference between the technology levels in the two states will be stationary. If there is no catch-up ($\lambda = 0$), then the difference of productivity in state i from that in state 1 will contain a unit root. The drift term $\gamma_i - \gamma_1$ will typically be small but nonzero if the states' technologies are driven by different processes (i.e. under the hypothesis of no convergence). Under the hypothesis of convergence, $\gamma_i = \gamma_1$ is plausible.

Unlike most previous empirical work on convergence, which has used either cross-section or time series techniques, we employ both methodologies for testing convergence in this paper. The definitions of convergence implied by the two econometric approaches are distinct. Cross-section analyses focus on the transition to equilibrium growth paths. Convergence is taken to be a narrowing of initial differences in productivity levels over some time horizon, less productive states growing faster than more productive ones (β-convergence), or the reduction in cross-region variance of productivity (σ-convergence), although one does not necessarily imply the other. This distinction between β-convergence and σ-convergence is particularly important for work on sectoral productivity convergence. If, for a given sector, states are in steady state, then we should expect to find no evidence of σ-convergence. We may, however, find a negative and significant coefficient in the growth rate regression.[15]

To reconcile any inconsistencies in the cross-section evidence and to provide another testable definition of convergence, we also employ a time series testing methodology. Time series studies generally define convergence as transitory deviations from identical long-run trends, either deterministic or stochastic. Tests in this framework look for permanent deviations in relative income paths using cointegration or unit root techniques. Due to the relatively short time period for our sample, we employ recent advances in panel unit root analysis to test the convergence hypothesis.

First, we consider evidence on the time paths of cross-section variance of sectoral labor productivity levels as well as regressions of long run productivity growth rates on initial levels. Sectors display widely varying behavior; some show no reduction in variance, others substantial reductions. To complement this analysis, we look for convergence within the time series framework, testing for transitory versus permanent differences in productivity levels. Finally, to reconcile these varying patterns across industries with aggregate convergence for total industry, we calculate contributions of shifting share and sectoral productivity growth to aggregate convergence.

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[14] For potential problems with this type of regression, see Bernard and Durlauf (1996) and Quah (1993).

[15] See Quah (1993) for a detailed discussion of this version of Galton's fallacy.

3.2 Cross-Section Evidence: σ and β Convergence

As in other studies, we find substantial evidence of catch-up and convergence in aggregate labor productivity across the U.S. states from 1963–1989. The first panel of Figure 4 shows the cross-section standard deviation for the log of aggregate labor productivity for all states (dashed line) and for non-mining states (solid line). Both series show substantial drops in the variance of cross-state productivity throughout the period, providing evidence of convergence in total labor productivity. The inclusion of the mining states dramatically increases the overall dispersion of productivity and is the source of substantional year-to-year variation as well.[16]

The remaining panels of Figure 4 show the movements in the cross-section standard deviations for the seven aggregate sectors, again for all states and non-mining states separately. While dispersion in aggregate labor productivity declined steadily over the period, the individual sectors differ dramatically from one another. Most sectors show no evidence of declining cross-section dispersion; in particular, there is significant evidence for σ-convergence only in mining and manufacturing. In mining, the cross-section standard deviation drops by half over the period, whether or not mining states are included in the sample. Similarly in manufacturing, there is a dramatic reduction in the variance of labor productivity through the early 1980s and only a slight rise thereafter. Except for the dramatic rise in the standard deviation for the construction sector, most other sectors show little trend in the dispersion of labor productivity across states over the period.

The inclusion of the mining states substantially raises the variation in labor productivity across states without affecting the movements in the standard deviation over time. Work on state convergence by Keil and Vohra (1993) suggested that convergence results for U.S. states were driven by the mining sector, while Barro and Sala-i-Martin argued that oil-related industries were the source of divergence in the 1970s. While we find that mining productivity is substantially different from that of other sectors, there is no evidence that the exclusion of the mining states affects the conclusions on catch-up and convergence.

Table 5 contains the results from cross-section regressions of long-run labor productivity growth on log labor productivity levels in 1963 of the form

$$\Delta \ln y_i = \alpha + \beta \ln y_{i,1963} + \varepsilon_{it} \ .$$

[16] These results differ from those in Barro and Sala-i-Martin (1991) who find increases in dispersion after 1973 which they attribute to large impacts of relative oil price movements in mining states. Our results suggest that the inclusion of mining states does not affect the overall downward trend in cross-state variation.

