Economic Policy Institute

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DID TECHNOLOGY HAVE ANY EFFECT ON THE GROWTH OF WAGE INEQUALITY IN THE 1980S AND 1990S?

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ABSTRACT

Did Technology Have Any Effect on the Growth of Wage Inequality in the 1980s and 1990s?

This paper examines the empirical literature on the role of technology in the growth of wage inequality. First, we examine a series of issues that are not dealt with in most research on the topic. Their absence from the debate leads us to be skeptical that technology is the "principal explanation" or "major cause" of growing wage inequality.[1] One of these silences relates to the relationship between technology and within-group wage inequality. Another is that growth in the returns to education or skills (i.e., education and experience), which is the focus of much of the discussion about technology, is not the major cause of growing wage inequality. Skills differentials account for "only" 30-40% of the overall growth in inequality, particularly in the 1990s. Another major failure is the lack of any discussion of the events of the 1990s, a troublesome omission since the prima facie case for a technology story is not evident in the current decade or business cycle.

Second, we directly assess the information presented in some recent research efforts (Berman, Machin, Bound 1996; Johnson 1997; and Autor, Katz and Krueger 1997) which offer evidence supporting a technology explanation of growing wage inequality. Our conclusion is that these efforts provide neither indirect nor direct evidence to support such a technology explanation.

Third, we present new estimates of technology's impact on the wage structure. Motivated by Autor, Katz and Krueger (1997) we extend our previous work to include the 1960s and make several other improvements on our earlier efforts.

Our conclusion is that technological change played at most a limited role in the growth of wage inequality in the 1980s and the 1990s. In fact, it is possible that technology has not played any role in the post-1979 growth of wage inequality, especially in its impact on the lowest wage workers (the bottom 20% or so). Moreover, technological change In the 1990s has been either neutral with respect to skill or complementary with the use of low wage workers.

It is important to be clear about what we are not saying. We have every reason to believe that capital-skill complementarity—a growing demand for skills accompanying capital or R&D investments—played an important secular role in our labor markets in the 1960s, 1970s and 1980s. We believe that technology continues to have an important and large impact on labor markets and skill demand. However, we would note that there has been rapid growth in the supply of skills over the last twenty-five years and we have seen no evidence that technology-induced demands for skill have outpaced this supply.

This paper examines the empirical literature on the role of technology in the growth of wage inequality. First, we examine a series of issues that are not dealt with in most research on the topic. Their absence from the debate leads us to be skeptical that technology is the "principal explanation" or "major cause" of growing wage inequality.[1] One of these silences relates to the relationship between technology and within-group wage inequality. Another is that growth in the returns to education or skills (i.e., education and experience), which is the focus of much of the discussion about technology, is not the major cause of growing wage inequality. Skills differentials account for "only" 30-40% of the overall growth in inequality, particularly in the 1990s. Another major failure is the lack of any discussion of the events of the 1990s, a troublesome omission since the prima facie case for a technology story is not evident in the current decade or business cycle.

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There is nothing in our analysis that suggests that high school students should not pursue college educations (or beyond) or other types of skill training. After all, the college-high school wage premium is historically high and it is clear that those with more education will fare better than those who have a terminal high school degree.

Nor would we deny that there are many evident applications of technology that improve well-being. We would note, however, that much of the technology that captures our imaginations affects our lives as consumers (CDs, VCRs, microwaves, satellite TV, electronic and computer games and toys) and not as producers. The impact of technology on labor markets, as conventionally modeled, is through changes in the methods of producing goods and services that lead to shifts in the relative demand for skill. That is, it is only technological change in the workplace that matters for labor market outcomes. Innovations in telecommunications technology that affect the location (rural versus urban, home versus office, domestic versus foreign) but not the skill mix of production is not considered to generate a "technology" effect on wages.

I. Some Unexamined Issues

At its best, a technological explanation of rising wage inequality has been based on showing a positive correlation between an industry's use of technology and its use of skilled workers. Other studies have presented indirect evidence, such as the increased use of "skilled" workers as the wage premium for skill has risen. While these findings are necessary, such evidence is far from sufficient to convict technology of raising wage inequality. This section of the paper discusses six major holes in the technology story. The literature that is generally cited as indicating a major role for technology in wage inequality is largely silent on each of these issues.

A. Where's the Productivity Payoff?

It is widely known that productivity growth does not seem to reflect a surge in technological innovation in workplaces in the 1980s and 1990s. Thus, the technology story of wage inequality requires us to believe that there was a change in technology in recent decades that dramatically transformed our wage and income structures but did not change the trajectory of productivity growth. We would add, parenthetically, that the failure of productivity growth to accelerate in the 1980s or 1990s relative to the 1970s era of stagflation also raises the issue of whether a series of laissez-faire policies introduced since the late 1970s (industry deregulation; more open trading markets; reduced capital taxation; reduced health, safety and environmental regulations; reduced social protections and income support; weaker unions and minimum wages) have had any positive effects on efficiency.

Table 1 presents the trends in the two main indicators of productivity for the private non-farm business sector. Clearly, productivity growth has been slower since 1973, but the question before us is whether there was an acceleration of productivity growth in the 1980s and/or the 1990s. The available data reveal no such acceleration of productivity growth in the 1980s or 1990s. Throughout the 1979-95 period, labor productivity (output per hour) has been growing a steady 1% per year while multi-factor productivity growth (a measure of output growth due to a more efficient use of labor and capital together) has been miserably low throughout the entire 1979-95 period. This is strong evidence, in terms of fundamental efficiency, that the economy has not become better able to generate faster growth.

Two possible objections to this analysis are that productivity is mismeasured or understated (particularly in "services") and that the payoff is yet to come as we better learn to exploit microelectronic/computer technologies. Productivity may or may not be mismeasured, but the only relevant issue here is whether there has been a greater understatement of productivity growth in the 1980s or 1990s relative to the 1970s or earlier periods. No analysis has shown that there is more mismeasurement in recent than in earlier years. For instance, any errors in measuring service sector productivity have been present for decades. A growing mismeasurement problem can only arise from a growth in the relative size of service sector output.[2] The services that are likely to be mismeasured (such as financial services), however, comprised only about five percent of business output in 1995.

Though commonly argued, it is incorrect to suggest that errors in service sector productivity measurement necessarily lead to an understatement of aggregate productivity growth. Aggregate productivity growth is not measured by adding up the productivity growth in individual industries. Rather, overall productivity trends are based on examining the growth in GDP, as measured by changes in the final demand components of consumption, investment, government purchases and net exports (after subtracting imputed housing, general government and nonprofit output). As such, service sector mismeasurement affects aggregate productivity measures only insofar as they affect the components of final demand. However, 39% of final business sector demand was generated by the service sector in 1995, with medical care and financial services comprising 16% (Mishel 1997). Most service sector production is an input into other sectors. Thus, if financial services have been producing more output than we have been tracking, it primarily means that manufacturing and non-financial service industries have been using more financial service inputs with no greater value-added in the economy.

As to the other objection, it is obviously not possible to know whether a payoff awaits us in the future or not. Nevertheless, one expects that a large future payoff would have provided some initial, observable down payment almost two decades into the process. A down payment on future higher productivity growth appears nowhere in sight.

B. *Wage Inequality Versus Skill Premiums*

Much of the literature that describes itself as addressing wage inequality actually addresses a lesser issue—skill or education premiums. This is a tradition we feel should end. We agree that explaining the shifts in the production worker/non-production worker skill premium, as Berman, Machin and Bound (1996) do, is comparable to explaining education premiums in manufacturing (we find comparability between education and occupation shifts). The main problem is that many studies incorrectly equate explaining skill or education premiums with explaining wage inequality. This is incorrect because the changes in the returns to education and experience can account for substantially less than half of the growth of overall wage inequality. Within-group wage inequality ("WGWI")—the growth of inequality among workers of comparable education and experience—is the dominant source of the rise in overall inequality since the early 1970s.

If a study does not address WGWI then it does not address *wage* inequality. What is missing from the literature is an argument that WGWI is driven by technology. Labeling WGWI as the higher returns to unobservable skills may be comforting to some, but leaves us hungry for empirical support—or at least some argument that the growth of WGWI over time or across industries or education groups fits a pattern one would expect if it reflects a higher return to unobservable skills. In our work we have not found a very strong link between technology indicators and growing WGWI within industries.

It is important to be clear of the magnitudes involved. We have decomposed growing wage inequality into that due to WGWI and the "returns to skills" (growing education and experience differentials). These were first presented in the *The State of Working America, 1996-97* and are included as **Tables 2** and **3**. According to this analysis of the CPS Outgoing Rotation Group (ORG) data, the higher returns to skill account for only a "small" share of the growth of the 90/10 differential over the 1973-95 period—35% for men, 43% for women. In the most recent 1989 to 1995 period the role of skill returns was even lower. For instance, higher skill returns would explain only 16.9% of the continued growth of the 90/50 differential among men or 30% of the growth of the 90/50 differential among women. Gary Burtless (1995) has found similar results using the March CPS over the 1969-89 period—only about a third of wage inequality is associated with changes in skill returns.[3] In sum, labor economists cannot solely address the limited role of changing skill returns and presume to be addressing the growth of *wage* inequality. This is a major reason why we believe the claims in the literature are rather overdrawn.

Acknowledging the importance of WGWI even changes the label on what needs to be explained. The current conventional formulation is "Why are employers using more educated workers even though the costs of hiring educated workers is becoming (relatively) more expensive?" If we take this notion seriously, we might want to use a worker's hourly wage as a proxy for "skill." This is exactly what Juhn and Murphy have done in a series of papers and what is implicit in the aggregate production functions that are the basis of the estimating equations used in the literature including Berman, Machin and Bound (1996) and Autor, Katz and Krueger (1997). If one examines the trend in the share of workers earning low, middle and high wages, one would frame the inquiry quite differently: "Why are employers increasing their use of low-wage workers, decreasing their use of middle-wage workers and only marginally increasing their use of high-wage workers?" For instance, the share of all workers earning poverty-level wages (the poverty threshold for a 4-person family divided by 2,080 hours) has grown from 23.7% in 1979 to 29.7% in 1995. Among men, the growth was from 13.4% to 23.3%. This shift towards low wage work, of course, comes in spite of a near halving in the proportion of workers that did not attain a high school degree. Perhaps the question should be "Why are workers getting paid less even though they have more education?"

Last, we would note that interpreting changes in the returns to education and experience as "returns to skills" is mistaken to the degree that the erosion of labor market institutions affect education and experience differentials. For instance, deunionization clearly affects the college-high school wage gap; a lower minimum wage clearly affects the wage gap between college graduates and high school dropouts. We will return to this point in our review of indirect measures of relative demand for education.

C. *Recent Changes in Wage Differentials*

The literature is silent about the pattern of wage differentials in the late 1980s and in the 1990s, patterns which do not match what one would expect if technology is driving wage inequality. The technology story presumably holds that skill-biased technological change ("SBTC") has been as powerful a force in the 1990s as in the 1980s. There is every reason to believe technological change has been as great in the late-1980s and in the 1990s as in the early 1980s. In fact, the business press has included many stories about an accelerated technological change in the 1990s that has led us to a new, higher trajectory of productivity growth (see Shephard 1997). One key indicator of technological change, the share of the workforce using computers, has continued its rapid growth into the 1990s (Autor, Katz, and Krueger 1997). Our data show an acceleration of R&D spending and computerization (but not of equipment accumulation) in the 1990s. Nevertheless, the technology story told to explain the 1980s does not do well in explaining the 1990s pattern of wage inequality.

Our expectation is that the SBTC story (assuming no acceleration of the relative supply of skill) implies increased wage divergence across the entire wage range: high-wage workers should be doing better than middle-wage workers who should be doing better than low-wage workers. In terms of education differentials, one might expect a continued growth in the college/high school as well as the high school/high school dropout differentials. Given the widespread focus on the falling wages of "unskilled" workers we might especially expect to see the lowest wage workers doing the worst.

The pattern of wage growth over the last ten years or so do not easily conform to such a technology story. **Figures 1** and **2** present the 90/50 and 50/10 hourly wage differentials over the 1973-96 period based on the CPS Outgoing Rotation Group (ORG) data. Among men, wage differentials have grown over the entire 1979-96 period but have exhibited a different pattern since the mid-1980s: The 90/50 differential grows strongly and smoothly over the entire period, but the 50/10 differential among men has been flat or declining in the ORG from 1986 through 1996. We have also examined wage differentials in the March CPS, (**Figure 3**) and find that the male 50/10 differential was flat over the 1984-87 period and has declined over the 1987-95 period to the level of the early 1980s. Among men, therefore, there has been little divergence (or a decline) in the 50/10 differential for roughly ten years. If technology is driving wage inequality, then why is it not differentiating between the middle and the bottom or between the "unskilled" and the "semi-skilled?"

Among women, the story is a bit more complicated. In the ORG CPS, (Figure 2) the patterns for women parallel those for men—a continued growth of the 90/50 differential and a flattening of the 50/10 differential (from 1987 to 1995). Thus, the same question arises: Why did SBTC increasingly differentiate between high-, middle- and low-wage women from 1979 to 1987 and then only differentiate between high-wage and middle-wage women over the last eight years? The March CPS (**Figure 4**) data show a continued growth of the 90/50 and 50/10 differential over the entire 1979-95 period, but both differentials grow more slowly after 1987. Was there a shift in the pace of technological change around 1987 or a more rapid growth in skill supply?

If the 1980s technology trends have continued to accelerate in the 1990s, then one would also expect that education wage differentials, reflected by the college/high school wage premium, would continue to expand, barring an acceleration of the relative supply of college graduates. In fact, there has been no significant acceleration of the relative supply of college graduates, except perhaps among women. Yet, the male college-high school wage premium, which grew rapidly in the early 1980s, has grown slowly in the late 1980s and hardly at all in the 1990s. This can be seen in the estimates in **Table 4** of the college-high school wage premium (estimated in both the March or the ORG CPS data). For instance, the college wage premium among men grew about five percentage points from 1985 to 1995 but grew roughly nine or ten percentage points in the six years from 1979 to 1985. If one examines the recent period from 1989 to 1996, one sees almost no change in the college wage premium among men, including the trend during the 1992-96 recovery estimated with the new education coding. In fact, these data overstate the growth in the college wage premium over the 1989-96 period because of the change in the CPS coding of educational attainment in 1992[4]. These data suggest that the relative demand for education among men has grown far more slowly in the late 1980s and in the 1990s than in the early 1980s. This creates a puzzle: Why has the relative demand for male college graduates grown more slowly when technological change is assumed to have continued to grow strongly or even more rapidly?

