Regional Research and Development Intensity and Earnings Inequality

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Over the past two decades earnings and income inequality have increased substantially. During this same period, investment in technology has also rapidly increased, leading some to conclude that "we have witnessed the creation of a New Economy" (President 2001, 19). This "new economy" is marked by rapid productivity growth, rising incomes, low unemployment, and moderate inflation, resulting in part from advances in technology (President 2001). The new economy, with its advancements in technology, creates a "rising tide that lifts all boats." However, economists have also argued that technological change is the leading cause of the increase in earnings inequality because it favors high-skilled workers relative to low-skilled workers (President 1997). In this instance, not all workers benefit equally from the strength of the new economy. This article examines the effect of technology—the engine of the new economy—on earnings and income inequality.

Between 1979 and 1994, earnings and income inequality increased in the United States not only between groups defined by schooling and experience but also within these groups (Levy and Murnane 1992; Bound and Johnson 1992; Juhn, Murphy, and Pierce 1993; Katz and Autor 1999; Ginther 2000). Between-group inequality can be measured by the college wage premium, the ratio of the mean or median earnings of college graduates over the mean or median earnings of high school graduates. By 1993 the median male college wage premium grew to over 70 percent (President 1997). Within-group or residual earnings inequality is measured as the inequality of earnings within groups defined by schooling and experience; it can also be calculated by measuring the dispersion in earnings residuals after controlling for these factors in a regression model. The within-group component accounts for approximately two-thirds of the overall increase in earnings inequality (Katz and Autor 1999).

Studies show that this increase has not been uniform across regions of the country. Bound and Holzer (1996) report significant geographic variation in the degree of earnings deterioration for less-educated workers during the 1980s. Topel (1994) argues that rising inequality from 1972 to 1990 did not occur at the same pace in all areas and that distinctly local factors affected relative wages. McCall (2000) documents that within-group wage inequality across regions varies more widely today than over the past several decades and uses regional variation in labor market conditions and levels of inequality to examine the relationship between the two.

Explanations for the increase in inequality include shifts in the relative supply of and demand for skilled workers, changes in economic institutions, and technological change, with most economists viewing technological change as the strongest contributing factor (President 1997). As a result, this article focuses on technology's role in explaining the increase in earnings inequality and uses regional variation in technological investment to examine regional income differences and earnings inequality.

The Correlation between Technology and Inequality

Many researchers cite skill-biased technology change as the reason for changes in between-group earnings inequality and the rising relative wages of college graduates. Katz and Murphy (1992) examine the change in the earnings distribution from 1963 to 1987, concluding that an increase in the relative demand for more skilled workers was responsible for the observed changes in earnings; they also identify technological change as a likely cause of this increase in relative demand. Berman, Bound, and Griliches (1994) argue that the shift in demand from unskilled workers to skilled workers reflects production labor–saving technological change. Berman, Bound, and Machin (1998) find evidence for skill-biased technological change in developed countries and show that the proportion of skilled workers increased in most industries despite rising or stable relative wages. Acemoglu (1999) argues that a larger proportion of skilled workers causes a change in the composition of jobs as employers respond by creating appropriate jobs.

The effect of technology on within-group earnings inequality is less clear. Bound and Johnson (1992) examine between- and within-group earnings inequality using data from 1973, 1979, and 1988. After examining alternative explanations, such as shifts away from manufacturing employment and the decreasing power of unions, they attribute observed changes in the earnings distribution to skill-biased technological change—a measure approximated by the residuals from a mean wage regression. Juhn, Murphy, and Pierce (1993) examine the timing and magnitude of changes in wage distribution using data from 1959 to 1988. They conclude that this increase in within-group inequality, measured by residuals from a mean regression, reflected increasing returns to unobserved skills that are uncorrelated with years of schooling and experience. They, too, suggest skill-biased technological change as the leading cause of increased within-group earnings inequality.

Even though researchers point to technology as the leading explanation for the increase in within-group earnings inequality, "direct evidence of the importance of skill-biased technological change in explaining trends in within-group inequality is difficult to come by," according to the 1997 *Economic Report of the President* (174). The report also points out that many researchers simply attribute any residual within-group inequality to skill-biased technological change because it is so difficult to establish a cause-effect relationship empirically.

Furthermore, McCall (2000) finds little evidence that increased technology affects within-group wage inequality when measured at the local labor market level. Mishel and Bernstein (1996) are skeptical of the often-expressed view that technological change can account for recent increases in the relative earnings of more educated and experienced workers. They report evidence that technology was more favorable to men in the bottom half of the earnings distribution in both the 1980s and the 1990s than in the 1970s, directly contradicting the notion that those with lower earnings were being left behind because their skills did not keep up with technological change. They also point out that the conclusion that skill-biased technological change is largely responsible for increased inequality rests on an assumption that the effect of technology began to accelerate during the 1980s, meaning that there should be a discernable rise in the rate of technological expansion, either qualitatively or quantitatively. Mishel and Bernstein find no support for an accelerated technology effect working against men in the bottom half of the earnings distribution during this period.