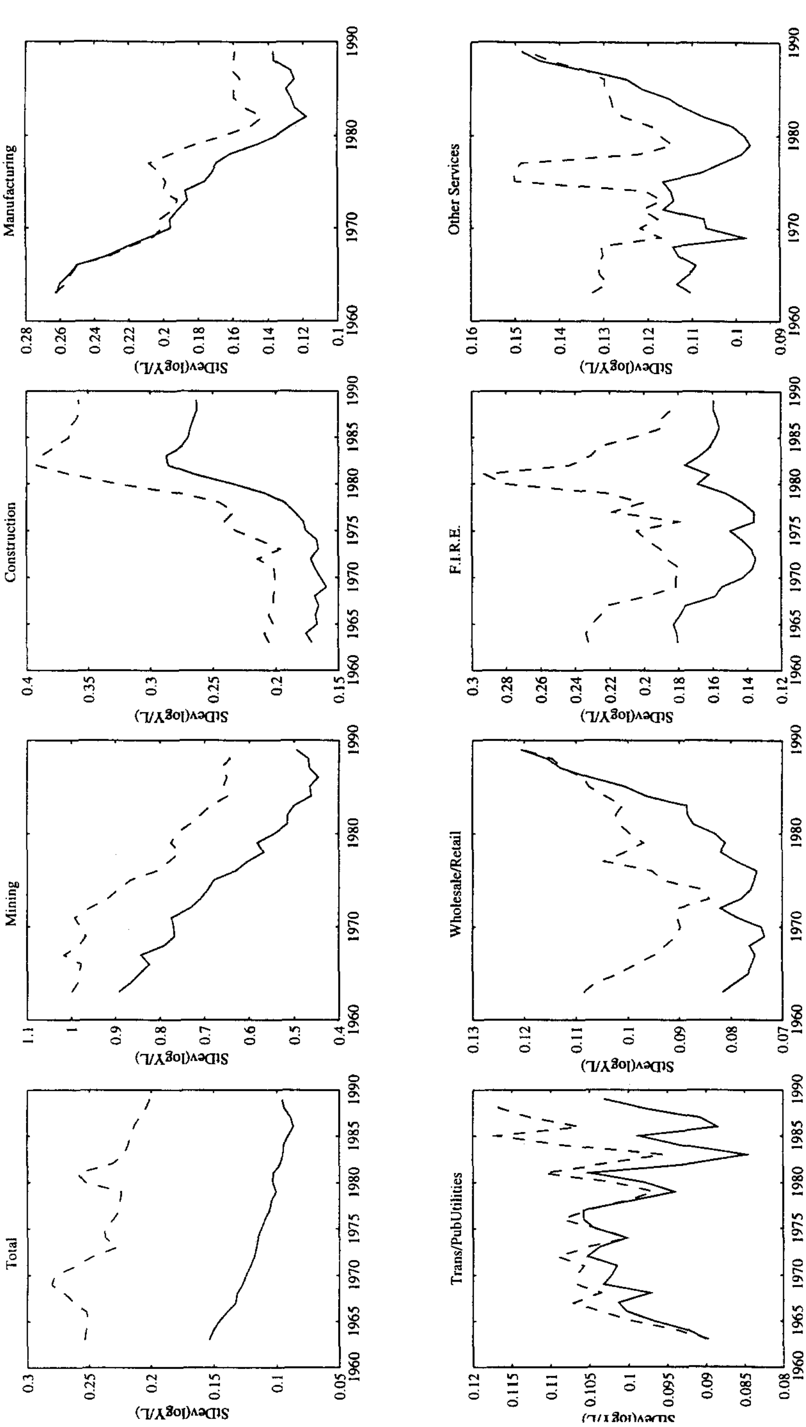

Fig. 4. Cross-section standard deviations by state. Solid is the non-mining sample. Dashed is full sample

Table 5. Convergence regressions

Sector	β	SE	t-stat	λ	t-stat	$\bar{R}^2$
Mining	−0.0281	0.0034	−8.19	0.0512	3.81	.72
Construction	−0.0111	0.0107	−1.04	0.0131	0.87	.00
Manufacturing	−0.0310	0.0032	−9.62	0.0649	3.52	.73
Trans/Utilities	−0.0216	0.0089	−2.43	0.0318	1.55	.16
Wholesale/Retail	−0.0043	0.0065	−0.66	0.0045	0.62	−.01
F.I.R.E.	−0.0215	0.0050	−4.28	0.0317	2.73	.25
Other Services	−0.0029	0.0050	−0.59	0.0030	0.56	−.02
Total	−0.0253	0.0028	−9.08	0.0418	4.94	.65

Note: Heteroskedasticity robust standard errors and t-statistics are reported. λ is the speed of convergence, as in equation (8).