In contrast, the college-high school wage premium has grown steadily among women throughout the 1979-95 period, even though there was a stronger growth in the relative supply of women college graduates. Can technology trends explain this faster growth in relative demand for education among women relative to men since the mid-1980s?

Last, the estimates in Autor, Katz and Krueger (1997) raise the same questions even more powerfully. For instance, these authors found a one percentage point growth in the college wage premium from 1990 to 1995, confirming the flattening of the growth of education differentials (among all workers, men and women). Their data also indicate a deceleration in the relative supply of college graduates in the 1990s relative to the 1980s, strengthening our suspicions that the growth in the relative demand for education has decelerated in the 1990s.[5]

D. *Recent Quantity Shifts*

The literature is also silent about employment shifts in the mid-'80s through the mid-1990s. These recent shifts in the occupational composition of employment seem inconsistent with a technology story that presumes skill-biased technological change grew strongly, or even more strongly, in the late 1980s and 1990s than it did in the 1970s or earlier periods. First, consider the shift to white-collar and higher-paying occupations. Mishel and Bernstein (1996) present an index of occupational upgrading for each year over the 1972-95 period using employment data on thirteen major occupations and the relative wage and compensation structure. This index captures the degree to which employment is shifting toward higher-paying and presumably more skilled occupations. Again, there has been very modest occupational upgrading in the 1989-95 period (0.14 annually) relative to the occupational upgrading over the 1979-89 period (0.23% annually). If technology is boosting the need for "more skill" then one would expect there to be a continued strong growth in white-collar, knowledge-intensive employment in the "information age." In our review of Berman, Machin and Bound (1996) below, we focus on the failure of the nonproduction worker share of employment in manufacturing to rise over the last ten years, providing further evidence against technology-induced occupational upgrading.

The high and growing dislocation of white-collar workers in the 1990s (as Farber has shown) and the deceleration of the shift towards white-collar employment might also be seen as a further indication that there was an over-hiring of white-collar workers in the 1980s.

E. *Relative Versus Absolute Wages*

The technology story rests heavily on a discussion of "relative wage" trends in which one compares how the wages of one group have fared relative to those of another. For example, the growth in the much discussed college-high school differential, or college wage premium, is about relative wages. When one examines the growth of "absolute wages," or actual wage levels, however, the technology story has far less intuitive appeal. This is because the winners in the technology story—white-collar and college-educated workers—have not done so well in terms of real wage growth: They have done relatively well but not absolutely well.

This contrast between growing relative and flat absolute wage trends is a reflection of the fact that average wages have grown slowly, a phenomenon reflecting slow productivity growth. Since, as reviewed earlier, technological change has not generated faster productivity growth it should not be surprising that even the winners are not thriving. How have the real hourly wages of "knowledge-workers" been faring? Among men, not so well.[6] White-collar male wages barely rose over the 1979-89 period (up 0.6%) and then fell 1.4% from 1989 to 1995. Male managerial, professional and executive workers saw their wages rise by only six percent in the sixteen years since 1979. Similarly, the real wages of men with a four-year college degree did not improve over the 1979-95 period and are now less than they were in 1973. The failure of real hourly wages at the 90th percentile among men to grow over the 1979-95 period is another indication that high-"skill," or at least high-wage, men have not benefitted from the shift to a knowledge-age economy. These high-wage men have also seen a slight erosion in health and pension coverage.

Women's wages have grown more than men's in every category—by education, occupation or percentile. Reflecting this wage catch-up, women white-collar and college-educated workers have seen strong wage growth since 1979, although women's wages are still below those of men in every category.

There is one area of common ground among men and women that should give special pause to those believing that knowledge-workers are benefitting from a surge of technology: The real hourly wages paid to new college graduates has fallen in recent years. This can be documented in several independent sources. For instance, in the ORG CPS the hourly wages of those with one to five years experience—the entry level wage—fell over the 1989-95 period, by 9.5% for men and by 7.7% for women. In fact, the entry level college wage for men and women is now, respectively, 11% and 5% below its 1973 level (see **Figure 5**).

A second source is the Department of Education's series based on the Survey of Recent College Graduates. As **Table 5** shows, the median salary of recent college graduates working full-time (and not enrolled) fell from 1986 to 1990 and fell further by 1993. It is also of interest that the relative wage of technology-related majors, such as science, computers, and engineering, did not improve over the 1977-93 period.

A third source of information on new college graduate salaries come from the annual survey of job offers conducted by the National Association of Colleges and Employers, as seen in **Table 6**. Between 1989 and 1996 the salary offered to new college graduates fell considerably, including those of computer-related majors, engineers and scientists.

It is difficult to square these findings of declining wages for new college graduates, including those in technology-related fields, with the notion of an information-age economy generating an excess demand for education in the 1990s. Young college graduates, one would presume, are the most flexible, computer-literate and best-educated part of the workforce.

These wage trends in the 1990s should inform our analyses of the 1980s. For instance, as we discuss below, simple demand and supply analyses of the 1980s interpret the growth of education differentials as a reflection of unmet or unfulfilled demand for educated workers. How can this interpretation be squared, however, with the collapse of wages for young college graduates in the early 1990s or with the slower relative employment growth of white-collar jobs and of nonproduction employment in manufacturing in the 1990s?

F. *No Acceleration*

For technology to be a central factor in the growth of wage inequality in the 1980s and 1990s requires that the growth of the relative demand for skill/education *accelerated* and that technological change played a major role in this acceleration of relative demand. Simply put, if the relative demand for education/skill was rising only at its long-term secular rate then what was new about the 1980s was the *supply-side* deceleration. If so, then technology or trade are factors driving up relative demand for education at their historical, secular rate, but cannot be seen as the source of the sharp increase in wage inequality since 1979. A technology story, therefore, only makes sense if there was a demand-side acceleration and if technology is responsible for this acceleration.

Alan Greenspan, Gary Becker and others telling a technology story typically ignore the issue of acceleration. Autor, Katz and Krueger (1997) is a major exception. It is as if there has not been a rapid growth in the educational attainment and the skill level of the workforce. Yet, we have doubled the share of the workforce with a college degree (to 25% in 1995) and drastically cut the share of the workforce without a high school degree (to 11% in 1995 from 29% in 1973). In fact, the average private sector worker had nearly two more years of education in 1995 (13.3 years) than in 1973 (11.6 years).

Another way of saying this is to note that a decade of research has led labor economists to conclude that the source of the growth of wage inequality since 1979 is to be found on the "demand-side" (meaning, actually, non-supply factors such as demand and institutional factors). The research on the role of trade and technology is motivated as an attempt to locate the source of the demand-side shifts that have taken place since 1979. This framework assumes an *acceleration* of demand side changes.

The rhetoric in the discussion of technology's role in growing wage inequality presumes that we have entered a new era of technological change, signified by the computer revolution. Either the rate of introduction of new technologies or the types of technologies being introduced are creating a qualitatively new situation in today's workplace and creating an enhanced demand for cognitive skills. Some analysts have explicitly talked in terms of a "technology shock" (Krugman 1994). This widely expressed view assumes an acceleration of technology's impact on relative demand and further motivates our test for acceleration.

We do not question that technological change and capital accumulation have historically been associated with the need for greater skills and education, i.e., the existence of capital-skill complementarity. Clearly, technology and capital accumulation have been major forces driving the long-term growth of skill demand. Mishel and Bernstein (1996) confirm this, as do many studies. A strong relationship between capital, computers or other factors and skill demand does not, however, imply that technology's impact was *greater* in the 1980s or 1990s than in earlier periods or that technology led relative demand to outpace relative supply.

There is no evidence that technology's impact accelerated in the 1980s or 1990s and mounting evidence against acceleration. For instance, Autor, Katz and Krueger (1997) reject that there was any acceleration in the relative demand for education between the 1970s and 1980s. Machin et al (1996) found no increase between the 1980s and the 1970s in the complementarity between R&D and skills in manufacturing in four countries. Mishel and Bernstein have examined the impact of technological change on the use of more educated and more "skilled" (higher wage) workers within industries in the 1970s, 1980s and 1990s in several studies and find no acceleration. More work on this topic is presented below.

In short, the technology story suffers from numerous shortcomings. First, we are asked to believe that technology is capable of radically restructuring our incomes and wages but is somehow unable to raise productivity growth. Second, growing wage inequality is said to be the consequence of an increasing premium for skills and education. Yet, the increasing "returns to skill" can explain only a third or so of the overall growth in wage inequality since 1973 and an even smaller share of more recent trends. Third, the technology story focuses exclusively on relative wages (differences between workers) rather than absolute wages (actual wage levels). It is curious that (especially among men) the emergence of an information-age economy has been associated over the last ten years with stagnant or falling real wages of white-collar workers and college graduates. It is especially curious to see the wages of new college graduates, including those with scientific, engineering and computer majors, fall substantially in the 1990s. Fourth, the behavior of key wage differentials over the last ten years, especially among men, does not correspond to a simple technology story. Specifically, there has been a flattening or decline in the pay gap between middle- and low-wage workers and a slowdown in the relative demand for college graduates. Fifth, there has been a flattening or slowdown in the employment shift to white-collar (or higher wage) occupations and to nonproduction worker employment. These facts do not easily square with a presumed continuous and strong shift toward knowledge-based employment. Sixth, since skill-based technological change has been with us for several decades, the technology story is only true if technology has had a greater impact in the 1980s and 1990s than in earlier periods. Tests for "acceleration" show this has not been the case.

II The Skill-Based Technological Change Hypothesis of Berman, Machin and Bound

The recent Berman, Machin and Bound (1996) paper, hereafter referred to as "BMB," makes the strongest claim for the technology hypothesis, suggesting that skill-based technological change ("SBTC") is the "champion explanation of increased wage inequality" and "can explain most of the phenomenon (wage inequality)." We undertake an evaluation of their evidence as a way of examining the strength of the evidence for the technology hypothesis. In our view, the weakness of the evidence presented in BMB reflects the weakness of the direct and indirect evidence for the belief that technology is a major, or even minor, cause of growing wage inequality in the 1980s or 1990s. In fact, we find no evidence for the technology hypothesis in the BMB analysis.

BMB examine the growth of the nonproduction worker share of manufacturing employment in the U.S. and the U.K. and in a group of ten other advanced countries in the 1970s and 1980s. Their two main findings are:

1. There was a shift towards nonproduction worker employment within manufacturing industries in the U.S. and other countries while the relative price of skill was stable or rising; and,
2. This skill upgrading primarily occurred in a similar set of industries across countries.

This evidence has a very limited scope, however, because it does not address the issues elaborated earlier. For instance, their data can address a change in the skill premiums in manufacturing but can neither address the economy as a whole nor the changes in within-group wage inequality (and therefore the overall change in wage inequality). There is no consideration of events (both employment shifts and changes in wage differentials) after the 1980s, labor market outcomes which we have argued are hard to reconcile with a technology story. Most importantly, because BMB fails to address the issue of acceleration, their findings, even within the narrow scope of skill differentials within manufacturing, do not answer the question they claim to be asking: Was technology the principal cause of growing wage inequality in the 1980s?

It is also important to note that BMB provide no quantitative estimate of the impact of technology on relative wages. In contrast, researchers examining the role of unions, the minimum wage, trade, and deregulation attempt to measure an impact on wages which can be compared to an overall change. Such an effort is possible with technology as well. It would start with an estimate of technology's impact on relative employment. The next step would be to link employment shifts to wage shifts (leaving aside the question of acceleration, i.e., whether this impact was greater than in earlier periods). The estimated relative wage effect could then be compared to the overall shift in the wage structure, indicating technology's ability to explain wage inequality. The findings in BMB are at best "suggestive" of a technology hypothesis. It is also possible, however, that BMB's findings reflect nothing more than the ongoing existence of capital-skill complementarity.

To be fair, the motivation of the BMB paper was to address Leamer's critique of the SBTC story within the Hecksher-Ohlin-Samuelson framework. As such, the paper makes several important contributions. For our purposes here, however, we focus on the more general claim made in BMB for the technology hypothesis. The remaining part of this section elaborates how their evidence falls short, even within the framework and empirical standards they establish.

A. *What Do Shifts in Skill Shares Tell Us?*

According to BMB, the heart of the matter is what is happening to the share of skilled workers in manufacturing. As BMB note: "The key feature of the data is that, despite increased relative wages of skilled labor, industries and plants substituted toward their use." BMB provide evidence that the skilled worker share increased in 12 developed economies in the 1980s (see their Table III). While these data are supportive of a technology story, they fall short even on BMB's own terms. First, extending their data for the United States into the 1990s, yields a very different story (see **Figure 6**). Using data from the "Annual Survey of Manufactures," the nonproduction share (BMB's preferred skill measure) is unchanged between 1989 and 1994 (declining from 35.0% to 34.9%); using data from the BLS establishment survey, the share of nonproduction workers in manufacturing actually falls slightly between 1989 and 1996 (from 31.8% to 30.9%). As Schmitt and Mishel (1996) emphasize, these data probably overstate growth in the nonproduction worker share over the period since a large and growing share of production workers hired through temporary agencies are excluded from these counts of production workers in manufacturing. This sudden flattening or even decline in the skilled-worker share in the 1990s is not consistent with the standard motivation for the SBTC story, which generally does not argue that SBTC suddenly decelerated at the end of the 1980s.

Second, Figure 6 also indicates that the skilled-worker share did not grow smoothly over the 1980s. As Howell (19XX and 1994) has pointed out, all of the rise in the skilled-worker share occurred between 1979 and 1982—before any significant dispersion of personal computers and before the major acceleration in computer investment (see Berman, Bound, and Griliches 1993, Table 13). (The flattening of the skilled worker share in the 1990s, then, actually began in 1983.) The positive relationship that BMB find between changes in industry-level technology indicators and changes in industry-level skilled-worker shares in the 1980s, then, appears to be strongly influenced by the rise in skilled-worker shares that took place largely *before* the increase in PC use (IBM PCs were first marketed in 1981) and other computer investment.

Third, BMB's analysis does not address the issue of acceleration in the overall impact of technology and is therefore hard-pressed to explain the rise in wage inequality in the 1980s versus the 1970s. We are confident that an analysis similar to BMB's for the 1970s (measuring the relationship between changes in industry-level capital investment and changes in industry-level skilled-worker share) would also show a strong, positive relationship. The question, as Autor, Katz and Krueger (1997) recognize, is whether technology's impact has accelerated. BMB's data, however, do provide some indication that skill-upgrading (one outcome of technological growth) *decelerated* in the 1980s. Of ten advanced countries for which BMB report the necessary data (see their Table III), seven showed a slower rate of skill-upgrading in the 1980s than the 1970s.[7]

It is tempting to argue as BMB (p. 18) and Robert Lawrence do that the flat trajectory of skilled-worker shares for the past 13 years is not inconsistent with technology-based explanations of wage inequality. They maintain that the failure of the skilled-worker share to increase after 1982 is simply a market response to the higher wages that skilled workers now command. This argument, at best, confuses movements along relative demand curves with shifts in relative demand curves. At worst, it concedes that the growth in relative demand for skills decelerated or even became negative sometime after the early 1980s.