The major obstacle to empirical work on the relationship between technology and earnings inequality is the difficulty associated with quantifying and measuring technology. This article uses research and development (R&D) expenditures within a state to evaluate the effect of technological change on income and earnings inequality. R&D expenditures have been used extensively in other studies that evaluate technology's effect on earnings. For example, Allen (2001) uses R&D expenditure as a proxy for technology, pointing out that this measure is widely used by such agencies as the Bureau of Labor Statistics and the Organisation for Economic

Co-operation and Development to identify which industries qualify for high-tech status. Previous studies have employed other technology proxies, such as the usage of various forms of high-tech capital, growth in the capital-labor ratio, growth in total factor productivity, the recentness of capital, and the number of computers used per worker. Of these measures, Allen (2001) reports the strongest correlation between R&D expenditure and returns to schooling, based on an analysis of 1979 and 1989 wage differentials by industry. Bartel and Sicherman (1999) also use R&D expenditures as one of several measures of technology by industry to examine the wage premium associated with technology. They suggest that the wage premium associated with technological change reflects the sorting of more skilled workers into high-tech industries, and they confirm that the demand for skilled workers has risen.

This article builds on previous research and examines the correlation between technology and inequality by exploiting interstate differences in technology, proxied by R&D expenditures. In 1995 six states accounted for half of the nation's expenditure on R&D (Bennof and Payson 1998). This statistic demonstrates that significant geographic variation in technology can be used to clarify the role technology plays in the wage structure and earnings inequality. While earnings and income inequality increased between 1979 and 1994, real expenditure on research and development over the same time period grew rapidly in many states, contributing to a growing regional technology gap. If technology is the major factor contributing to between- and within-group earnings inequality, there should be a clear pattern in the regional data, with those areas experiencing the greatest gains in technology also experiencing the largest increases in earnings and income inequality, other things being constant.

The analysis conducted in this article shows that workers in states with high levels of technological investment earn a wage premium. In addition, the analysis indicates that states with lower levels of technological investment are correlated with higher measures of between-group earnings inequality as measured by the college wage premium—likely the result of the relative scarcity of skilled workers in low-technology states. After controlling for unobserved differences in economic conditions across states, the analysis shows that higher rates of technological investment are weakly correlated with increased family income inequality; however, these effects dissipate when additional covariates are added to the model. Finally, this article evaluates the effect of technology on within-group male earnings inequality. The results show that technology explains approximately one-third of the increase in within-group inequality. Thus, technological investment is correlated with inequality; however, the effects are smaller than expected. These results indicate that technology is not the sole factor contributing to the marked increase in earnings inequality.

The Data

This article uses two data sets to examine the effect of technology on income and earnings inequality. The first set examines technology's role in explaining income inequality. It contains income inequality measures, demographic characteristics, macroeconomic conditions, and R&D expenditures for a panel of fifty states and the District of Columbia. Family income inequality is measured by the Gini coefficient—an index ranging from zero (perfect equality) to one (absolute inequality)—using data from the 1970, 1980, and 1990 decennial censuses.[1] Additional variables include unemployment rates, average Aid to Families with Dependent Children (AFDC) payments, and other state-level variables collected from the U.S. Census Bureau's *Statistical Abstracts* (various years), as well as *Social and Economic Characteristics* from 1970, 1980, and 1990. AFDC payments, median family income, and R&D expenditures were converted to constant dollars using the personal consumption expenditure deflator with 1992 as the base year.

The evidence presented here leads to the conclusion that changes in technology do affect the wage structure, but the effects are smaller and affect wage inequality differently than expected.

The second data set examines the effect of technological change on male earnings inequality. The data are extracted from the outgoing rotation group data from the Current Population Survey (CPS) for 1979 and 1994 (Bureau of Labor Statistics 1979, 1994). This study uses log weekly earnings, and all earnings figures are reported in 1992 dollars, using regional consumer price indices to deflate nominal wages. The CPS survey does not provide measures of actual work experience; thus, potential experience

1. The Gini index values were calculated using a program provided by the Census Bureau and data on income shares from the decennial censuses.

measured by age minus schooling minus six is used instead. Since the potential experience formula is more accurate for workers with a strong attachment to the labor force, only male workers are used in this study. Additional variables include years of schooling and indicators for ten industry and eight regional categories.[2]

Both data sets include state-level measures of real R&D expenditures that were computed using data from the National Science Foundation Division of Science Resource Studies. Total state expenditures on R&D have been reported by the National Science Foundation (NSF) since 1987; however, these data are not available for earlier years. This measure is the sum of expenditures on R&D by the federal government, industry, and universities and colleges.

In order to evaluate the effect of state R&D expenditures on earnings inequality over the time period studied and to have consistent variable definitions over time, this study creates measures of total state expenditures from the three component measures collected by the NSF: total federal, university, and industrial expenditures on R&D. The NSF has compiled information on federal government and university and college R&D expenditures for the fifty states and District of Columbia yearly beginning in 1972. Industrial expenditures on R&D make up the largest component of total R&D and are available in odd-numbered years starting in 1977. Total R&D expenditures by state are the sum of total federal, university, and industrial expenditures in odd-numbered years.[3] When even-numbered years are used in the analysis, data from the nearest odd-numbered year for total state expenditures on R&D are used.[4] To avoid disclosing information about individual companies, some states did not make data available on industrial expenditures on R&D in some years. When a state's industrial R&D is not reported, this study adds federal expenditures on industrial R&D (one component of total industrial R&D) to create the state total. In these cases, total state R&D expenditures will be understated and changes in R&D expenditures are potentially overstated.