A negative and significant coefficient is taken to be evidence in favor of β-convergence.[17] Confirming the evidence from the cross-section standard deviations, we find a negative and significant coefficient on the initial (log) level of total labor productivity. The point estimate of the rate of catch-up in total labor productivity is 4.18 percent per year, substantially higher than that found by Barro and Sala-i-Martin (1992). Also, 65 percent of the variation in growth rates across states is explained by differences in the initial level of productivity.

Sectors again show substantial variation, although all sectors have negative coefficients. Mining and manufacturing show the strongest evidence for convergence, with highly significant, negative coefficients. Estimates of the rate of catch-up for these sectors are 5.12 percent per year for mining and an astounding 6.49 percent per year for manufacturing. In addition, differences in initial levels explain more than 70 percent of the variation in productivity growth for these two sectors. While no other sectors showed systematic evidence for σ-convergence, both transportation and F.I.R.E. have estimated convergence rates of just over 3 percent per year, though the rate is not precisely estimated for the transportation sector.

While there is substantial evidence for convergence in total labor productivity, both sets of cross-section results suggest that sectors differ dramatically in their productivity characteristics over the period. Only mining and manufacturing are converging in both measures, while construction, wholesale/retail trade, and other services show no evidence of convergence. Moreover, for these sectors, the variation in initial levels explains virtually none of the variation in growth rates, as indicated by the adjusted R^2s.

[17] See Bernard and Durlauf (1996) and Quah (1993) for discussions of problems associated with this measure.

3.3 *Time Series Evidence*

In this section, we continue the study of sectoral convergence by examining time series evidence. We apply an extension of a recent advance in panel unit root econometrics to test for convergence within sectors across states. The sectoral data we employ is available for a relatively short time horizon of 27 years. With such a limited number of years, unit root testing would appear to be questionable due to known power problems in univariate tests. However, work by Levin and Lin (1992) and an extension by Bernard and Jones (1996) present an appropriate technique to test for unit roots in panel data. The basic findings are twofold: (1) that as both N and T go to infinity, the limiting distribution of the unit root estimator is centered and normal,[18] and (2) that the panel setting permits relatively large power improvements.

We consider the following general model with state-specific intercepts:

$$x_{it} = \mu_i + \rho x_{it-1} + \varepsilon_{it} \tag{9}$$

where the $\varepsilon_{it} \sim iid(0, \sigma_\varepsilon^2)$ and $\mu_i \sim iid(\bar{\mu}, \sigma_\mu^2)$. We also assume ε_{it} has $2 + \delta$ moments for some $\delta > 0$ and that $E\mu_i\varepsilon_{it} = 0$ for all i and t. Other standard regularity conditions are assumed to hold.

Let $\hat{\rho}$ and t_ρ be the OLS parameter estimate and t-statistic respectively. Under the null hypothesis of a unit root with nonzero drifts ($\mu_i \neq 0$), Bernard and Jones (1996) prove that asymptotic normality of $\hat{\rho}$ occurs as T goes to infinity.[19]

To examine the convergence hypothesis while taking advantage of the time series aspect of the data, we focus on cross state deviations in labor productivity levels. Letting state 1 denote the benchmark state, our tests will be based on

$$x_{ijt} \equiv D \ln y_{ij}(t) \equiv \ln y_{1j}(t) - \ln y_{ij}(t) \ , \qquad i = 2, \ldots, N \ . \tag{10}$$

Following Bernard and Durlauf (1995), we will say that state i is converging to state 1 if $D \ln y_{ij}(t)$ is stationary. We do not necessarily require $\ln y_{ij}(t)$ to exhibit a unit root with drift, although pretesting indicated that this null hypothesis could generally not be rejected.