The position amounts to saying that as the relative demand curve shifted out (reflecting greater demand for skilled workers) employers balked at the idea of paying the higher wage to an increasing number of skilled workers and therefore shifted toward hiring more less-skilled workers. On its face, this sounds as though the relative demand curve shifted at some point toward less-skilled workers (the opposite of what is supposed to have happened). Nevertheless, it might be possible to interpret the argument as suggesting that the relative demand curve continued to shift out, but some other force encouraged a simultaneous movement *along* each successive relative demand curve toward higher relative wages and lower relative employment of skilled workers.

The central question, then, is what might this force be?[8] **Figure X** displays data from the "Annual Survey of Manufactures" (NBER Productivity database) on the pattern of relative wages and employment for 1949, 1959, 1969, and for each year from 1979 through 1994. The relative wage-employment combinations move in a straight line from the end of each decade between 1949 and 1979 (for clarity, the presentation masks cyclical movements generally below the line connecting the decadal end points). As Krueger and Pischke (1997) have noted, the economy generally has for a long time accommodated large changes in relative employment with relatively minor adjustments in relative wages. During the recessionary period from 1979 through 1982, relative employment shifted strongly against less-skilled workers, with no change in the relative wages. From 1982 through 1994, the data points move almost due north—a roughly constant employment share accompanied by generally rising relative wages. In the 1990s, the skilled-worker share fell (typical of recoveries) to a point where the skilled-worker share was below its level at the 1989 cyclical peak.[9]

The challenge facing the technology thesis is to tell a simple supply and demand story on the data points. From 1979 through 1982, the relative demand curve shifts out along a constant (flat) relative supply curve. After 1983, however, relative demand shifts alone can no longer explain the annual pattern. If relative demand continues to shift out, only roughly offsetting inward shifts in the relative supply of skilled workers can keep the observed market outcomes at the intersections of relative supply and demand curves. After 1990, the decline in the share of skilled workers requires that the inward shifts in the relative supply curve be faster than the outward shift in relative demand.

The figure suggests that the posited relative demand shocks do a poor job explaining the pattern in annual changes in relative employment and relative wages after 1982. The observed pattern of the data is only consistent with positive relative demand shocks when relative supply simultaneously moves equally in the opposite direction. Given that outward shifts in both relative demand and relative supply have probably been the norm for most of the century, it seems odd to characterize the developments in the 1980s and 1990s as reflecting changes in relative demand for skills outpacing changes in the relative supply for skills.

The figure helps to make two other points. First, these aggregate data suggest that an analysis of the type originally conducted by Berman, Bound, and Griliches (1993) would conclude that, unlike the 1980s, technology played little role in the rise in relative wage and wage bill increases in the 1990s, since aggregate relative skilled-employment shares appear to have fallen in manufacturing in the 1990s. Second, the expansion between 1984 and 1986 in the relative employment of skilled workers—which runs counter to the usual experience during economic recoveries—looks suspiciously like it could be related to trade-induced effects of the strong dollar during this period, which might have led firms to reduce employment of less-skilled (production) workers due to loss of market share or outsourcing.[10]

III Indirect Measures of Trends in the Relative Demand for Education

Two new papers use a simple supply and demand model to construct decadal trends in the relative demand for education in the post-war period. Autor, Katz and Krueger (1997), hereafter referred to as "AKK," find an accelerated demand for education in the 1970-95 period relative to the 1940-70 period, evidence they claim supports a technology story of growing wage inequality. Johnson (1997) uses a similar model and finds an acceleration in relative demand for education in the 1980s and 1990s relative to the 1950s, 1960s and 1970s. Johnson concludes that globalization is not responsible for this demand acceleration, leaving skill-based technological change as the cause. This section examines this "indirect evidence" for a technology story.

A. *Autor, Katz and Krueger ("AKK")*

AKK update and extend the Katz and Murphy (1992) analysis of trends in the supply and demand for education to cover the entire 1940-95 period. This is a very useful contribution. AKK find,

> The results suggest that the relative demand for college graduates grew more rapidly on average during the past twenty-five years (1970-95) than during the previous three decades (1940-70). The increased rate of growth of relative demand for college graduates beginning in the 1970s did not lead to an increase in the college/high school wage differential until the 1980s because the growth in the supply of college graduates increased even more sharply in the 1970s before returning to historical levels in the 1980s.

This conclusion is drawn from their results which are reproduced as **Table 7**. There are many strengths but also important weaknesses of this approach.[11] The strengths are that AKK examine the entire labor market and not just manufacturing and that they explicitly acknowledge the need to show an acceleration of technology's impact to support a "technology (or other) explanation." It is also useful that AKK present some data for the 1990s.

There are several limitations as well. First, by focusing only on the demand for education and education wage differentials, AKK's analysis addresses only the part of growing wage inequality associated with education differentials, about a third of the total growth of wage inequality since 1973. Although AKK acknowledges the growth of within-group wage inequality they simply assume that education differentials are "a proxy for the relative price of more-skilled labor." In fact, education differentials are a poor proxy for growing wage inequality, as seen by the fact that the trends strongly differ in both the 1970s and 1990s. As AKK noted, those using the ORG data, as we, Card (19XX) and DiNardo et al (1996) do, show within-group wage inequality stable in the 1970s, as the return to education fell. Juhn et al (1993) and Katz and Murphy (1992), using the March CPS, show growing within-group wage inequality in both the 1970s and the 1980s. One common finding is that neither the March nor the ORG data show within-group wage inequality having the same trends as education differentials which fell in the 1970s. In the 1990s it appears that overall wage inequality among men and women has grown even through education differentials have been relatively stable. Previous research by Mishel and Bernstein (1996) also shows a weaker and different relationships between technology and the growth of within-group wage inequality within industries versus the increased use of more educated (college graduate) workers. Consequently, any analysis of education differentials can only tell a part of the story of growing wage inequality.

A second limitation of this simple supply and demand analysis is that it does not directly, or possibly even indirectly, address the role of technology. Their estimates of the growth of the relative demand for education reflect, as AKK acknowledge, all non-supply factors including both other demand factors and institutional factors. Moreover, the growth of relative demand is not equivalent to the growth of technology-driven demand since other factors, most prominently trade, may also affect demand shifts. As we show below, an analysis incorporating very modest roles for institutions and trade in the 1980s and other periods suggests that, in this simple framework, technology's impact has been decelerating every decade from the 1950s to the 1990s.

Third, AKK ignore their own findings for the 1990s, which show a substantial deceleration of the relative demand for education. This result is driven by a flattening of the growth of the college wage premium, up only one percentage point over the 1990-95 period and a supply deceleration. Given their own findings of a steady growth of computer use in the 1989-93 period it is hard to see how to reconcile their own data in the 1990s with the technology story they tell.

We now turn to their specific results. The main conclusion drawn from their analysis is based on a comparison of the 1940-70 and 1970-95 periods in Table 7. AKK, however, do not explain their reasoning for aggregating the information into these two time periods. If one examines their estimated demand trends on a decade by decade basis, the data are not supportive of a post-1970 acceleration story of technology's impact. As Table 7 and **Figure 8** show, both the 1940s and the 1990s are clear outliers. In the 1940s, the relative wage of college graduates fell by one-third; and the 1990s, as discussed above, have been remarkably different from the 1980s. AKK's preferred estimates, based on an elasticity of 1.4, tell no simple pre- and post-1970 story: Relative demand growth decelerates from the 1950s to the 1970s, accelerates strongly in the 1980s (to 4.52) and then drops dramatically in the 1990s.[12] One can select any elasticity in **Table 8** and not find any dramatic difference between the 1950-70 period and the 1970-90 period. We would argue that these results suggest either a strong secular growth of relative demand over the entire 1950-90 period (dropping in the 1990s), or an acceleration in the 1980s over the earlier decades (again dropping in the 1990s).

Of course, as we have said, an acceleration of demand in the 1980s is a necessary but not sufficient condition for technology to be the cause of growing wage inequality. It is also necessary to show that the impact of technological change accelerated and was responsible for the overall acceleration in relative demand. Since both trade and labor market institutions have arguably affected the growth of AKK's measures of relative demand through effects on relative wages and relative employment, AKK must purge their demand measures of these nontechnology effects before arguing that any estimated rise in demand can be attributed to technology.

Table 8 presents one attempt to adjust AKK's measures to incorporate these factors. We are particularly concerned about the 1980s, since extensive research has found that changes in institutional factors such as unionization rates (Card 199?; Freeman 199?), minimum wage levels (Fortin and Lemieux 1996; Mishel and Bernstein 1995), product market deregulation (Fortin and Lemieux 1996), and trade and immigration regimes (Cline 1997; Krugman 199?; Borjas, Freeman, and Katz 199?) have played a significant role in rising inequality. Existing research seems to safely establish that changes in labor market institutions can account for at least 20% of the rise in inequality in the 1980s versus the 1970s. A consensus also appears to be emerging that trade probably was responsible for at least 10% of the rise in inequality between the same two periods. In Table 8, then, we deflate the growth in relative wages and the relative wage bill by 30% over the 1980s and recalculate the growth in relative demand, now purged of these probably conservative estimates of the effects of trade and institutions. The exercise reduces the shift in relative demand from roughly 4.52 log points (x100) per year to about 3.17 log points (x100) per year—almost identical to the unadjusted growth rate estimated by AKK for the 1970s. If this comparison is reasonable, it suggests that no acceleration in demand took place between the 1970s and the 1980s.

The rest of the table adjusts the relative wages and relative wage bills for the other decades. While the estimates are subjective, they are not on their face unreasonable and suggest the fragility of AKK's basic conclusions to assuming relatively modest roles for labor market institutions' and trades' influence on employment determination and wage setting. Specifically, we assume that the war economy and its aftermath in the 1940s acted to reduce inequality, lowering growth in the relative wages and the relative wage bill by 30%.[13] In the 1950s, strong unions and extensions in coverage of the minimum wage slowed the growth in the relative wage and wage bill by 20% and the strong trade position of the United States had a similar, though weaker effect (10%). In the 1960s, unionization rates declined as the federal minimum wage climbed to high rates by today's standard while unemployment remained low. We assume that these developments slowed the rise in relative wages and the relative wage bill by 10%, while trade policy continued to slow the growth of inequality by a similar margin. Since the research on the role of institutions in wage inequality has generally used the 1970s or the late 1970s as a benchmark, we have "zeroed" our adjustments to relative demand in the 1970s and assume no effect. As outlined above, changes in labor market institutions and globalization contributed to a rise in relative wages and the relative wage bill, contributing to about one-third of the observed growth. With unionization rates apparently bottoming out and some recovery in the real value of the minimum wage, institutional decay played a smaller role in the 1990s (10%), while trade continued to pinch noncollege-educated workers at the same rate as the 1980s (10%).

Figure 8 summarizes the implied trend in technology-related relative demand (total demand purged of trade and institutional factors) using AKK's preferred elasticity (1.4). As with AKK's original estimates, the new estimates indicate a deceleration in relative demand between the 1950s and 1960s, and the 1960s and 1970s. Unlike AKK, however, they show no acceleration in relative demand between the 1970s and the 1980s. Both estimates suggest a strong deceleration between the 1980s and the first half of the 1990s. All in all, the estimated relative demand shifts, when purged of nontechnology factors such as institutions and trade, show no acceleration in the 1980s over the 1970s, no acceleration of the 1970s and 1980s over the 1950-70 period but definitely show a deceleration of relative demand in the 1990s to a rate far less than that of any of the previous four decades. There is no support here for a technology story of the growth of wage inequality although there is evidence of a continuing strong growth of relative demand for education over the post-war period.

That is, this recomputation of AKK's results draws an opposite conclusion from their main finding of a post-1970 acceleration (which they assume is technology driven). In sum, we find AKK's simple supply and demand analysis to be strongly supportive of a view that there has been no acceleration of technology's impact in recent years (1979-95 or even 1973-95) that can explain the growth of education differentials, let alone wage inequality.

Last, regardless of what conclusions one draws from AKK's estimated trends in relative demand, we have some reservations about the possibility of deducing demand trends from employment trends and changes in relative wages. Our concern is that a rise (fall) in the college wage premium is interpreted as reflecting excess (deficient) demand for college graduates. Yet, this would seem to be an incorrect interpretation of both the 1940s and 1980s and provide a false sense of precision in all time periods. Is it really believable that there was a fall in the relative demand for college graduates in the 1940s? Or, should one believe that the war effort, militant unionism and low unemployment led to wage compression? The events of the late 1980s through the mid-1990s also cast doubt on the development of a large growth in unmet demand for college graduates in the 1980s. After all, the period following this supposed pent-up demand saw a large drop in the wages of young college graduates, a decelerated growth in the relative demand and supply of all college graduates, a slowdown in the shift to white-collar employment and a falling share of nonproduction worker employment in manufacturing.

B. ***Johnson's Indirect Measures of Relative Demand for Education***

George Johnson's (1997) recent paper also presents a decade by decade series of the implied shifts in the relative demand for education (college graduate equivalents), which are presented in **Table 9**. Johnson interprets these results as showing a slight acceleration of relative demand in the post-1980 period relative to earlier decades.

Some of the limitations of the AKK analysis discussed earlier apply to Johnson's analysis as well: the focus on education differentials rather than wage inequality; and, the labeling of relative demand shifts as technology-induced with no effort to account for trade and institutional factors.

At first blush, Johnson's estimates of the decadal shifts in relative demand for college graduate workers appear to differ significantly from those of AKK. In particular, Johnson shows a slight acceleration in the demand for college graduate workers between the 1980s and the 1990s (from 4.7% per year to 5.0% per year), while AKK find a sharp reduction (from 4.5% per year to 1.9-2.4%) (see columns (1) and (2) of Table 9). Several differences with Johnson's approach, however, account for the differences between the two estimates. First, Johnson defines skilled workers using an "equivalents" measure that assigns a portion of workers with more than 12 but less than 16 years of schooling to be "high-school equivalents" and a portion to be "college equivalents." There is both a data construction problem and a substantive problem with combining those with "some college" with those having at least a four-year college degree. The data problem is that the CPS coding for education changed in 1992 in a way which artificially exaggerates the growth of the supply of skills. For instance, the share of the workforce (in the ORG CPS) with "some college" jumps from 23.1% in 1991 to 28.2% in 1992, a larger change than over the entire 1979-89 period (up 3.1 percentage points). The substantive issue is whether those with "some college" should be grouped with those with a four-year college degree. Since nearly all (87%) of the "some college" workforce has no degree past a high school diploma (see Mishel et al 1997, Table 3.21) and their wages are closer to and move together with those of high school graduates (Katz and Murphy 1992) it may not be appropriate to group them with college graduates (although Johnson adds in less than half of them).