Mishel and Bernstein (1996) argue that increasing inequality can be attributed to technological change only if there is an acceleration of technology's effects on earnings. To evaluate whether it is the level of or change in technology expenditures that contributes to increased income and earnings inequality, this study constructs two measures of R&D expenditures. The first measure divides R&D expenditures for the year by gross state product (GSP). The second measure is the percentage change in real R&D expenditures. In the CPS data sets, this variable is the change in R&D expenditures between 1977 and 1979 for the 1979 data and the change in R&D expenditures between 1979 and 1993 for the 1994 data.[5]

Tables 1 and 2 contain descriptive statistics for both data sets. Earnings inequality, R&D expenditures, and years of schooling increased between 1979 and 1994 in the CPS samples. The log of average real weekly earnings fell between 1979 and 1994 while the standard deviation increased significantly. Even though the size of R&D expenditures divided by gross state product is small, the increase between 1979 and 1994 was substantial; the same holds true for changes in R&D expenditures.

Empirical Methods

This study uses three empirical approaches to evaluate technology's impact on income and earnings inequality. In the first approach, the CPS data from 1979 and 1994 are used to make two simple earnings comparisons for groups of high- and low-technology states. The first measure used is the technology premium, defined as the median earnings of workers in high-technology states divided by the median earnings of workers in low-technology states. This measure is used to examine how earnings vary depending on R&D intensity for the state. Estimates of the technology premium control for differences in industrial composition by grouping the data according to industry. The second measure calculated is the median college wage premium in

TABLE 1
Mean Characteristics by State

Gini Coefficient	0.511 (0.118)
Unemployment Rate	5.344 (1.584)
Real Average AFDC Payments	453.703 (182.644)
Real Median Family Income	39.676 (7.492)
Number of Single-Parent Households	22.131 (7.605)
R&D/GSP	0.019 (0.034)
Real R&D Expenditures	2,077,035 (3,094,747)

Note: Standard deviations appear in parentheses.

Sources: U.S. Census Bureau *Statistical Abstract of the United States*, various years, and *Social and Economic Characteristics* 1970, 1980, 1990; National Science Foundation Division of Science Resource Studies

TABLE 2
Mean Characteristics of 1979 and 1994 CPS Outgoing Rotations Group Data

	1979	1994
Years of Schooling	12.754	13.324
	(2.905)	(2.588)
Potential Experience	18.494	19.138
	(12.928)	(11.033)
Log Real Weekly Earnings	6.352	6.207
	(0.468)	(0.571)
R&D/GSP	0.019	0.024
	(0.012)	(0.019)
Change in R&D	0.104	0.912
	(0.220)	(2.387)
Sample Size	64,281	61,364

Note: Standard deviations appear in parentheses.

Sources: Bureau of Labor Statistics 1979, 1994; National Science Foundation Division of Science Resource Studies

high- and low-technology states. This measure evaluates the correlation between technological investment and between-group earnings inequality.

Designation as either a high-technology state or low-technology state is based on the rankings of the two R&D expenditure measures. Over time, those states with the largest absolute investment in technology have remained roughly the same. According to the National Science Foundation, "each of the ten states that ranked highest in terms of 1991 R&D performance was also among the top ten in 1975, although the order of their ranking has shifted somewhat. The largest three (California, New York, and Michigan) were unchanged from 1975" (National Science Foundation 1995).[6] The groupings of high- and low-technology states are somewhat arbitrary and differ significantly depending on whether the change in R&D expenditures or the ratio of R&D expenditures to gross state product is used.[7]

To create high- and low-technology states measured by R&D divided by GSP, this study selected the five highest-technology states in 1994 and 1979. In order to maintain similar sample sizes, ten low-technology states were selected for 1994 and nine were selected for 1979. To create high- and low-technology states measured by change in R&D expenditures, this study selected the eight states with the highest change in technology between 1994 and 1979. Nine low-technology states were selected for 1994 and seven were selected for 1979. The study uses these rankings (see the appendix) to evaluate whether significant differences in wages and inequality exist across high- and low-technology states.

In the second approach, the study uses the state panel data set to regress the transformed Gini coefficient on variables that contribute to inequality. The Gini coefficient measures income inequality within states and can take values ranging from zero to one. A Gini coefficient of zero indicates perfect equality (equal distribution of income) and a Gini of one indicates perfect inequality. As shown by Hayes, Slottje, and Shackett (1992), the difficulty associated with using the Gini index in a regression equation can be avoided by transforming the index.[8] A regression equation can then be estimated using the transformation of the Gini index as the dependent variable. The analysis begins by using the Dadres (1998) specification of family income inequality that regresses the transformed Gini coefficient on log family income and its square, the unemployment rate, average real AFDC payments, and the number of single-parent households. This model controls for the effects of welfare generosity and macroeconomic conditions on family income inequality; the study adds to it controls for census years and R&D expenditures. To control for unobserved heterogeneity