The cost of the short time horizon is that we cannot examine the hypothesis that only a subset of the fifty states are converging. The panel test focuses on the

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[18] Quah (1990) first noted this asymptotic normality result using a random fields data structure and rejected convergence of per capita output for a large cross-section of countries from 1960–1985. His estimator does not permit country-specific intercepts.

[19] The asymptotic normality results are driven by the time trends in x_{it}. This is a multivariate extension of the results in West (1988).

When state-effects are included in the specification, a small-sample bias enters the distribution but disappears as T goes to infinity. This bias is independent of N and is analogous to the bias in standard panel data analysis described by Nickell (1981). As a result, t-statistics require a correction in order to be centered at zero: the uncorrected t-statistics are biased in the negative direction.

extremes: we test the null hypothesis that all fifty states are converging against the alternative that as a group they are not converging. With the difficulty of constructing longer time series for labor productivity by sector, we are unlikely to be able to test convergence in smaller groups of states.

A related issue is how to choose the benchmark state. Asymptotically, of course, this choice should not matter, but in small samples it will be important. We report results when state 1 is chosen in four different ways: first, we choose California as the reference state due to its prominence in the aggregate economy and because it is a productivity leader in many sectors; second, we pick the most productive state in each sector in 1963; third, we use U.S. productivity levels over the period; and finally, we select the median state in terms of sectoral productivity in 1963. The results of our time series tests for convergence are reported in Table 6.

Columns 1 and 2 report the point estimates and t-statistics of the panel unit root tests when California is the benchmark state. The reported estimates of ρ have been bias-adjusted using Monte Carlo simulations and therefore should be centered at their true values. It should be noted that the point estimates may be biased upward if there are deterministic trends in the deviations. The point estimates for total industry, mining, and manufacturing are all significantly less than unity, providing evidence against the unit root null in these sectors and confirming the results from both the cross-section measures. Convergence is occurring in aggregate and in the mining and manufacturing

Table 6. Time series tests of sectoral convergence

Sector	Deviations form:							
	CA		Most		U.S.		Median	
	ρ	t-stat	ρ	t-stat	ρ	t-stat	ρ	t-stat
Mining	0.957	−8.73**	0.961	−7.81**	0.961	−8.28**	0.736	−14.21**
Constr.	1.020	−4.50	0.998	−6.27	1.024	−3.91	1.019	−5.21
Manuf.	0.962	−8.52**	0.985	−4.72*	0.989	−5.80	0.965	−7.81*
Trans/Util.	0.963	−8.38	1.020	−4.83	0.987	−7.07	0.969	−8.07
Wh/Re Trade	1.014	−5.17	0.949	−7.57*	1.036	−1.71	1.020	−3.18
F.I.R.E.	0.997	−4.94	0.917	−9.41**	0.962	−7.95	0.951	−8.59*
Services	1.025	−4.36	1.052	−1.49	0.986	−5.36	0.930	−8.62**
Total	0.968	−6.47**	0.993	−4.61	1.005	−3.53	0.988	−7.05

Note: Asterisks are used to indicate rejection of the null hypothesis of no convergence at the following significance levels: 10 percent (*) and 5 percent (**). This table reports results from panel unit root regressions, as discussed in the paper. All regressions include state-specific intercepts. Lag length was chosen according to the Schwarz information criterion. The bias-adjusted estimate of ρ and the critical values for the t-statistics are taken from Monte Carlo simulations with 2500 iterations. For the Monte Carlo simulation for each sector, log productivity deviations were differenced, and then the means and the standard deviations of these first differences were used to generate the data for the appropriate sample size.

sectors. In contrast, the results for all other sectors fail to reject the null of no convergence with point estimates close to unity.

The alternative specifications for the benchmark state produce variation in the results. Mining shows significant evidence of convergence for all specifications while manufacturing rejects the no convergence null at the 10 percent level in two of the three remaining cases; the point estimate for manufacturing is below one for all variants. Surprisingly, total industry does not reject in any other case and the point estimates remain near one. Construction and transportation/public utilities do not reject in any cases.[20] Other sectors show varying results: other services and wholesale/retail trade reject in only one and typically show large point estimates.