To see how Johnson's treatment of the "some college" group affects his results we have constructed column (3) of Table 9 which recalculates Johnson's estimates using his data for college (4 years or more) versus noncollege graduates—a grouping much less sensitive to the 1992 education coding change—instead of his college equivalents measure.[14] As with the college-equivalent measure, the college-noncollege data show roughly constant growth in relative demand in the 1950s, 1960s, and 1970s, and an acceleration in demand during the 1980s. Where Johnson's college-equivalent estimates suggest a slight further acceleration in demand between the 1980s and 1990s, however, Johnson's college-noncollege data show a sharp deceleration in the 1990s, consistent with that observed by AKK, who are careful to use consistent measures of education across the 1992 change (using data from the decennial 1990 Census or the February 1990 CPS supplement, both of which use post-1992 education definitions, as the base year data). We conclude that Johnson's estimates of relative demand trends for the 1990s (relative to the 1980s) are very sensitive to his grouping of "skilled" workers.

The second difference is that Johnson's estimated trends in the college-high school wage premium show continued strong growth in the 1990s while AKK show a stagnation (our own trends are closer to AKK than to Johnson). This may be because Johnson uses raw college-noncollege wage differentials (not ones that have been regression adjusted) or is somehow related to the coding change. In column (4) of Table 9, we have used changes in the regression adjusted differential from AKK for periods roughly comparable to those in Johnson to further adjust the college-noncollege estimates in column (3). Again, these adjustments make little difference to the pattern from 1940-89, but further reduce the estimates for the growth in relative demand in the 1990s.

Our conclusion is that indirect measures of the growth of relative demand for college-educated workers clearly show a deceleration in the 1990s, a trend at odds with the usual technology story. Moreover, making any reasonable accounting for nontechnology factors, such as trade and institutional changes, would show a decelerating impact of technology over the post-war period.

IV. Estimating Technology's Impact

The starting point of our empirical effort is that educational and skill upgrading (the shift towards the use of more skilled and more educated workers) was strong in the 1980s and that it occurred primarily within industries (rather than being driven by the change in the composition of employment across industries). These facts plus the growth in the relative wage of educated (i.e., college graduates) and "skilled" workers (reflected in the 90/50 and 90/10 differential) is the basis for the belief that the relative demand for education grew strongly in the 1980s (and outpaced relative supply). It is usually assumed that technology explains the within-industry shifts toward more educated/skilled workers. In this section we present our results based on a methodology which allows us to estimate technology's impact on skill demand (the use of high wage versus low wage workers and educational upgrading) in particular time periods. This allows us to test for an acceleration of technology's impact in the 1980s versus earlier decades (and the 1990s) and provides information on technology's role in the growth of education differentials and overall wage inequality.

A. Methods and Data

In order to measure technology's impact on the within-industry use of skill, we use a variation on models employed by Berman et al (1993, 1996), Goldin and Katz (1996) and others (Machin et al 1996, Berndt et al 1992). In these models, technology indicators are quasi-fixed and labor shares are the variable factors (see Berman et al (1993) for the derivation). As Goldin and Katz (1996) point out, if a translog function is assumed for the variable cost function, cost minimization produces an equation where a labor input's share is a function of the following factors:

(1)

$$SK_{it} = \alpha_{it} + \beta_1 \log Y_{it} + \beta_2 TECH_{it} + \beta_3 (W_{sk} / W_{un})_{it}$$

SK is the share of skilled workers in industry i, time t; Y is a measure of output, and TECH is a measure of capital intensity. The theoretical model includes a measure of relative wages of the skilled to the unskilled. The first term above, α_{it}, serves to capture industry-specific fixed effects. In this model, β_2 is a measure of capital-skill complementarity, with $\beta_2 > 0$ implying complementarity in the cross-section.

The coefficient on the relative wage term is a measure of the elasticity of substitution between skilled and unskilled workers. The relative wage term, however, is typically dropped because the industry-specific relative price of labor does not vary across industries and will thus be captured by the constant.

While (1) measures complementarity in the cross-section, we are interested in capturing the change in complementarity across time. Differencing (1) accomplishes this plus removes the fixed effects. In this case, the coefficient on $\Delta TECH$ (the change in technology within industry i) measures the complementarity of a technological factor in that time period. This is the test seen in much of the literature cited above (e.g., Autor et al). Note that this type of model restricts the change in complementarity to be constant across time periods.

However, the effect of technological change can differ across time periods, i.e., accelerate or decelerate, because of shifts in the rate of technological change and/or changes in the skill bias (perhaps from a qualitative shift in the type of new technologies such as computerization). To examine this possibility, we extend (1) further by introducing fixed effects for the time period, and more importantly, the interaction of these time-dummies with the technology variables, which permit test for changes in complementarity:

$$\begin{aligned} &\Delta SK_{it} = \alpha_1 T_2 + \beta_1 \Delta \log Y_{it} + \beta_2 \Delta TECH_{it} \\ (2) \quad &+ \lambda_1 (\Delta TECH_{it} * T_2) \end{aligned}$$

In (2), which examines changes in complementarity over two time periods (the reference period, T_1, is omitted), skill shares, value added, and technology are all measured as first differences. The interaction term measures the extent to which technology's impact on within-industry skill demands differed over the time periods under analysis. For example, $\lambda_1 > 0$ implies that technology's complementarity with skilled workers within industries was greater in T_2 than in T_1.

Our goal, however, is not only to examine whether complementarities have changed over time but to quantify technology's impact on the employment and wage structure in specific periods. Such an impact must incorporate changes in both complementarities and changes in the pace of technological change (as proxied by the growth in technology indicators, like computer and R&D investment).

Specifically, we compute:

$$TI_t = \sum_{k=1}^{2or3} \beta_{kt} * \Delta \overline{TECH_{kt}} \tag{3}$$

TI is the impact of technology on a dependent variable in time period t. The coefficients used in (3) are those relevant to the particular time period and the variables of interest. We generate predictions for each time period for two models, with and without the growth in computer accumulation. Thus, k includes either only the changes in equipment accumulation and R&D or these changes plus those of computerization (the data we use for these technology indicators in explained below). Likewise, $\Delta \overline{TECH}_{kt}$ is the average within-industry change of each of these technology indicators. Calculating differences in these predictions (along with their standard errors) allows us to identify significant acceleration of trends across time periods.

Specifically, we estimate variations of the following model:

$$\Delta y_{it} = \alpha + \beta_1 60s + \beta_2 80s + \beta_3 90s + \sum_{k=1}^{3} \beta_k \Delta TECH_{it} +$$

$$\sum_{j=1}^{3} \beta_j \Delta TECH_{it} * 60s + \sum_{m=1}^{3} \beta_m \Delta TECH_{it} * 80s + \sum_{n=1}^{3} \beta_n \Delta TECH_{it} * 90s + \varepsilon_{it}$$

All non-dummy variables are measured as annualized changes. The subscript i denotes the unit of observation, i.e., the industry; we observe changes within 31 (16 manufacturing, 15 non-manufacturing) private sector industries over four time periods (1963-73, 1973-79, 1979-89, 1989-94), resulting in 124 observations. It is noteworthy that our data includes the entire private sector and is not limited to manufacturing as is much of the literature (e.g., Berman et al, 1994, 1996). Separate models are run for men and women (F-tests for various models reject the hypothesis of equal coefficients by gender).[15]

The subscript t denotes one of the four time periods noted above; α is the constant term; 60s, 80s, and 90s are dummies equal to one in their respective time periods and zero otherwise; ϵ is an iid error term. We also add employment growth, N, as a proxy for the growth of output.

The dependent variable is a measure of change in the composition of employment. We use two measures, explained below: education and wage quantities. The independent variables, in the vector "TECH," are changes in our technology indicators: accumulation of equipment per full-time equivalent worker (FTE), accumulation of computers per FTE, and R&D. We interpret equation (2) as a reduced form model with the technology indicators shifting demand and supply shifts captured by the time period dummies.

The parameters in (2) are estimated by weighted least squares. Since all variables are measured as first differences, we do not fix effects. As we expect changes in larger industries to disproportionately effect changes in the wage structure, we control for the relative size of each industry by weighting the regressions by gender-specific employment shares. These shares are simply the average of employment by industry taken at the two endpoints of each period.

This reduced-form model permits us to test the technology hypothesis. The coefficients on the technology indicators measure the complementarities or skill bias of technology indicators with particular types of workers; the interactions with the time period dummies allow these complementarities to shift—accelerate or decelerate—across time periods. Thus, the coefficients in β_j represent the change in skill complementarities in the 1960s over the 1970s; likewise, the coefficients in B_m represent the change in skill complementarities in the 1980s relative to the 1970s. The direct effect in the 1980s and 1990s is simply the interaction term plus the non-interacted term. Thus, to compare the 1980s effect to that of the 1990s simply calls for comparing β_n to β_m.

i. *Dependent Variables*

Our two dependent variables reflect two dimensions of wage inequality, between-group (education quantities) and overall wage inequality (wage quantities).

Education quantities are simply the share of workers in a given education category within an industry. For example, in one set of regressions, Δy_{it} will represent the annual percentage point changes in the share of high-school graduates in each of the 34 industries in each of three time periods. We present separate estimates for those with a four-year college degree from those with advanced degrees because the wage trends for the two groups have differed significantly (the wages of workers with advanced degrees have risen much more quickly than those with terminal college degrees (see Mishel et al, 1996, Table 3.18)).

"Wage quantities" are our measure of an industry's utilization of low, middle or high wage workers. If one assumes that wage levels correspond to skill levels, observable and unobservable, then "wage quantities" provide the most comprehensive measure of skill utilization by industry. In any case, the wage quantity measures capture the dimension in which we are most interested: is there an association between technological change and the share of workers in low-paying, middle-paying or high-paying jobs.

We calculate wage quantities for five groups within each industry, with the wage quantities defined relative to the male 1979 private sector wage distribution.[16] The first step was to determine the percentile cutoffs for the groups of interest. We chose 0-20, 21-50, 51-75, 76-90 and 91-100 so that we would clearly separate the bottom and the top half, have a measure of low wage employment (the 20th percentile roughly corresponds to the share of workers earning "poverty level" wages in 1979), have groups which aggregate to the bottom 75% (the non-college educated share of employment), and be able to separate out the highest wage workers. Using the estimated cutoffs (deflated by the CPI-U-X1) for 1979 we compute the share of workers in each "wage quantity" in each industry in each year. The annual percentage point change in these "wage quantity" shares in each time period are the dependent variables used in the regressions.

More formally, wage quantities are defined as:

$$w_{it}^{1} = \sum_{0}^{y_{0.20}} x_{it}, w_{it}^{2} = \sum_{y_{0.20}}^{y_{0.50}} x_{it}, w_{it}^{3} = \sum_{y_{0.50}}^{y_{0.75}} x_{it}, etc.$$

For each quantity, x_{it} is the number of workers at a given wage level (in 1979 dollars) within industry i at time t, in ascending order by wage, weighted by CPS demographic weights and normalized to one. The y's in each summation are wage cutoffs at the given percentile taken from the entire male private sector in 1979. Thus, each summation returns the share of workers in the industry in the relevant wage range for the time period in question. The dependent variable is the annualized difference in these shares across time periods.

There are a number of reasons why we judge wage quantities to be an appropriate endogenous variable subject to skill-biased technological change. Since we are interested in the impact of technological change on the wage structure within industries, we need a way to measure the wage structure that avoids spillover effects between industries. Since workers can be mobile across industries, there is reason to believe that changes in the relative wage in one industry can spill over into other industries. Thus, if the relative price of skill/education rises in industry x, an employer who wants to hire a worker with similar credentials in industry y has to meet that "skill premium." This implies that there will not necessarily be any observable correlation between changes in wage differentials within industries and technological change because all industries, including technology laggards, will see wage differentials grow (this explains why the relative wage term from equation (1) is omitted from our estimating equations).[17]

"Wage quantities," however, are the wage equivalent of education level shares in that they do not reflect spillover effects across industries; wage quantities reflect employer decisions about the needed mix of employment for their production technology given the existing structure of relative wages. Technological change in other industries does not affect an employer's calculation of how many low-wage (or "low-skilled") workers to hire. Other industries will affect a particular industry's utilization of high, middle and low wage workers only insofar as relative wages change, which should affect industries uniformly. There is no spillover when a particular industry decides to change its employment mix of workers among wage quantities because that decision does not affect any other industry's wage quantity mix.[18]

In the interest of maximizing data consistency, we tried to use similar data sources for each specific period. Thus, for the 1960s (1963-73), the dependent variables come from the March CPS, which has industry, education, and wage data going back to 1963. For the 1970s (1973-79), we used the May CPS and the annual CPS Outgoing Rotation Group (ORGs) files (the ORG files begin in 1979).

Another consistency challenge comes from the change in education coding in the 1992 CPS, from years of schooling completed to degree attained. In this case, we make use of the fact that both the 1994 ORG and the 1990 PUMS (with education attainment data for 1989) use the new coding. Thus, we developed two sets of 1989 data on education shares, one with the old coding (from the ORG) for comparison with 1979 and the other with new coding for comparison with 1994. Since we cannot be certain (but are suspicious) about the measurement error introduced in this process, we de-emphasize the 1990s results on education shares and focus on wage quantity outcomes. Last, the new survey introduced in 1994 required some adjustments to increase comparability, particularly in measuring weekly hours (see Appendix in Mishel et al, 1996).

Due to various changes in the CPS over the past 20 years, the development of a consistent series requires a few other data adjustments. Since the 1973 data use no imputations (or, in Census terminology, "allocations") in the wage data (later CPS's include assigned values when observations have missing values), we developed two sets of data for 1979. One set, without imputations, was used to calculate differences with 1973 data; the other set, with allocated values, was used to difference with 1989.

ii. *Independent Variables*

We use three indicators of technological change. Two are measures of capital accumulation: the changes in the gross real equipment stock and gross computer stock per full-time equivalent (both are deflated by chain-weighted indices). These are drawn from BEA's tangible wealth series and full-time equivalents (FTEs) from the NIPA series.[19] "Computers" are actually measured as the category "office, computing, and accounting equipment," which is a subset of the equipment category. Since the growth in computerization is by far the dominant factor behind the growth in this category, we refer to this variable as computer investment per FTE.[20]

As Berndt et al (1992) point out, the fact that computers are a subset of equipment has useful econometric properties when both are entered as independent variables. The coefficient on the computer variable represents the impact of this type of investment relative to that of equipment. Thus, an insignificant coefficient on the computer variable does not mean that computers have no impact on demand for different types of labor. It does mean, however, that the impact of computers is not quantifiably different than that of other types of capital equipment.