2. The CPS data are top-coded, biasing estimates of mean wages. Median comparisons are not affected by top coding. When used in regression models, 1.5 percent of observations are trimmed from the top and bottom tails of the 1979 and 1994 CPS samples in order to avoid biased estimates of means and variances caused by top coding. Top coding assigns one income level for some top percentage of individuals in the CPS. The nominal top code for weekly earnings was $999 in 1979 and $1,923 in 1994.
3. Some federal R&D dollars are allocated for industrial and university R&D; thus, net federal expenditures equal to total federal expenditures less federal expenditures on industrial and university R&D are used in creating total R&D expenditures by state.
4. In the 1970 wave of the state panel data set, R&D expenditures and gross state product data are available only beginning in 1977. The 1977 measure is used in this data set. The 1981 and 1991 measures are used to measure R&D within states in 1980 and 1990. R&D expenditures in 1993 are used as the measure of R&D in 1994.
5. This study accounts for changes in R&D expenditures in the state panel data set by using fixed-effects estimation and real R&D expenditure levels. R&D expenditures were deflated by the personal consumption expenditure deflator.
6. This result holds using the sum of the components of state R&D created in this study.
7. The appendix lists the high- and low-technology states ranked by R&D/GSP and change in R&D expenditures.
8. Since the Gini is a zero-to-one function, it has a truncated normal disturbance that violates the standard assumptions needed for ordinary least squares (OLS) estimation. This problem can be avoided by using $\ln[(1 - \text{Gini})/\text{Gini}]$ as the dependent variable.

across states, the study estimates models that control for state fixed effects.

The third empirical approach evaluates the effect of technological change on within-group earnings inequality. This analysis starts by using a baseline specification from Juhn, Murphy, and Pierce (1993).[9] Since technology also varies by industry and region, the analysis adds dummy variables for industry and region to the baseline model. Next, the analysis adds technology measures to control for technology and interaction terms between education and technology to the specification in order to capture the residual earnings inequality not explained by these factors. The study calculates two within-group earnings inequality measures using the residuals from the wage equations described above: the standard deviation and the difference between the 90th and 10th percentiles of the residuals. These inequality measures relate to inequality within groups defined by the control variables in the wage equations.

Results

R&D Expenditures and the Technology Premium. The technology premium, defined as the median earnings of male workers in high-tech states divided by the median earnings of male workers in low-tech states, is presented in Tables 3 and 4. In Table 3, the ranking is based on the ratio of R&D expenditure to gross state product; the designation in Table 4 reflects the change in R&D expenditure for the 1977–79 and 1979–94 periods. A technology premium is indicated when the estimates in Tables 3 and 4 are greater than one.

When technology is measured as the ratio of R&D to gross state product (Table 3), there is a signifi-

TABLE 3
Technology Premium by Industry Ranked by R&D/GSP

Industry	1979	1994
Agriculture, Forestry, and Fishing	1.002 (0.972, 1.021)	1.029 (1.009, 1.048)
Mining and Construction	0.980 (0.970, 0.991)	1.003 (0.991, 1.011)
Durable Manufacturing	1.034 (1.028, 1.045)	1.070 (1.063, 1.077)
Nondurable Manufacturing	1.010 (1.005, 1.016)	1.024 (1.017, 1.035)
Transportation, Communications, and Utilities	0.990 (0.983, 0.996)	1.014 (1.006, 1.023)
Wholesale and Retail Trade	1.012 (1.002, 1.018)	1.025 (1.016, 1.032)
Finance, Insurance, and Real Estate	1.016 (0.988, 1.029)	1.017 (1.000, 1.027)
Personal and Entertainment Services	0.995 (0.974, 1.029)	1.011 (0.994, 1.035)
Business Services	0.990 (0.970, 1.011)	1.055 (1.039, 1.072)
Professional Services and Public Administration	1.009 (1.003, 1.014)	1.016 (1.010, 1.024)
All Industries	1.011 (1.008, 1.011)	1.030 (1.029, 1.035)

Note: The technology premium is defined as median earnings in high-technology states divided by median earnings in low-technology states. Numbers greater than one indicate the presence of a technology premium. Numbers in parentheses are bootstrapped 95 percent confidence intervals from 500 subsamples.

Sources: Bureau of Labor Statistics 1979, 1994; National Science Foundation Division of Science Resource Studies

TABLE 4
Technology Premium by Industry Ranked by Change in R&D

Industry	1979	1994
Agriculture, Forestry, and Fishing	0.963 (0.943, 0.995)	1.009 (0.995, 1.033)
Mining and Construction	0.969 (0.963, 0.979)	0.985 (0.977, 0.996)
Durable Manufacturing	1.042 (1.033, 1.048)	1.049 (1.042, 1.056)
Nondurable Manufacturing	0.979 (0.971, 0.991)	1.004 (0.988, 1.016)
Transportation, Communications, and Utilities	0.988 (0.981, 0.995)	1.004 (0.996, 1.012)
Wholesale and Retail Trade	0.989 (0.985, 1.000)	1.010 (1.000, 1.018)
Finance, Insurance, and Real Estate	0.998 (0.976, 1.022)	1.014 (0.994, 1.029)
Personal and Entertainment Services	0.985 (0.961, 1.017)	0.985 (0.963, 1.006)
Business Services	0.984 (0.970, 1.007)	1.013 (1.000, 1.033)
Professional Services and Public Administration	0.991 (0.983, 0.995)	1.012 (1.002, 1.017)
All Industries	0.993 (0.992, 0.996)	1.013 (1.010, 1.019)

Note: The technology premium is defined as median earnings in high-technology states divided by median earnings in low-technology states. Numbers greater than one indicate the presence of a technology premium. Numbers in parentheses are bootstrapped 95 percent confidence intervals from 500 subsamples.