An interesting exception is F.I.R.E. which rejects in two of four specifications and has low point estimates of ρ. F.I.R.E. showed no evidence of σ-convergence in Figure 4 but had a negative and significant estimate of λ in the β-convergence regression. Looking at the log levels of labor productivity for the sector in Figure 2, we see substantial churning in the distribution across states. This may represent a sector that has largely reached steady state, i.e. has already converged.

The time series results broadly confirm the σ-convergence and β-convergence results.[21] Mining and manufacturing show the strongest evidence of convergence. There is some evidence of convergence in F.I.R.E. and less so in total industry, wholesale/retail trade, and other services.

3.4 Sectoral Contributions to Convergence

The cross-section and time series results highlight significant variation across sectors in terms of convergence. A key question remaining is how convergence within sectors and the changing sectoral composition combine to generate the aggregate convergence result. To answer this question, we construct a measure of productivity growth for each state relative to a benchmark as follows:

$$\%\Delta y_{follower} - \%\Delta y_{leader} \tag{11}$$

which is decomposed into productivity growth and share effects:

$$\sum_j \underbrace{[PGE_{follower} - PGE_{leader}]}_{\text{Productivity Growth Effect}} + \sum_j \underbrace{[SE_{follower} - SE_{leader}]}_{\text{Share Effect}} . \tag{12}$$

[20] These results corroborate the faster convergence observed in the cross-section results for mining and manufacturing and the lack of convergence in construction and transportation/public utilities.

[21] This is in contrast to much previous work on convergence. Typically, cross-section results and time series results conflict for a given data set. See Bernard and Durlauf (1996) for a theoretical explanation. Exceptions are the studies of sectoral convergence in OECD countries in Bernard and Jones (1994, 1996).

For this exercise, one would ideally like to choose the state with the highest initial private non-farm productivity level and then consider convergence relative to that state. Unfortunately, this means that idiosyncrasies associated with that particular state will drive the results.[22] Because of the difficulty in picking a lead state in aggregate productivity, we consider convergence to productivity levels of the U.S. as a whole. In this case, the U.S. will be considered the "leader" relative to states that begin with a productivity level below that of the U.S. and a "follower" relative to states that begin with a productivity level above the U.S. Convergence for a state with high initial productivity requires slower than average growth while convergence for a state with low initial productivity requires faster than average growth.

To understand the importance of within-sector growth and changing sectoral composition to convergence, we construct relative productivity growth and share effects for each state for each sector. The effects are then averaged across states and the percentage contributions of each effect calculated. If sectoral labor shares remained unchanged, then all convergence would be due to within-sector productivity improvements. Since the actual composition of employment changed differentially across states, some convergence might arise from high productivity states shifting out of high productivity sectors such as manufacturing.

The results for the sectoral decomposition of convergence are given in Table 7. As with the sectoral contributions to labor productivity growth, manufacturing plays the dominant role in state labor productivity convergence. Almost two-thirds of the total convergence for the average state comes from changes in manufacturing productivity. Interestingly, manufacturing's contribution to the rate of convergence would have been even higher except for the negative share effect over the period. This negative share effect represents the fact that, on average, high initial total productivity states shifted out of manufacturing less quickly than the U.S.

Mining, construction, and F.I.R.E. all had negative productivity effect contributions to convergence; high productivity states had relatively high productivity growth in those sectors. All three of these sectors had positive share effects. Tranportation/utilities, wholesale/retail trade, and other services had small positive contributions to convergence from both within sector productivity growth and changing employment shares.

Looking at the relative importance of within sector growth and changing sectoral shares, the overall results from Table 7 are twofold. First, we find that if sectoral shares had been constant, i.e. the share effect had been zero, the average state would have converged more slowly to the U.S. Share effects

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[22] For example, we might think to use California as our benchmark state. However there is relatively little convergence to California during 1963–1989, especially in the manufacturing sector. This contrasts with research on cross-country convergence where the U.S. is typically the clear productivity leader.