Research and development activities by industry were proxied, as in Allen (1993, 1996), by the share of scientists and engineers in each industry, derived from the CPS. Allen has shown that this measure correlates highly with more direct measures. In order to avoid an endogeneity problem in the coefficient estimate of this variable, we removed scientists and engineers prior to calculating our dependent variables.[21]

Note that our capital per worker variables are entered as (annualized) real dollar changes in capital accumulation per worker. Our intention here is to avoid large percentage changes that result from increases in accumulation over a small base. Thus, if the workforce in two industries were equal yet the base capital stock were larger in one case, we treat a $1,000 dollar increase in stock per worker the same in both cases. Our implicit assumption is that complementarities are a linear function of gross dollar changes, or simply put, a dollar of investment should be allowed to effect quantities the same in industries with large or small base levels of capital. Earlier models in the form of (1) which used percent changes yielded similar results (Mishel and Bernstein 1996).

One final addition to equation (2) is the inclusion of a variable measuring industry employment growth. The purpose of this variable is both to control for differential rates of industry growth that might mistakenly be assigned to one of the other regressors and to proxy for the output variable in equation (1). Other models in the literature (e.g., Berman et al (1993), Goldin and Katz (1996)) use industry value added or shipments as a control. In our models, we use the growth of FTEs.

The impact of technological change in a time period in our analysis depends on two factors: (1) the relationship, or complementarity, between particular technology indicators and changes in the skill/wage/education composition of the workforce reflected in the coefficients on the interaction terms from equation (2) above. The second factor is the rate of introduction of new technologies reflected in the within-industry growth of various "technology indicators." The growth rates of these variables (along with those of the dependent variables) are given in appendix **Tables A** and **B**.

B. Results

As a first step we estimate the complementarities between our technology indicators and skill measures using our data as pooled cross-sections for 1963, 1973, 1979, 1989 and 1994. **Table 10** presents the results for two measures of skill which are summary measures—the shares of an industry's employment which are high school equivalents or in the bottom three-fourths of the wage structure (using 1979 cutoffs). Two models are presented, one with equipment per worker and the employment share of scientists and engineers (our R&D variable) and the other which adds computer equipment per worker.

The results provide strong evidence in support of skill complementarity in the cross-section, as greater capital per worker and R&D activity is associated with proportionately fewer high school equivalent workers. The coefficients are generally negative and significant, for both men and women. For example, the equipment per FTE variable in model (1) is significant at the 1% level for both genders in the model with high-school equivalents as the dependent variable.

By adding computer equipment while retaining the equipment variable, we can test the extent to which computer investment has a quantifiably different impact on within-industry skill demands than other equipment (i.e., in the cross-section). The results for high-school equivalents show that, controlling for equipment investment, those industries with higher levels of computer investment per FTE were those with smaller relative shares of high-school equivalent workers. The result for males is particularly strong; entering the computer variable renders the equipment coefficient insignificant, suggesting that skill complementarities are more highly correlated with computer than equipment investment. It is interesting to note that in models (unreported) which predict high school equivalents we do not find equipment complementary with more education unless there are industry effects included, underscoring the within-industry nature of technology's impact.

In the wage quantity models, the pattern of complementarities are similar to the education results for men, but less so for women. In the male regressions, equipment per FTE and our R&D proxy reveal significant negative complementarities with workers in the bottom 75% of the wage scale. The computer variable, however, is negative but insignificant. For female wage quantities, the coefficients on equipment and R&D have the expected negative signs, but only the equipment variables are significant and the computer variable, while also insignificant, has the "wrong" sign.

These results, like others in the literature, show skill complementarity, but do not address whether technology's impact on skill demands was greater in the 1980s or 1990s, a result of increased complementarities and/or faster growth in the factors (such as equipment and R&D) complementary with skill. To answer this set of questions we turn to estimates of equation (2), which allows us to measure complementarity between specific technology indicators and the dependent variables over time in each of the four time periods.

We also present estimates of technology's impact on education and wage upgrading (**Tables 12-14**) based on equation (3). These estimates capture the effect of shifts in complementarities and the acceleration/deceleration of technology indicators across time periods. Our estimates of technology impact by period provide the bottom-line test of whether technology had a larger effect in one period relative to another.

The first step in the process of estimating "technology impact" by time period is a set of regressions (based on equation (3)) establishing the relationship between technology indicators and educational upgrading and shifts in wage quantities. However, we present only a subset of the regression estimates, specifically, those with the dependent variable "college or more" (the annualized change in the within-industry share of those with at least a college degree [16 or more years of schooling] by gender). The full set of regressions is relegated to the appendix. Estimates are provided for two specifications, one which includes a measure of computerization (model (2)) and the other (model (1)) which does not. This allows us to explore the role of computerization and to examine the sensitivity of our results.

The estimated coefficients in **Table 11** allow us to assess the relationship between technological change and within-industry shifts in the utilization of college graduates. For males, none of the interaction terms are statistically significant, suggesting no shifts in complementarity between these technology indicators and educational upgrading. In addition to being insignificant, many of the coefficients have the "wrong" sign. For example, for males, the R&D proxy and, in model (2), the computer variable are negative in the 1980s, suggesting less capital/skill complementarity between these indicators and skill upgrading in the 1980s relative to the 1970s. In the case of the capital variables, the technology indicators are negative in the 1990s (relative to the 1970s) as well.

The female college graduate-share regressions also reveal no evidence of a significant change in complementarities. The only significant coefficient–equipment per FTE in the 1990s relative to the 1970s—suggests *less* intensive use of female workers in industries where equipment investment grew the most in the period.

The fact that the coefficients on computers per FTE are insignificant is initial evidence that the impact of computer equipment on educational upgrading does not differ from that of other types of equipment investment.

Table 12 combines (using equation (3)) the information of shifts in complementarity from the regressions with the growth in capital and R&D, to present estimates of "technology's impact" on educational upgrading for each period and the shifts across time periods. Standard errors for these predictions were computed and used to note when a "technolo????? Like others who have run similar models, we find significant complementarity between education and capital deepening over the periods we examine. Note for example, the impacts from model (1) for males are significant and positive in the 1970s, 1980s, and 1990s. That is, technology is associated with educational upgrading in each period. But, most importantly for our purposes, there is no evidence indicating a significant *acceleration* (either statistically or quantitatively) of technology's impact in the 1980s or 1990s relative to the 1970s. Only in the 1970s relative to the 1960s is there evidence of an acceleration of technology's impact, a finding consistent with Autor et al (1997).

The results for high school equivalents (see appendix for complete results) can be used to quantify the wage effects of shifts in technology's impact. Using model (1) for men, technology's impact was to shrink the employment share of high school equivalent workers by 0.172 percentage points per year in the 1980s, a rate .031 faster than the -0.140 rate in the 1970s. Note, however, that while both of these period specific impacts are statistically significant, their difference—which measures the acceleration of technology's impact—was not. Equally important, the magnitude of the acceleration, –.031 percentage points a year, implies an additional 0.31 percentage point shrinkage in the relative employment of high school equivalent workers over the entire 1979-89 period. Using the Katz and Murphy elasticity of –.709 employed in Borjas, Freeman and Katz (1996), an 0.31 percentage point employment effect implies technology's effect in the 1980s was to reduce the relative wage of male high school equivalents by 1%.[22] When computerization is included in the model, as in model (2), one finds again that technology's impact was small quantitatively and statistically.

Ignoring the fact that this demand-shift estimate is statistically insignificant, a one percentage point technology-induced decline in relative wages is not a trivial effect. It does serve, however, to deflate the elevated role of technology in the wage inequality debate, putting technological change well behind other factors which explain the growth of education premiums such as industry shifts, international trade, deunionization and a lower minimum wage.

The bottom line estimates for the technology story are those relating to wage quantities, results which examine whether technology is associated with the increased (decreased) use of high (low) wage workers. We relegate the regression-based estimate of complementarities to the appendix and present the technology impacts (equation (4)) in **Tables 13** and **14**.

The data do tell a technology story but it is not the conventional one, as there is no evidence of a significant technology-driven acceleration in demand for high paid workers. Looking first at the male results, the negative shift in technology's impact was greater in the 1980s than in the 1970s (by 0.042 points per year) but this impact is statistically insignificant. Furthermore, technology's impact in the 1990s relative to the other periods appears to be favorable to low-wage workers, the opposite of what the conventional technology story would suggest. For this lowest paid group of male workers, the only significant technology-induced deceleration occurred in the 1970s relative to the 1960s, in model (1) only.

Interestingly, technology's impact on low-middle wage male workers (21%-50%) shifted favorably (or, more precisely, was less adverse) in the 1980s and 1990s relative to the 1970s, in both models (1) and (2). For example, model (2) suggests that equipment, computer, and R&D accumulation had a neutral impact in the 1980s (-.008 per year), a .398 statistically significant improvement over the -.407 tech impact in the 1970s. Conversely, at the higher end of the wage scale, technology's impact led to a statistically significant *de*celeration in demand for high wage workers in the 1980s and 1990s (relative to the 1970s). Note, for example, the significant negative shift of -0.292 against male workers in the 76-90% quantity in the 1980s relative to 1970s (model (2)). For the top male wage quantity, the 1980s deceleration (over the 1970s) is insignificant, but the 1990s deceleration in model (2) is significant with $p<0.05$.

The wage quantity results for men are not supportive of the Autor et al (1997) finding of a post-1970 acceleration of technology's impact (relative to the 1960s). That is, the estimates in Table 13 do show an acceleration of technology's impact in the 1970s over the 1960s, but it is totally reversed in the 1980s. Therefore, according to the wage quantity results, there is no acceleration of the 1970s and 1980s taken together relative to the 1960s.

Table 14 combines wage quantities into the bottom half of the work force and the top 25% (a grouping comparable in size to those with at least a college degree). The results clearly reveal that, relative to the 1970s, technological change in the 1980s was less adverse for the bottom half and less favorable to the highest paid 25% of men. Moreover, the skill-bias of technology in the 1990s was either neutral (model (1)) or far more favorable to low and low-middle wage men and more adverse for high wage men (model (2)), with the shifts in the latter case being statistically significant.

The results for female wage quantities also challenge the conventional story. Technology appears to have strengthened demand for the low wage female workers, and weakened demand for female workers in the top three wage quantities (Table 13). For example, the technology impacts for the 1980s and 1990s relative to the 1970s are positive and significant for females in the 21%-50% wage quantity in both models. The technology impact switches sign, however, for females in the 51-75% group and above. The combined female wage quantities in Table 14 underscore this pattern; technology-induced demand shifts are uniformly positive and significant in both models for women in the bottom half of the wage quantities, and negative (though not always significant) for those in the top 25%. The results for the 1990s for women parallel those for men: either technology has had no skill bias (model (1)) or has recently favored lower wage women and been adverse for high wage women (model (2)).

Model (2) in Table 14 also points out that when we: 1) combine the impact of both changing complementarities and changes in investment patterns (as in equation (3)); and, 2) test for acceleration, the impact of computers on the wage structure is quite different than is commonly believed. All of the acceleration tests for model (2) except one are significant and show the impact of technology to be shifting against higher paid workers (only the female 1980s vs. 1970s result is insignificant).

Conclusion

We believe our analysis provides a more complete analysis of the impact of technology on the wage structure than previous work. In particular, we broaden the analysis by focusing on: wage quantities as well as education quantities; acceleration; the entire private sector rather than just manufacturing; disaggregated groups rather than a dichotomous breakdown (college/non-college, production/non-production); shifts in complementarities; an analysis of descriptive trends and technology impacts in the 1990s; and examining both male and female trends. This more complete analysis produces a technology story different from the conventional one.

While we do find an acceleration in technology's impact on the wage structure in the 1970s over the 1960s, we find no evidence that there was a technology shock in the 1980s that adversely affected "better educated" (college graduates) or "more skilled" (high wage) workers relative to those with "less education" (noncollege graduates) or "less-skilled" (the bottom three-fourths) workers. Our estimates show that technology's impact on college-educated workers was not significantly greater in the 1980s than the 1970s.

Our results using wage quantities provide strong evidence against any accelerated technology impact in the 1980s or 1990s. Our estimates for high wage men (Table 14) find a quantitatively large (0.4% per year) and statistically significant deceleration of technology's effect in the 1980s versus the 1970s or in the 1990s versus the 1970s (an 0.6% to 0.8% annual deceleration). There are comparable (though smaller in magnitude) results for women. Technology was more favorable to the bottom half of men in both the 1980s and the 1990s than in the 1970s, directly contradictory to the notion that the bottom half was being left behind because their skills did not keep up with technological change.

Our findings are *not* that technology had no impact on the wage structure in any time period. We continue to be convinced of the critical and ongoing role played by technology in the skill upgrading of the labor force over the long-term. Rather, we do not find any *increased* association of technological change with the increased utilization of the most educated or best-paid workers, and without such an acceleration technological change cannot be seen as the source of growing wage inequality in the 1980s or 1990s.

How can this be reconciled with the stylized facts of the wage inequality literature? First, within-industry change represents the potpourri of factors that do not affect the industrial composition of employment. This includes within-industry effects of trade and capital mobility, and of institutional changes (unions, deregulation, minimum wage). If one aggregates these effects—the impact of trade, industry shifts, immigration, deunionization and the lowering of the minimum wage—the total impact accounts for a large majority of the growth of wage inequality. Skill biased technological change—an important factor in the long-term composition of employment—has contributed very little to the recent increase in overall wage inequality.

Endnotes

1. These are terms used by Berman, Machin and Bound (1996).

2. Some mistakenly invoke the growing service sector share of employment as evidence of growing measurement error. It is only output shares, however, that matter.

3. The fact that this result can be shown on both the ORG and the March CPS means that the differences in WGWI growth in the 1970s in these two data sets are not driving the finding of a proportionately minor (but quantitatively large) role for changes in skill returns over the last two decades.

4. For instance, there is a significant jump in the ORG CPS college wage premium series when the coding changes, 1991-92. The March CPS series, where coding was constant (and new) for the 1991-92 period, shows a lesser jump in the college wage premium, especially among women.

5. Our data do not show a supply deceleration (especially among women) and show a somewhat larger increase in the college wage premium, suggesting a lesser deceleration in the relative demand for college workers than shown by Autor, Katz and Krueger (1997).

6. These data are drawn from Mishel, Bernstein, and Schmitt (1996).

7. BMB show an acceleration in skill-upgrading in the United States during the 1980s. This, however, is entirely dependent on the growth between 1979 and 1982. Their Figure 4 shows the share of nonproduction workers falling during the 1980s in Canada, a country excluded from their Table III.