Sources: Bureau of Labor Statistics 1979, 1994; National Science Foundation Division of Science Resource Studies

cant increase in the technology premium between 1979 and 1994 for all industries combined and for durable and nondurable manufacturing; transportation, communication, and utilities; and business services. In 1994 the technology premium for all industries combined is 3 percent, indicating that workers in high-technology states earn 3 percent more than those in low-technology states. In addition, the technology premium is statistically significantly greater than one in nearly all of the industry categories in 1994, meaning that high-technology states are correlated with higher median earnings in almost all of the industries analyzed.

When technology is measured as the change in R&D investment (Table 4), there is a statistically significant increase in the technology premium between 1979 and 1994 for all industries; transportation, communications, and utilities; and professional services and public administration. In 1994, the technology premium for high-technology states measured by the change in R&D is 1 percent. Furthermore, measuring technology as the change in R&D yields a surprising result: only four industries have technology premiums that are significantly greater than one, so workers in states that have experienced the most rapid growth in research and development do not appear to benefit equally from technology in terms of higher earnings. These results indicate that the level of technology in a state relative to gross state product contributes to higher earnings, in turn contributing to greater earnings inequality between high- and low-technology states.

9. Log wages are regressed on a linear term in schooling, four schooling dummies, and a quartic in experience fully interacted with the schooling dummies.

R&D Expenditures and Between-Group Inequality. Between-group earnings inequality as measured by the college wage premium in high- and low-technology states is shown in Tables 5 and 6. In Table 5 the college wage premium increased significantly between 1979 and 1994 for all industries, durable manufacturing, and professional services and public administration in both low- and high-technology states. However, in both 1979 and 1994 the college wage premium is significantly greater in low-technology states than in high-technology states for all industries combined, indicating that when technology is measured as R&D divided by GSP, between-group inequality is somewhat higher in low-technology states.

In Table 6, where technology is measured as the change in R&D expenditures, there is a statistically significant increase in the college wage premium between 1979 and 1994 in low-technology states for all industries, in professional services and public administration, and in durable manufacturing. In addition, the college wage premium increased significantly in high-technology states for all industries combined during the same period. As in Table 5, the college wage premium is higher in low-technology states than in high-technology states for all industries combined.

In one sense the results in Tables 5 and 6 are at odds with the technology story that suggests that technology increases the relative demand for college-educated (high-skilled) workers, in turn contributing to higher wages and greater between-group earnings inequality. If technology is the major factor driving the increased relative demand for skilled workers,

TABLE 5
College Wage Premium by Industry Ranked by R&D/GSP

	1979		1994	
Industry	Low-Tech	High-Tech	Low-Tech	High-Tech
Agriculture, Forestry, and Fishing	1.056 (1.023, 1.127)	1.121 (1.090, 1.150)	0.981 (0.955, 1.069)	1.129 (1.108, 1.171)
Mining and Construction	1.038 (1.019, 1.072)	1.041 (1.020, 1.056)	1.079 (1.051, 1.103)	1.054 (1.036, 1.067)
Durable Manufacturing	1.067 (1.060, 1.075)	1.031 (1.012, 1.052)	1.091 (1.080, 1.101)	1.086 (1.065, 1.105)
Nondurable Manufacturing	1.054 (1.044, 1.072)	1.052 (1.037, 1.066)	1.092 (1.068, 1.114)	1.084 (1.058, 1.113)
Transportation, Communications, and Utilities	1.029 (1.021, 1.048)	1.044 (1.016, 1.053)	1.045 (1.034, 1.067)	1.042 (1.027, 1.058)
Wholesale and Retail Trade	1.047 (1.025, 1.071)	1.059 (1.043, 1.074)	1.079 (1.061, 1.094)	1.053 (1.039, 1.070)
Finance, Insurance, and Real Estate	1.097 (1.062, 1.147)	1.045 (1.014, 1.089)	1.082 (1.052, 1.112)	1.047 (1.015, 1.082)
Personal and Entertainment Services	1.084 (1.028, 1.108)	1.063 (1.016, 1.112)	1.053 (1.015, 1.093)	1.029 (0.997, 1.056)
Business Services	1.115 (1.075, 1.152)	1.047 (1.013, 1.086)	1.058 (1.037, 1.084)	1.054 (1.018, 1.086)
Professional Services and Public Administration	1.060 (1.052, 1.072)	1.045 (1.033, 1.057)	1.081 (1.073, 1.091)	1.072 (1.059, 1.090)
All Industries	1.055 (1.048, 1.058)	1.033 (1.031, 1.040)	1.080 (1.075, 1.085)	1.066 (1.061, 1.073)

Note: The college wage premium is defined as median earnings of workers with sixteen or more years of schooling to median earnings of workers with twelve years of schooling in states ranked by technology. Numbers greater than one indicate a college wage premium. Numbers in parentheses are bootstrapped 95 percent confidence intervals from 500 subsamples.