Table 7. Sources of convergence

Sector	Growth effect	%	Share effect	%	Total effect	%
Mining	−0.03	−9	0.07	23	0.04	14
Contruction	−0.03	−11	0.02	6	−0.02	−5
Manufacturing	0.25	83	−0.06	−19	0.19	64
Trans/PubUtilities	0.02	6	0.01	2	0.02	8
Wholesale/Retail	0.02	7	0.01	4	0.03	10
F.I.R.E.	−0.01	−3	0.02	6	0.01	3
Other Services	−0.00	−0	0.02	6	0.02	6
Total	0.22	73	0.08	27	0.30	100

Note: This table reports the average of the convergence decompositions for the non-mining states. Several other states are excluded because of missing data. See text for discussion.

account for about one-quarter of aggregate convergence. Second, without the share changes, growth of productivity within manufacturing would have accounted for all total labor productivity convergence over the period. Within sector growth for the other sectors is relatively unimportant as an explanation of aggregate convergence.[23]

4 Conclusion

This paper explores the large heterogeneity in productivity levels and movements across industries and states in the U.S. Using gross state product per worker as a measure of labor productivity, we document the large and persistent variation of sectoral productivity levels and output shares across states. Rapid growth in manufacturing productivity provided the main source of total state productivity growth; however, the shift of employment out of highly productive sectors such as manufacturing into less productive service sectors reduced annual aggregate productivity growth by 28 percent from 1963 to 1989.

In addition to the variation in productivity levels across sectors, we find substantial heterogeneity in convergence outcomes at the industry level. Using standard cross-section and recent time series techniques, we find the strongest evidence for convergence in the manufacturing and mining sectors. Sectors such as construction, wholesale/retail trade, and other services have almost no evidence of convergence by any measure. Decomposing convergence into within

[23] In work on sectoral convergence in OECD countries, Bernard and Jones (1994, 1996) find comparable net contributions of growth and share effects. However, in those studies, services played a strong role in aggregate convergence, while there was little convergence in manufacturing.

and across sector components reveals that manufacturing contributed almost two-thirds of total catch-up across states.

These sectoral convergence results are in stark contrast to work on OECD industry productivity movements. Analyses of aggregate productivity catch-up from 1970–87 for a sample of 14 OECD countries shows little evidence for convergence in manufacturing and a substantial role for the service sector.[24] The contradiction between these sets of results remains to be explored in future work.

References

Baily MN, Gordon R (1988) The productivity slowdown, measurement issues, and the explosion of computer power. Brookings Papers on Economic Activity 2:347–431

Barro R, Sala-i-Martin X (1991) Convergence across states and regions. Brookings Papers on Economic Activity 107–58

Barro R, Sala-i-Martin X (1992) Convergence. Journal of Political Economy 100:223–51

Bernard A, Durlauf S (1995) Convergence in international output. Journal of Applied Econometrics 10:97–108

Bernard A, Durlauf S (1996) Interpreting tests of the convergence hypothesis. Journal of Econometrics 71:forthcoming

Bernard A, Jones C (1994) Comparing apples to oranges: productivity convergence and measurement across industries and countries. MIT Economics Working Paper 94-12

Bernard A, Jones C (1996) Productivity across industries and countries: time series theory and evidence. Review of Economics and Statistics: forthcoming

Carlino GM, Mills LO (1993) Are US regional incomes converging? A time series analysis. Journal of Monetary Economics 32:335–46

Dowrick S, Nguyen D (1989) OECD comparative economic growth 1950–85: catch-up and convergence. American Economic Review 79:1010–30

Griliches Z (1994) Productivity R&D and the data constraint. American Economic Review 84: 1–23

Keil M, Vohra R (1993) What's Wyoming got that we don't? Mimeo, Northeastern University

Levin A, Lin C (1992) Unit root tests in panel data: asymptotic and finite-sample properties. Discussion Paper 92-23, Department of Economics, University of California San Diego

Mankiw NG, Romer D, Weil D (1992) A contribution to the empirics of economic growth. Quarterly Journal of Economics 107:407–38

Nickell S (1981) Biases in dynamic models with fixed effects. Econometrica 49:1417–26

Quah D (1990) International patterns of growth: I persistence in cross-country disparities. Working Paper, MIT Department of Economics, January

Quah D (1993) Galton's fallacy and tests of the convergence hypothesis. Scandinavian Journal of Economics 95:427–43

Quah D (1994) Convergence empirics across economies with (some) capital mobility. Suntory-Toyota International Centre, LSE Discussion Paper No EM/94/275

[24] See Bernard and Jones (1994, 1996).

Trott EA, Dunbar A, Friedenberg H (1991) Gross state product by industry 1977–89. Survey of Current Business 71:43–59

West K (1988) Asymptotic normality when regressors have a unit root. Econometrica 56:1397–1418

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