8. Note that the effect that BMB and Lawrence are appealing to is *precisely* the mechanism of the Stolper-Samuelson effect. Under Stolper-Samuelson, the movement along a given relative demand curve reflects the induced change in relative skill supply. As international trade reduces output in the less-skill-intensive industry, it disproportionately releases less-skilled workers. The relative abundance of less-skilled workers causes the relative supply of skilled workers to shift inward—to a new equilibrium where relative wages of skilled workers are higher but relative employment of skilled workers in each industry is lower.

9. Data from the BLS's Establishment Survey show relative nonproduction worker employment in 1996 still below its 1989 level; the survey, however, does not provide relative wage data.

10. Dean Baker suggested this interpretation of the data.

11. We focus on the results with the "college or more" shares rather than the "college equivalent" shares because most of those with "some college" have no degree past high school and their wage trends correspond more closely to those of high school graduates.

12. An argument offered by one of the AKK authors for aggregating the 1940s with the 1950s is that one should treat the 1940-60 period as one unit because the 1940s wage structure shifts are

clearly driven by institutional factors that are somewhat offset in the 1950s. Maybe so. But this comment only raises the issue of the impact of institutional factors on every decade, something AKK overlook. We propose a method of adjusting their estimates for trade and institutional factors below.

13. Not much rides on the 1940s in any event.

14. Unfortunately, using a "college or more" definition understates the shift to college graduates because of the new coding ("college graduates" no longer are people with 16 or more years of schooling but have a college degree). The March CPS series for 1991-92 (which uses the new coding in both years) shows a 0.5 percentage point greater growth in the college share relative to the ORG CPS series.

15. For example, the null hypothesis of equality of coefficients in a model with college graduate shares of employment as the dependent variable was rejected at the 5% level.

16. In earlier work, we used gender-specific cutoffs to calculate wage quantities. Here we shift to a single cutoff for both genders to heighten the comparability between the wage quantities and the education quantities. That is, as the education categories have the same definition for both genders, we impose the same definition for wage quantities as well. The results from our earlier work are qualitatively and quantitatively similar to those in this study.

17.This is a potential criticism of our earlier work (Mishel and Bernstein (1994)) and of the various versions of Allen's research (Allen 1994, Allen 1996).

18. Except indirectly through a change in relative demand and prices.

19. We did not have NIPA FTEs for 1994 so we took the ratio of FTEs in 1993 to BLS payroll employment (by industry) in 1993 and multiplied that ratio by BLS 1994 employment.

20. The capital investment variable available from BEA are measured in real 1987 dollars using a fixed weight deflator. This introduces an upward bias, particularly in computer investment. The BEA intends to address this with chain-weighted price indexes but they have yet to release such indexes by industries. We were, however, able to get chain-weighted indexes for equipment and computers. We used the growth rates in these indexes to adjust the fixed-weighted series, applying the same factor to each industry. We will improve on this in later work.

21. Ignoring this bias should force the coefficient on this variable to have an expected value of one.

22. Given the quantities in our data, this 0.86 demand shift results in a 0.039 log point increase in the supply of high-school equivalent males over that which would have occurred in the absence of the accelerated impact of technology.

Bibliography

Autor, David, Lawrence Katz and Alan B. Krueger, 1997. Revised from July 1996. "Computing Inequality: Have Computers Changed the Labor Market?" Princeton University Working Paper No. 377.

Berndt, Ernst R., Catherine J. Morrison, and Larry S. Rosenblum. 1992. "High-Tech Capital Formation and Labor Composition in U.S. Manufacturing Industries: An Exploratory Analysis." National Bureau of Economic Research Working Paper No. 4010. Cambridge, MA: NBER.

Berman, Eli, John Bound, and Zvi Griliches. 1993. "Changes in the Demand for Skilled Labor Within U.S. Manufacturing Industries: Evidence from the Annual Survey of Manufacturing." National Bureau of Economic Research Working Paper No. 4255. Cambridge, MA: NBER.

Berman, Eli, Stephen Machin and John Bound. 1996. "Implications of Skill-Biased Technological Change: International Evidence." (July, revised in December).

Burtless, Gary, 1995. "Widening U.S. Income Inequality and the Growth in World Trade."

DiNardo, John, Nicole Fortin, and Thomas Lemieux. "Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semi-Parametric Approach." Economometrica 64 (September 1996): 1001-44.

Fortin and Lemieux (1996)

Goldin, Claudia and Lawrence F. Katz. 1996. "Technology, Skill, and the Wage Structure: Insights from the Past." American Economic Review Papers and Proceedings of the Hundred and Eighth Annual Meeting, San Francisco, CA, January 5-7, 1996, Vol. 86, No. 2, pp. 252-257.

Howell, David, 1994. The Collapse of Low-Skill Male Earnings in the 1980s: Skill Mismatch or Shifting Wage Norms?.

Howell, D.R. and E.N. Wolff. 1991. "Skill Changes in the U.S. Labor Force, 1960-1985." Industrial and Labor Relations Review, (April).

Juhn, Chinhui, Kevin M. Murphy, and Brooks Pierce. 1993. "Wage Inequality and the Rise in Returns to Skill." Journal of Political Economy, Vol. 101, (June), pp. 410-442.

Juhn, Chinhui. 1994. "Wage Inequality and Industrial Change: Evidence from Five Decades." National Bureau of Economic Research Working Paper No. 4684. Cambridge, MA: NBER.

Juhn, Chinhui and Kevin M. Murphy. 1995. "Inequality in Labor Market Outcomes: contrasting the 1980s and Earlier." *Economic Policy Review*, Federal Reserve Bank of New York, Vol. 1, No. 1, pp. 26-32.

Krugman, Paul. 1994. "Past and Prospective Causes of High Unemployment." Jacksonhole

Conference (August).

Lawrence F. Katz, and Kevin M. Murphy. 1992. "Changes in Relative Wage, 1963-1987: Supply and Demand Factors." *The Quarterly Journal of Economics*, Vol. CVII, Issue 1, (February), p.72.

Machin, S., A. Ryan and J. Van Reenan. 1996. "Technology and Changes in Skill Structure: Evidence From an International Panel of Industries." London: Centre for Economic Performance, Discussion Paper No. 297, (June).

Mishel, Lawrence and Jared Bernstein. Revised 1994. "Is the Technology Black Box Empty?: An Empirical Examination of the Impact of Technology on Wage Inequality and the Employment Structure." Washington, DC: Economic Policy Institute, Technical Paper.

Mishel, Lawrence and Jared Bernstein. 1996. "Did Technology's Impact Accelerate in the 1980s?" Proceedings of the Industrial Relations Research Association Meetings, San Francisco, CA.

Mishel, Lawrence, Jared Bernstein and John Schmitt. 1996. *The State of Working America, 1996-97*. Economic Policy Institute Series. Armonk, NY: M.E. Sharpe, Inc.

Mishel, Lawrence and Jared Bernstein. Revised 1997. "Technology and the Wage Structure: Has Technology's Impact Accelerated Since the 1970s?" Paper presented at the NBER Labor Studies Workshop, July 1996.

Mishel, Lawrence. 1997. "Productivity Measurement Errors: The Relationship Between Sectoral, Product and Aggregate Productivity Measures." Forthcoming.

Schmitt, John and Lawrence Mishel. 1996. "Did international Trade Lower Less-Skilled Wages During the 1980s? Standard Trade Theory and Evidence." Economic Policy Institute, Technical Paper.

Table 1
Productivity Growth and Capital Accumulation, 1948-95

Year	Productivity*		Capital Accumulation	
	Output per Hour	Multifactor	Capital Services Per Hour	Equipment Per Worker
Annual Growth**				
Pre-1973				
1948-73	n.a.	1.8%	2.8%	n.a.
1959-73	2.9%	1.9	2.9	3.7%
Post-1973				
1973-79	1.1%	0.3%	2.4%	4.2%
1979-89	1.0	0.0	2.4	2.8
1989-94	0.9***	0.2	1.4	2.3

*Nonfarm business sector.
**Log growth rate.
***1989-95.

Source: Authors' analysis.

Table 2

TABLE

Decomposing the Change in Overall Wage Inequality Among Men, 1973-95

Change Period	Change in Differential*			Percent of Overall Change		
	90-10	90-50	50-10	90-10	90-50	50-10
(a) 1973-79						
Overall	2.1	-1.4	3.5	100.0%	100.0%	100.0%
Returns to "Skill"**	-2.1	-0.4	-1.6	-100.0	30.5	-46.7
Other***	4.1	-1.0	5.1	200.0	69.5	146.7
(b) 1979-89						
Overall	14.3	10.3	4.0	100.0%	100.0%	100.0%
Returns to "Skill"**	8.7	5.4	3.3	61.0	52.7	82.5
Other***	5.6	4.9	0.7	39.0	47.3	17.5
(c) 1989-95						
Overall	6.9	6.9	0.0	100.0%	100.0%	100.0%
Returns to "Skill"**	1.5	1.2	0.3	21.7	16.9	n.a.
Other***	5.4	5.7	-0.3	78.3	83.1	n.a.
(d) 1973-95						
Overall	23.2	15.7	7.5	100.0%	100.0%	100.0%
Returns to "Skill"**	8.1	6.2	2.0	35.0	39.1	26.4
Other***	15.1	9.6	5.5	65.0	60.9	73.6

* In logs.
** Change in between-group inequality, i.e., change in returns to education and experience.
*** Changes in within-group inequality and change in levels of education and experience.

Source: Authors' analysis of Outgoing Rotation Group of CPS.

TABLE 3

Decomposing the Change in Overall Wage Inequality Among Women, 1973-95

Change Period	Change in Differential* 90-10	90-50	50-10	Percent of Overall Change 90-10	90-50	50-10
(a) 1973-79						
Overall	-16.0	1.8	-17.8	100.0%	100.0%	100.0%
Returns to "Skill"**	-6.5	-3.0	-3.5	40.8	-166.9	19.8
Other***	-9.5	4.8	-14.2	59.2	266.9	80.2
(b) 1979-89						
Overall	35.2	9.5	25.6	100.0%	100.0%	100.0%
Returns to "Skill"**	13.0	6.2	6.8	37.0	64.5	26.7
Other***	22.2	3.4	18.8	63.0	35.5	73.3
(c) 1989-95						
Overall	2.7	6.0	-3.3	100.0%	100.0%	100.0%
Returns to "Skill"**	2.8	2.0	0.8	104.9	34.0	-23.9
Other***	-0.1	4.0	-4.1	-4.9	66.0	123.9
(d) 1973-95						
Overall	21.9	17.3	4.6	100.0%	100.0%	100.0%
Returns to "Skill"**	9.3	5.2	4.1	42.6	30.0	90.2
Other***	12.6	12.1	0.4	57.4	70.0	9.8

* In logs.
** Change in between-group inequality, i.e., change in returns to education and experience.
*** Changes in within-group inequality and change in levels of education and experience.

Source: Authors analysis of Outgoing Rotation Group of CPS.

Table 4

Estimated College-High School Wage Premium, 1973-1996

	ORG CPS				March CPS			
	Men		Women		Men		Women	
Year	Simple Model*	With Indy Controls**	Simple Model*	With Indy Controls**	Simple Model*	With Indy Controls**	Simple Model*	With Indy Controls**
1973	32.5%	35.9%	43.0%	39.6%	n.a.%	n.a.%	n.a.%	n.a.%
1974	32.4	35.3	38.6	36.4	n.a.	n.a.	n.a.	n.a.
1975	34.0	36.3	40.2	36.6	31.9	34.8	37.8	34.9
1976	33.4	35.8	36.6	33.5	30.3	33.0	35.4	33.3
1977	30.6	33.8	34.1	31.6	29.8	32.8	35.6	33.7
1978	28.3	31.9	33.0	30.6	27.3	30.1	33.5	31.5
1979	27.3	30.5	30.8	28.6	26.6	30.1	32.6	31.2
1980	28.8	31.6	31.9	29.5	28.0	31.4	33.1	31.3
1981	30.1	32.6	32.3	29.5	29.5	31.8	33.6	31.4
1982	32.8	34.7	33.8	30.5	32.4	35.5	34.7	32.7
1983	34.6	36.7	36.2	32.2	35.7	37.8	36.9	34.3
1984	37.4	38.7	38.8	34.6	37.5	39.1	39.2	36.4
1985	39.1	39.9	40.5	35.9	39.5	40.5	41.8	38.4
1986	38.7	39.6	42.2	37.2	40.3	41.0	45.1	41.4
1987	39.2	39.8	43.6	38.3	40.2	40.0	42.6	39.5
1988	39.2	39.8	44.0	38.8	40.0	41.0	46.3	42.8
1989	41.8	42.4	46.0	40.8	40.9	41.7	49.3	44.9
1990	42.4	42.8	47.7	42.6	43.2	43.4	48.7	44.8
1991	42.3	42.4	46.5	41.1	41.9	42.2	48.4	44.7
1992	44.3	44.5	49.8	44.1	43.4	43.4	49.9	45.7
1993	45.0	44.9	50.2	44.5	45.0	44.7	52.1	47.9
1994	44.6	44.7	52.2	46.7	44.0	44.4	50.3	45.6
1995	44.1	44.4	52.2	46.3				
1996	43.3	43.5	50.7	45.7				
New Coding								
1991	n.a.	n.a.	n.a.	n.a.	33.8%	35.4%	42.5%	40.1%
1992	36.9%	38.3%	43.7%	39.6%	35.4	36.7	44.1	41.1
1993	37.6	38.7	44.3	40.0	36.8	37.8	46.7	43.7
1994	37.5	38.5	46.3	42.2	36.8	38.4	45.5	42.0
1995	37.3	38.5	46.7	42.1	35.4	36.9	45.9	42.6
1996	36.8	37.9	45.4	41.5				

* Estimated with controls for experience (as a quartic), region(4), marital status, and race/ethnicity and education specified as dummy variables for less than high school, some college, college and advanced degree. Education levels in the top panel based on years of schooling completed, with "imputed years" used after the coding change.

**Adds 12 industry controls to the simple model.

Table 5
Wage Offers to New College Graduates, by Major, 1989–96

Major	Annual Salary ($1996) 1989	1996	Percent Change
Business Admin.	$28,406	$27,274	– 4.0 %
Accounting	31,915	29,375	– 8.0
Advertising	24,750	23,679	– 4.3
Elementary Ed.	$23,746	$22,731	– 4.3 %
History	29,543	24,627	– 16.6
Psychology	24,547	22,312	– 9.1
Nursing	31,526	31,413	– 0.4
Engineering:			
Aerospace	$37,242	$35,418	– 4.9 %
Civil	34,222	31,308	– 8.5
Electrical	38,711	38,025	– 1.8
Computers:			
Comp. Science	$36,263	$35,222	– 2.9 %
Comp. Programming	35,829	32,546	– 9.2
Comp. Engineer	38,268	37,529	– 1.9
Sciences:			
Biology	$27,198	$23,248	– 14.5 %
Chemistry	33,287	29,743	– 10.6
Mathematics	33,413	29,745	– 11.0
Physics	35,457	30,484	– 14.0

Source: EPI analysis of National Association of Colleges and Employers' salary surveys.