Sources: Bureau of Labor Statistics 1979, 1994; National Science Foundation Division of Science Resource Studies

one would expect to see higher college wage premiums in high-technology states. This study finds the opposite—higher levels of technology investment are associated with lower measures of between-group earnings inequality. However, this result may stem from skill-biased technological change having a greater impact in low-technology states where skilled labor is relatively scarce. When technology is measured by R&D divided by gross state product, average education levels are higher in seven of the ten industries studied in high-technology states; using the change in R&D as the technology measure, this result is true for eight of ten industries. In addition, when both technology measures are used, the college wage premium is greater in 1979 in low-technology states in the majority of industries. Taken together, these differences imply that the relative scarcity of skilled workers causes the higher college wage premium in low-technology states.

R&D Expenditures and Family Income Inequality. Another consideration is whether technology measured by R&D expenditures is correlated with family income inequality. Table 7 uses the ratio of R&D to gross state product as the technology measure. The models in Table 7 regress the transformed Gini coefficient on the ratio of R&D to gross state product and additional covariates suggested by Dadres (1998). Given the transformation of the dependent variable, one interprets a negative coefficient as being correlated with increased family income inequality.

In Table 7, model 1 regresses family income inequality on technology. The negative sign on R&D divided by GSP indicates that increased investment

TABLE 6
College Wage Premium by Industry Ranked by Change in R&D

Industry	1979 Low-Tech	1979 High-Tech	1994 Low-Tech	1994 High-Tech
Agriculture, Forestry, and Fishing	1.077 (1.045, 1.118)	1.113 (1.067, 1.156)	1.112 (1.075, 1.143)	1.121 (1.096, 1.173)
Mining and Construction	1.053 (1.007, 1.072)	1.045 (1.028, 1.069)	1.067 (1.040, 1.094)	1.053 (1.035, 1.083)
Durable Manufacturing	1.070 (1.056, 1.076)	1.057 (1.034, 1.072)	1.088 (1.078, 1.099)	1.078 (1.056, 1.103)
Nondurable Manufacturing	1.070 (1.049, 1.091)	1.053 (1.042, 1.074)	1.107 (1.087, 1.126)	1.088 (1.061, 1.106)
Transportation, Communications, and Utilities	1.027 (1.014, 1.038)	1.028 (1.005, 1.047)	1.071 (1.037, 1.083)	1.040 (1.034, 1.055)
Wholesale and Retail Trade	1.052 (1.040, 1.068)	1.054 (1.029, 1.070)	1.070 (1.053, 1.096)	1.067 (1.053, 1.086)
Finance, Insurance, and Real Estate	1.083 (1.031, 1.116)	1.073 (1.021, 1.111)	1.131 (1.092, 1.166)	1.080 (1.036, 1.121)
Personal and Entertainment Services	1.064 (1.015, 1.092)	1.041 (0.988, 1.097)	1.079 (1.021, 1.115)	1.040 (1.014, 1.088)
Business Services	1.084 (1.039, 1.130)	1.050 (1.023, 1.095)	1.083 (1.059, 1.101)	1.058 (1.026, 1.107)
Professional Services and Public Administration	1.054 (1.035, 1.058)	1.043 (1.027, 1.057)	1.093 (1.079, 1.093)	1.061 (1.049, 1.080)
All Industries	1.042 (1.037, 1.048)	1.042 (1.035, 1.045)	1.084 (1.078, 1.090)	1.065 (1.060, 1.072)

Note: The college wage premium is defined as median earnings of workers with sixteen or more years of schooling to median earnings of workers with twelve years of schooling in states ranked by technology. Numbers greater than one indicate a college wage premium. Numbers in parentheses are bootstrapped 95 percent confidence intervals from 500 subsamples.

Sources: Bureau of Labor Statistics 1979, 1994; National Science Foundation Division of Science Resource Studies

TABLE 7
Log of Family Income Inequality Regressed on Technology Measured by R&D/GSP and Change in R&D

Variables	Model 1 OLS	Model 2 OLS	Model 3 OLS	Model 4 Fixed Effects	Model 5 Fixed Effects
R&D/GSP	**–0.848**	0.229	0.202	***–0.482***	0.110
	(0.244)	(0.180)	(0.147)	(0.244)	(0.120)
Log Income		1.087	0.837		0.699
		(0.974)	(0.831)		(0.478)
Log Income Squared		–0.141	–0.100		–0.102
		(0.131)	(0.111)		(0.067)
Unemployment		0.001	–0.006		**0.009**
		(0.004)	(0.004)		(0.003)
AFDC Payments		**0.0001**	8.010E-05		3.260E-05
		(0.00005)	(0.000)		(0.000)
Single Parents		**–0.012**	**–0.012**		**–0.013**
		(0.001)	(0.001)		(0.002)
1970 Indicator			0.027		
			(0.025)		
1980 Indicator			**0.066**		
			(0.013)		
Constant	***0.527***	–1.371	–0.991	**0.520**	–0.459
	(0.014)	(1.800)	(1.551)	(0.008)	(0.846)

Note: Standard errors appear in parentheses. Numbers in bold are significant at the 1 percent level. Numbers in bold italics are significant at the 5 percent level.

Sources: U.S. Census Bureau *Statistical Abstract of the United States*, various years, and *Social and Economic Characteristics* 1970, 1980, 1990; National Science Foundation Division of Science Resource Studies

in technology is correlated with higher levels of family income inequality, and the estimate is significant at the 1 percent level. When models 2 and 3 include controls for real median log family income and its square, the state unemployment rate, real AFDC payments, the percentage of single-parent families in the state, and dummy variables that control for the year of the census (in model 3), the results indicate that technology has no significant effect on family income inequality. The state fixed-effects results are similar in models 4 and 5. Fixed-effects estimates allow one to control for unobserved differences in state economies. Once the model controls for state fixed effects, technology has a statistically significant effect at the 1 percent level on family income inequality when no other covariates are included in the model. Once the model controls for macroeconomic conditions, welfare generosity, and demographic characteristics in the state, the effect of technology changes sign and is no longer statistically significant.

Table 8 presents estimates using real R&D expenditures as the technology measure. Real R&D expenditures are used instead of the percentage change because the fixed-effects estimates are identified by the change in R&D expenditures over time, and this study focuses on estimating the effect of changes in R&D expenditures on income inequality. The coefficients on technology in models 4 and 5 can be interpreted as the effect of changes in technology on inequality. In all but one model, the coefficient on R&D expenditures is quite small and not significantly different from zero. The one exception is model 4, the fixed-effects model with no additional covariates, in which the coefficient on technology is small, negative, and statistically significant. However, after adding additional covariates in model 5, technology no longer has a statistically significant effect on family income inequality.

The results in Tables 7 and 8 indicate that investment in technology is weakly correlated with higher levels of family income inequality. If technology does

TABLE 8
Log of Family Income Inequality Regressed on Technology Measured by Real R&D Expenditures

Log Gini	Model 1 OLS	Model 2 OLS	Model 3 OLS	Model 4 Fixed Effects	Model 5 Fixed Effects
Real R&D	–5.76E-09	–3.73E-09	–3.68E-09	**–3.13E-08**	–3.26E-09
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log Income		0.958	0.708		0.554
		(1.005)	(0.914)		(0.486)
Log Income Squared		–0.120	–0.078		–0.082
		(0.136)	(0.124)		(0.069)
Unemployment		0.002	–0.004		**0.009**
		(0.004)	(0.005)		(0.003)
AFDC Payments		**1.428E-04**	9.870E-05		3.830E-05
		(0.000)	(0.000)		(0.000)
Single Parents		**–0.011**	**–0.011**		**–0.012**
		(0.001)	(0.001)		(0.002)
1970 Indicator			0.035		
			(0.025)		
1980 Indicator			**0.069**		
			(0.012)		
Constant	**0.523**	–1.200	–0.838	**0.576**	–0.208
	(0.015)	(1.841)	(1.678)	(0.014)	(0.860)

Note: Standard errors appear in parentheses. Numbers in bold are significant at the 1 percent level. Numbers in bold italics are significant at the 5 percent level.

Sources: U.S. Census Bureau *Statistical Abstract of the United States*, various years, and *Social and Economic Characteristics* 1970, 1980, 1990; National Science Foundation Division of Science Resource Studies

affect family income, it operates through labor market earnings. This weak correlation between technology and family income inequality may be the result of greater inequality in nonlabor income; once additional covariates are added to the models, the effect of technology is no longer statistically significant, indicating that technological change does not explain increasing family income inequality.

R&D Expenditures and Within-Group Inequality. Table 9 evaluates the effect of technology on within-group male earnings inequality using the 1979 and 1994 CPS Outgoing Rotations Group data. This analysis focuses on within-group earnings inequality because it is the largest component of inequality in the 1980s and 1990s, and there is little direct evidence of the effect of technology on within-group inequality. In this table, model 1 is specified as follows: log earnings are regressed on a linear term in schooling, four schooling dummies, a quartic in experience interacted with the schooling dummies for each year, and indicators for region (8) and industry (10). Models 2 and 3 include technology measured by the ratio of R&D expenditures to gross state product and the percentage change in R&D expenditures, respectively. Models 4 and 5 add interaction terms between technology and the schooling dummies in order to account for the skill-biased matching of technology and schooling level. Within-group inequality is measured by the standard deviation and the difference in the 90th and 10th percentiles of the residuals from the various models.