Table 6
Percentage Difference Between Median Starting Salaries for All College Graduates and College Graduates in Major Fields of Study, 1977-93

Major Field of Study	Year of Graduation 1977	1980	1984	1986	1990	1993
	% Above or (Below) Median for All College Graduates					
Humanities	(20.3)	(15.4)	(18.6)	(17.1)	(13.6)	(11.1)
Social and Behavioral Sciences	(10.6)	(11.4)	(12.6)	(8.8)	(9.4)	(9.0)
Natural Sciences	(1.8)	(0.8)	(5.0)	(6.2)	(1.8)	(7.5)
Computer Sciences and Engineering	46.4	61.0	44.8	34.3	41.0	35.8
Education	(14.1)	(18.6)	(20.1)	(18.6)	(11.7)	(15.3)
Business and Management	14.4	13.2	4.8	2.6	4.6	10.4
Other Professional or Technical	2.8	6.8	(1.3)	(2.9)	2.2	3.3
Median Salary, All Graduates Full-Time, Not Enrolled in School ($1996)	$25,880	$23,283	$25,367	$27,017	$25,453	$23,600

Table 7
College Graduate Wage Bill Shares, Supply, and Demand Shifts, 1959-94
Modeled on Autor, Katz, and Krueger (1996), Tables 1 and 2

Implied Relative Demand Shifts Favoring College Graduates

Sigma =	1.4	0.5	1.0	2.0
1940-50	- 0.83	0.74	- 0.13	- 1.87
1950-60	4.09	3.35	3.76	4.58
1960-70	3.52	3.14	3.35	3.77
1970-80	3.18	4.03	3.56	2.62
1980-90	4.52	3.33	3.99	5.32
1990-95 (Cen-CPS)	2.36	2.19	2.28	2.47
1990-95 (CPS-CPS)	1.86	1.69	1.78	1.97

Source: Autor, Katz, and Krueger (1997), Table 2.

Table 8
Impact of Institutions and Trade on College Graduate Relative Demand, 1959-95
Modeled on Autor, Katz, and Krueger (1996), Tables 1 and 2
(Annualized Log Change (x100), unless otherwise specified)

(a) Estimated Relative Wage Adjusting for Institutions and Trade

	Assumed Impact (%)	Relative Wage	Relative Wage Bill
1940-50 Total (AKK)		-1.74	-0.13
1940-50 Institutions	-30	-1.22	-0.09
1940-50 Trade	0	-1.74	-0.13
1940-50 Secular**	-30	-1.22	-0.09
1950-60 Total (AKK)		0.82	3.76
1950-60 Institutions	-20	0.98	4.51
1950-60 Trade	-10	0.90	4.14
1950-60 Secular**	-30	1.07	4.89
1960-70 Total (AKK)		0.42	3.35
1960-70 Institutions	-10	0.46	3.69
1960-70 Trade	-10	0.46	3.69
1960-70 Secular**	-20	0.50	4.02
1970-80 Total (AKK)		-0.94	3.56
1970-80 Institutions	0	-0.94	3.56
1970-80 Trade	0	-0.94	3.56
1970-80 Secular**	0	-0.94	3.56
1980-90 Total (AKK)		1.33	3.99
1980-90 Institutions	20	1.06	3.19
1980-90 Trade	10	1.20	3.59
1980-90 Secular**	30	0.93	2.79
1990-95 Total (AKK)*		0.19	2.03
1990-95 Institutions	10	0.17	1.83
1990-95 Trade	10	0.17	1.83
1990-95 Secular**	20	0.15	1.62

* Average of Autor, Katz and Krueger's (1997) two estimates for 1990-95.
** Growth net of the effect of institutions and trade.

Source: Authors' analysis of Autor, Katz, and Krueger (1997), Table 2.

Table 8 (Continued)
Impact of Institutions and Trade on College Graduate Relative Demand, 1959-95
Modeled on Autor, Katz, and Krueger (1996), Tables 1 and 2
(Annualized Log Change (x100), unless otherwise specified)

(b) Implied Relative Demand Shifts Favoring College Graduates, Adjusting for Institutions and Trade

Sigma =	1.4	0.5	1.0	2.0
1940-50 Total Demand (AKK)	-0.83	0.74	-0.13	-1.87
1940-50 Institutions	-0.58	0.52	-0.09	-1.31
1940-50 Trade	-0.83	0.74	-0.13	-1.87
1940-50 Secular Demand**	-0.58	0.52	-0.09	-1.31
1950-60 Total Demand (AKK)	4.09	3.35	3.76	4.58
1950-60 Institutions	4.91	4.02	4.51	5.50
1950-60 Trade	4.50	3.69	4.14	5.04
1950-60 Secular Demand**	5.31	4.36	4.89	5.95
1960-70 Total Demand (AKK)	3.52	3.14	3.35	3.77
1960-70 Institutions	3.87	3.45	3.69	4.15
1960-70 Trade	3.87	3.45	3.69	4.15
1960-70 Secular Demand**	4.22	3.77	4.02	4.52
1970-80 Total Demand (AKK)	3.18	4.03	3.56	2.62
1970-80 Institutions	3.18	4.03	3.56	2.62
1970-80 Trade	3.18	4.03	3.56	2.62
1970-80 Secular Demand**	3.18	4.03	3.56	2.62
1980-90 Total Demand (AKK)	4.52	3.33	3.99	5.32
1980-90 Institutions	3.62	2.66	3.19	4.26
1980-90 Trade	4.07	2.99	3.59	4.79
1980-90 Secular Demand**	3.17	2.33	2.79	3.72
1990-95 Total Demand (AKK)*	2.11	1.94	2.03	2.22
1990-95 Institutions	1.90	1.74	1.83	2.00
1990-95 Trade	1.90	1.74	1.83	2.00
1990-95 Secular Demand**	1.68	1.55	1.62	1.78

* Average of Autor, Katz, and Krueger's (1997) two estimates for 1990-95.
** Total demand net of the impact of trade and institutions, implicitly the effect of technology.

Source: Authors' analysis of Autor, Katz, and Krueger (1997), Table 2.

Table 9
Estimated Demand Shifts, 1940-95

	Increased Relative Demand for College Graduate Workers			
	AKK (1)	Johnson Original (2)	Johnson Col. vs. Noncol. (3)	Johnson Col. vs. Noncol. with Regression Adj'd Differential (4)
1940-50	-0.8	0.7	0.2	-0.5
1950-63	..	3.3	5.1	5.5
1950-60	4.1	..	..	..
1963-70	..	3.6	4.8	4.2
1960-70	3.5	..	..	..
1970-79	..	3.7	5.0	4.6
1970-80	3.2	..	..	..
1979-89	..	4.7	5.9	6.0
1980-90	4.5	..	..	..
1989-93	..	5.0	3.2	1.8
1990-95 (Cen-CPS)	2.4	..	..	..
1990-95 (CPS-CPS)	1.9	..	..	..
Skill Group	4 years college or more	"College equivalents" (including some with 1-3 years)	4 years college or more	4 years college or more
Regression Adjusted Returns to Education	Yes	No	No	Yes
Elasticity of Substitution	1.4	1.5	1.5	1.5

Notes:
Column (1): annualized log change times 100 from Autor, Katz, and Krueger (1997), Tables 2.
Columns (2): average annual percentage change from Johnson (1997), Table 2.
College equivalents defined as "the total number of adults with four or more years of [post-secondary] schooling plus one half of the total number of adults with some college multiplied by the 1993 ratio of the full-time wage of 35-44 year old males with some college to those with four or more years of college." (p. 42)
Columns (3): average annual percentage change using estimated change in relative college or more to some college or less supply from Johnson (1997), Table 1.
Column (4): average annual percentage change as column (3), using regression adjusted changes in relative wages for college graduates from AKK (1997), Table 1.
Annual average relative wage changes for 1940-89 are proxied using annual averages for closest corresponding period in AKK; for 1989-93, proxied using the average of AKK's two estimates for 1990-95.
.. indicates data not available for specified time period.

Table 10

Relationship Between Technology Indicators and "Skill" and Education in Pooled Cross-Section (1)

Variable	% H.S. Equivalents				% Wage 0-75%			
	Men		Women		Men		Women	
Equipment Per FTE ($000)	-.029** (.011)	-.003 (.012)	-.061** (.012)	-.038** (.016)	-.049** (.019)	-.042* (.022)	-.020* (.012)	-.032* (.017)
Share of Scientists and Engineers	-.434** (.216)	-.332 (.205)	-.112 (.264)	-.097 (.259)	-.851** (.367)	-.823** (.360)	.030 (.273)	.108 (.099)
Computer Equipment Per FTE ($000)		-.440** (.108)		-.208** (.094)		-.118 (.191)		-.038 (.273)
Industry Effects (31)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects (4)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	.97	.97	.97	.97	.80	.80	.78	.78
N	155	155	155	155	155	155	155	155

(1) Pooling 1963, 1973, 1979 (with imputations), 1989 and 1994.

*p<0.10
**p<0.05

Table 11

The Effect of Technology Indicators on Industry Shares of College-Educated Workers, 1963 - 94

Independent Variable (b)	Men: % College or More (a) (1)	Men: % College or More (a) (2)	Women: % College or More (a) (1)	Women: % College or More (a) (2)
Equipment/FTE (EQ)	38.1	31.7	58.2	58.6
($ Millions)	(46.1)	(44.2)	(42.6)	(42.2)
EQ * T60	-65.3	-53.1	-36.7	-36.4
	(70.6)	(67.7)	(76.1)	(72.2)
EQ * T80	34.7	11.6	7.9	9.6
	(53.2)	(55.0)	(47.6)	(51.6)
EQ * T90	-25.7	-85.5	-60.1	-157.2**
	(54.2)	(56.9)	(48.0)	(51.8)
Share Science and Engineers (Sci)	0.883	0.679	-0.258	-0.272
	(0.726)	(0.706)	(.672)	(.627)
Sci * T60	-1.683	-1.734	0.334	0.246
	(1.101)	(1.073)	(1.064)	(.999)
Sci * T80	-0.111	-0.033	0.762	0.790
	(0.888)	(0.865)	(.840)	(.785)
Sci * T90	-1.005	1.054	0.858	.384
	(0.864)	(0.838)	(.772)	(.726)
Computers/FTE (Comp)		3,505*		252
($ Millions)		(2,141)		(1,240)
Comp * T60		18,901		7,295
		(14,758)		(9,558)
Comp * T80		-3,093		-257
		(2,163)		(1,255)
Comp * T90		-2,995		292
		(2,149)		(1,246)
Employment Growth	4.39**	3.86*	3.44**	3.96**
	(1.876)	(1.85)	(1.23)	(1.17)
Adj R(2)	.24	.31	.21	.32
N	124	124	124	124

* p < 0.10
** p < 0.05

(a) Weighted by industry shares of gender-specific employment.
(b) All models were estimated with a constant term and time dummies for the 1960s, 1980s and 1990s (not shown).

Table 12

Technology Impact on Annual Change in College-Educated Share of Workers, 1963 - 94

	Men		Women	
	Technology Impact (a)		Technology Impact (a)	
	Without Computers (1)	With Computers (2)	Without Computers (1)	With Computers (2)
Period				
1963 - 73	-.106	-.032	.020	.046
1973 - 79	.158**	.217**	.044	.050
1979 - 89	.170**	.220**	.115**	.117**
1989 - 94	.178**	.359**	.056	.181**
Differences				
70's Less 60's	.265**	.249*	.024	.003
80's Less 70's	.012	.004	.071	.067
90's Less 70's	.020	.142	.013	.131**
90's Less 80's	.008	.138	-.058	.064

(a) Technology impact on annual percentage point change in within-industry share of college-graduates (4 years or more).

* p< 0.10
** p< 0.05

Table 13

Technology Impact on Annual Change in Wage Quantities, 1963 - 94

Dependent Variable	Men: Technology Impact (a) Without Computers (1)	Men: Technology Impact (a) With Computers(2)	Women: Technology Impact (a) Without Computers (1)	Women: Technology Impact (a) With Computers(2)
0 - 20%				
1963-73	.098	.107	.124	.098
1973-79	-.104	-.092	.008	.047
1979-89	-.146	-.144**	-.049	-.106
1989-94	-.049	-.056	.148**	.168**
Differences				
'70s Less '60s	-.202*	-.199	-.116	-.052
'80s Less '70s	-.042	-.052	-.057	-.153
'90s Less '70s	.054	.036	.140	.121
'90s Less '80s	.097	.088	.197**	.274**
21 - 50%				
1963-73	-.177	-.195	-.221**	-.233**
1973-79	.-411**	-.407**	-.404**	-.409**
1979-89	.041	-.008	-.102**	-.069
1989-94	.002	.293**	-.091*	.053
Differences				
'70s Less '60s	-.234	-.212	-.183*	-.176*
'80s Less '70s	.452**	.398**	.302**	.340**
'90s Less '70s	.412**	.700**	.313**	.463**
'90s Less '80s	-.039	.301**	.011	.122*
51 - 75%				
1963-73	-.079	-.098	.039	.027
1973-79	-.108	-.104	.242**	.214**
1979-89	-.074	-.075	.088**	.115**
1989-94	-.007	-.050	-.047	-.122
Differences				
'70s Less '60s	-.029	-.007	.203**	.187**
'80s Less '70s	.035	.030	-.153**	-.100**
'90s Less '70s	.101	.055	-.289**	-.337**
'90s Less '80s	.066	.025	-.136**	-.237**

Table 13 (Continued)

Technology Impact on Annual Change in Wage Quantities, 1963 - 94

Dependent Variable	Men: Technology Impact (a) Without Computers (1)	Men: Technology Impact (a) With Computers(2)	Women: Technology Impact (a) Without Computers (1)	Women: Technology Impact (a) With Computers(2
76 - 90%				
1963-73	.089	.083	.022	.052
1973-79	.425**	.369**	.105**	.096**
1979-89	.042	.077	.030	.028
1989-94	.055	-.086	-.014	-.074**
Differences				
'70s Less '60s	.337**	.286**	.083	.044
'80s Less '70s	-.383**	-.292**	-.075*	-.068
'90s Less '70s	-.370**	-.455**	-.119**	-.171**
'90s Less '80s	.013	-.163	-.044	-.102**
91 - 100%				
1963-73	.069	.102	.037	.055
1973-79	.199**	.234**	.050**	.052*
1979-89	.137**	.150**	.034	.033
1989-94	.000	-.101	.005	-.024
Differences				
'70s Less '60s	.130	.132	.013	-.004
'80s Less '70s	-.062	-.083	-.017	-.019
'90s Less '70s	-.199**	-.335**	-.046	-.075**
'90s Less '80s	-.137	-.251**	-.029	-.056*

(a) Technology impact on annual percentage point change in within-industry share of workers by wage quantity.