Model 1 serves as a baseline measure of the change in within-group inequality between 1979 and 1994. Using both the standard deviation and ninety-ten difference of the residuals, the results show that male within-group earnings inequality increased significantly between 1979 and 1994, as observed in the previous literature (Juhn, Murphy, and Pierce 1993; Ginther 2000). When measures of technology are included in models 2 and 3, measures of within-group inequality do not significantly decrease in either 1979 or 1994. Taken at face value, technology

TABLE 9
Technology's Effect on Within-Group Male Earnings Inequality

Standard Deviation of Residuals		Difference in 90th and 10th Percentile of Residuals	
1979	1994	1979	1994
Model 1: No Technology Measure Included			
0.372 (0.371, 0.374)	0.428 (0.426, 0.430)	0.954 (0.949, 0.960)	1.102 (1.094, 1.108)
Model 2: R&D/GSP			
0.371 (0.369, 0.372)	0.426 (0.424, 0.428)	0.948 (0.943, 0.954)	1.093 (1.087, 1.101)
Model 3: Change in R&D			
0.372 (0.371, 0.374)	0.428 (0.426, 0.430)	0.954 (0.949, 0.959)	1.101 (1.094, 1.108)
Model 4: R&D/GSP Interacted with Education			
0.352 (0.350, 0.354)	0.416 (0.414, 0.417)	0.893 (0.888, 0.900)	1.064 (1.057, 1.070)
Model 5: Change in R&D Interacted with Education			
0.353 (0.351, 0.354)	0.416 (0.414, 0.418)	0.896 (0.891, 0.902)	1.064 (1.057, 1.070)

Note: Standard deviations and ninety-ten differences are calculated from the residuals of a regression where log wages are regressed on a linear term in schooling, indicators for schooling (4), a quartic in experience interacted with schooling indicators, and indicators for industry (10) and region (8). Measures of technology are included in the specification where noted. Numbers in parentheses are bootstrapped 95 percent confidence intervals from 500 subsamples.

Sources: Bureau of Labor Statistics 1979, 1994; National Science Foundation Division of Science Resource Studies

has no effect on within-group earnings inequality in models 2 and 3. However, when technology is interacted with schooling in models 4 and 5, one observes a significant reduction in within-group earnings inequality. Putting these results into perspective using models 3 and 5, the standard deviation of the residuals increased 15 percent in model 3 and 18 percent in model 5 between 1979 and 1994. When the study compares the standard deviation of the residuals in models 3 and 5 in 1994, one sees that controlling for technology decreases within-group inequality by only 3 percent.

The results in Table 9 demonstrate that within-group earnings inequality has risen substantially over the study period. Technology explains about one-third of within-group earnings inequality and seems to operate in conjunction with schooling—a result similar to that found by Bartel and Sicherman (1999). Juhn, Murphy, and Pierce (1993), on the other hand, argue that skill-biased technological change increases the demand for unobserved skills that are uncorrelated with schooling and experience. The above results belie their conclusion. Skill-biased technological change operates through an interaction between technology and schooling, if at all.

Conclusion

The evidence presented here leads to the conclusion that changes in technology do affect the wage structure, but the effects are smaller and affect wage inequality differently than expected. First, workers in high-technology states earn a wage premium ranging between 1 percent and 3 percent compared to those in low-technology states. To the extent that technology-rich states became richer between 1979 and 1994, increased investment in technology contributed to the observed increase in earnings inequality. Second, although college-educated workers in both high- and low-technology states earn a wage premium, this premium is higher for low-technology states, indicating that between-group earnings inequality is higher in states with less technology. However, these estimates of the college wage premium remain consistent with the possibility that skill-biased technological change causes increases in between-group inequality: technology improves wages for the high-skilled relative to the low-skilled as measured by the college wage premium, espcially in low-technology states. Finally, the evidence suggests that the role assigned to skill-biased technological change in explaining increasing within-group earnings inequality has been overstated. Based on the estimates in this study, two-thirds of the increase in within-group earnings inequality cannot be attributed to technology.

These conclusions should be tempered by the recognition that this study uses only one measure of technology that in some cases was measured with error. Taken together, these results suggest that skill-biased technological change is not the sole factor explaining increases in inequality between or within groups. Future research should consider additional measures of technology to look for more direct evidence that skill-biased technological change is important in explaining trends in inequality within groups.

APPENDIX

High- and Low-Technology Rankings of States

Ranked by R&D/GSP

High-Technology States

1979	1994
Michigan	Michigan
New Mexico	New Mexico*
Delaware*	Delaware
Maryland	Maryland
Massachusetts	Massachusetts

Low-Technology States

1979	1994
Arkansas	North Dakota*
Montana*	Arkansas
Alaska	Montana
Nevada	Alaska
Kentucky	Nevada
Wyoming*	Kentucky
Louisiana	Wyoming
Maine	Louisiana
South Dakota*	Maine
	South Dakota*

Ranked by Change in R&D

High-Technology States

1979	1994
District of Columbia	District of Columbia
Vermont	Vermont*
Hawaii*	Hawaii
Washington*	Washington
Idaho*	Idaho
South Carolina	South Carolina
Michigan	Michigan
North Carolina	North Carolina

Low-Technology States

1979	1994
Tennessee	Missouri
Alaska*	Alaska*
Kansas	Montana*
Kentucky	Tennessee
Wyoming*	Kansas
Maine	Kentucky
Nevada	Wyoming
	Maine
	Nevada

*The total industrial R&D expenditures are imputed using federal expenditures on industrial R&D.

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