* $p < 0.10$
** $p < 0.05$

Table 14

Technology Impact on Annual Change in Wage Quantities, 1963 - 94

Dependent Variable	Men: Technology Impact (a) Without Computers (1)	Men: Technology Impact (a) With Computers (2)	Women: Technology Impact (a) Without Computers (1)	Women: Technology Impact (a) With Computers (2)
0 - 50%				
1963-73	-.079	-.088	-.098	-.135
1973-79	-.515**	-.498**	-.397**	-.362**
1979-89	-.105	-.152	-.152**	-.176**
1989-94	-.048	.237	.057	.221**
Differences				
'70s Less '60s	-.437**	-.411**	-.299**	-.228*
'80s Less '70s	.410**	.346**	.245**	.187*
'90s Less '70s	.468**	.735**	.453**	.583**
'90s Less '80s	.058	.389**	.208**	.396**
76 - 100%				
1963-73	.158	.185	.059	.107
1973-79	.624**	.603**	.155	.148**
1979-89	.179**	.227**	.063*	.061
1989-94	.055	-.187*	-.009	-.098**
Differences				
'70s Less '60s	.467**	.418**	.096	.041
'80s Less '70s	-.445**	-.376**	-.091	-.087
'90s Less '70s	-.569**	-.790**	-.165**	-.246**
'90s Less '80s	-.124	-.414**	-.073	-.159**

(a) Technology impact on annual percentage point change in within-industry share of workers by wage quantity.

* $p < 0.10$
** $p < 0.05$

Appendix A

Within-Industry Trends Among Women, 1963 - 94

	1963-73	1973-79	1979-89	1989-94
Capital Accumulation (Annual Change)				
Equipment Per Worker ($000)	$0.68	$1.09	$1.40	$0.52
Computerization Per Worker ($000)	$0.00	$0.03	$0.27	$0.41
R&D (Annual Percentage Point Change)				
Share of Science and Engineers	0.067	0.077	0.044	0.095
Education (Annual Percentage Point Change)				
Less Than High School	-0.859	-1.165	-0.506	-1.305
High School (H.S.)	0.224	-0.199	-0.407	1.086
Some College	0.433	0.715	0.359	-0.355
College Only	0.150	0.476	0.355	0.602
Advanced	0.053	0.173	0.199	-0.027
College and Advanced Combined	0.202	0.649	0.554	0.575
Wage Quantities (Annual Percentage Point Change)				
0-20	-1.008	-0.348	-0.459	0.608
20-50	0.142	-0.078	-0.205	-0.718
50-75	0.309	0.233	0.327	-0.245
75-90	0.213	0.162	0.236	0.116
90-100	0.344	0.031	0.101	0.239
0-50	-0.866	-0.426	-0.664	-0.111
75-100	0.557	0.193	0.337	0.355

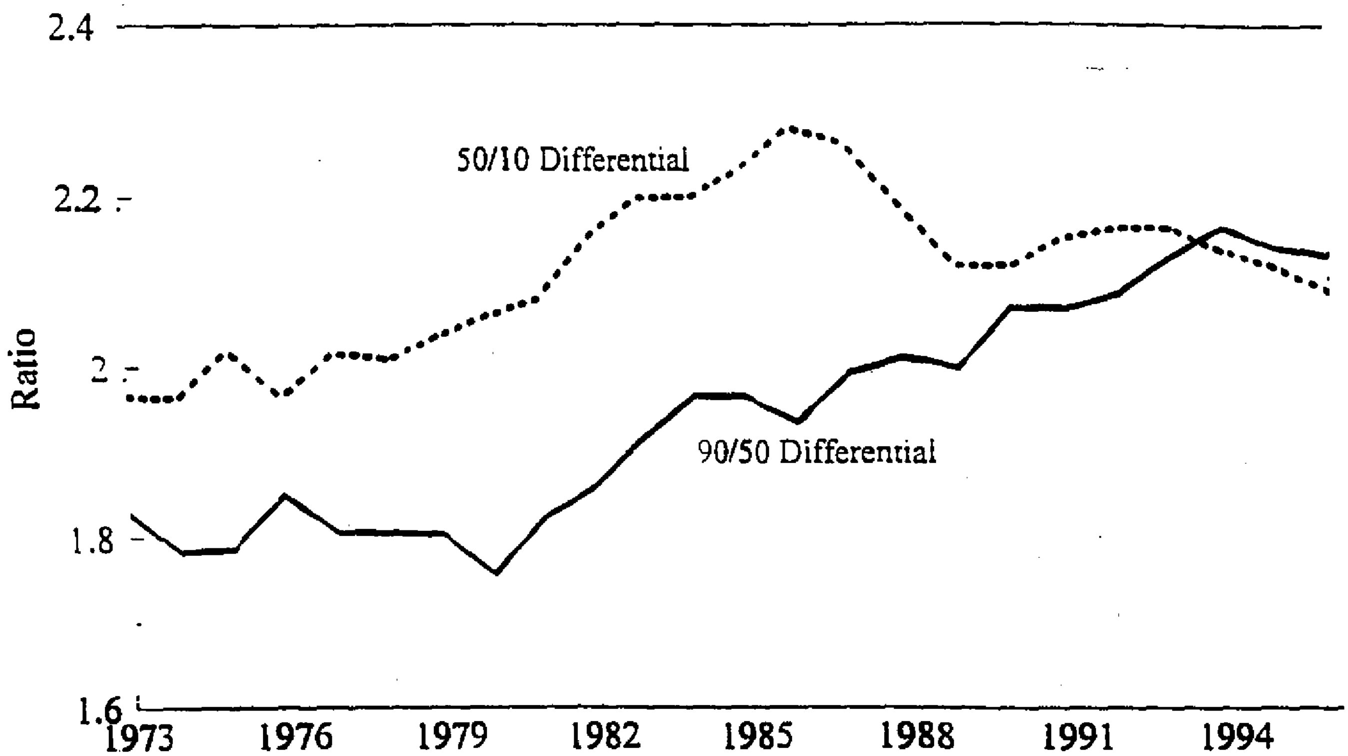
Appendix B

Within-Industry Trends Among Men, 1963 - 94

	1963-73	1973-79	1979-89	1989-94
Capital Accumulation (Annual Change)				
Equipment Per Worker ($000)	$1.17	$1.55	$1.56	$0.19
Computerization Per Worker ($000)	$0.00	$0.03	$0.26	$0.41
R&D (Annual Percentage Point Change)				
Share of Science and Engineers	0.093	0.112	0.073	0.093
Education (Annual Percentage Point Change)				
Less Than High School	-1.296	-1.339	-0.655	-1.371
High School (H.S.)	0.530	0.113	0.144	1.424
Some College	0.464	0.506	0.188	-0.395
College Only	0.197	0.473	0.226	0.356
Advanced	0.105	0.248	0.097	-0.015
College and Advanced Combined	0.302	0.721	0.323	0.341
Wage Quantities (Annual Percentage Point Change)				
0-20	-0.682	0.113	0.542	1.349
20-50	-0.592	-0.645	0.090	-0.429
50-75	0.011	-0.424	-0.250	-0.545
75-90	0.361	0.699	-0.315	-0.430
90-100	0.903	0.257	-0.067	0.055
0-50	-1.274	-0.532	0.632	0.920
75-100	1.263	0.956	-0.382	-0.375

Figure 1

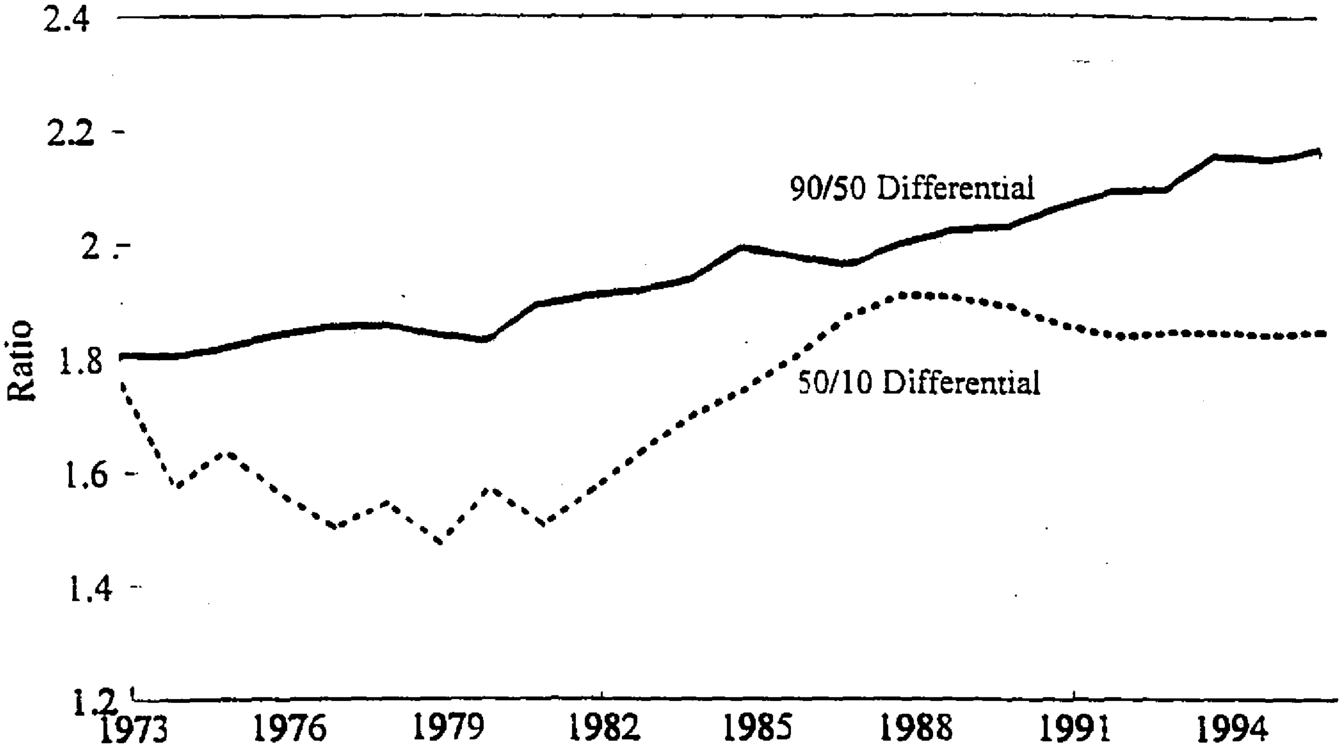
Men's Wage Inequality, 1973-96



Source: Economic Policy Institute analysis of CPS ORG data.

Figure 2

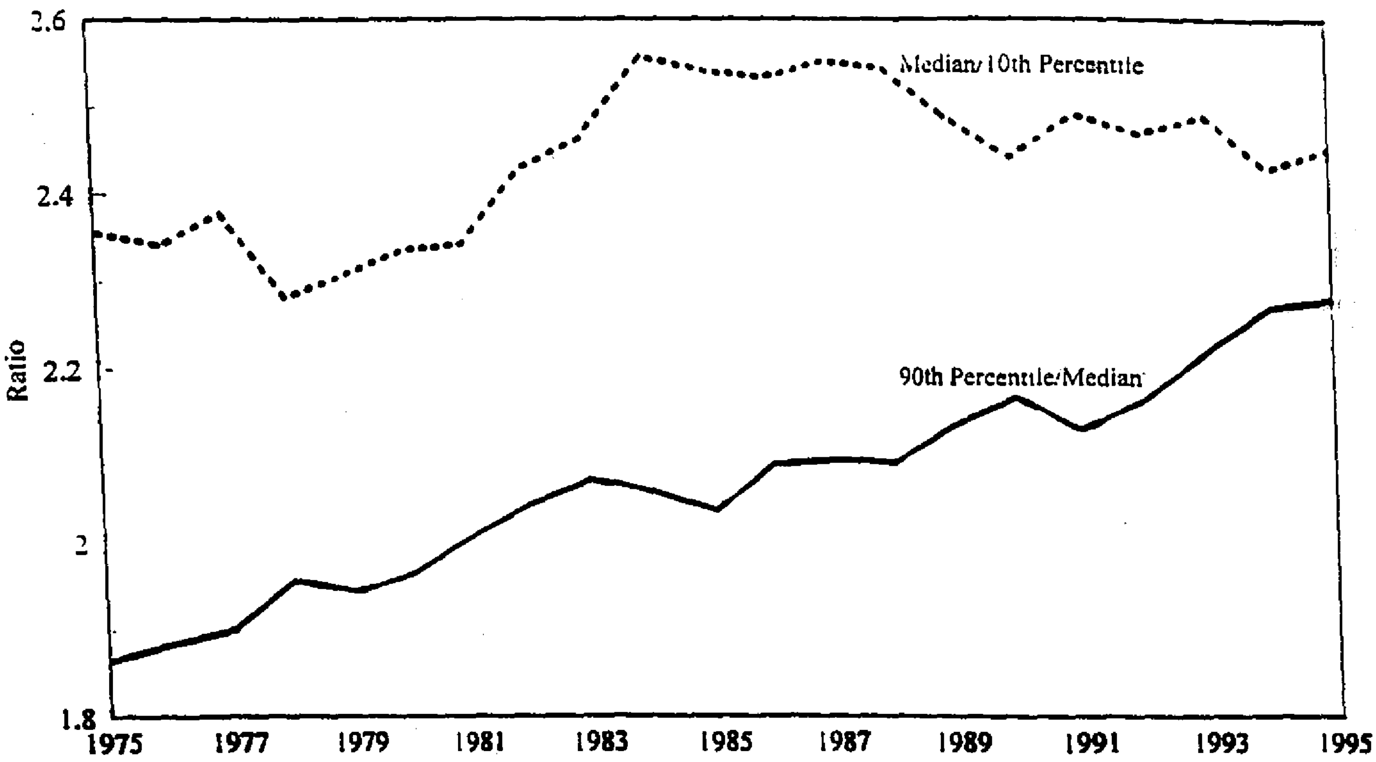
Women's Wage Inequality, 1973-96



Source: Economic Policy Institute analysis of CPS ORG data.

Figure 3

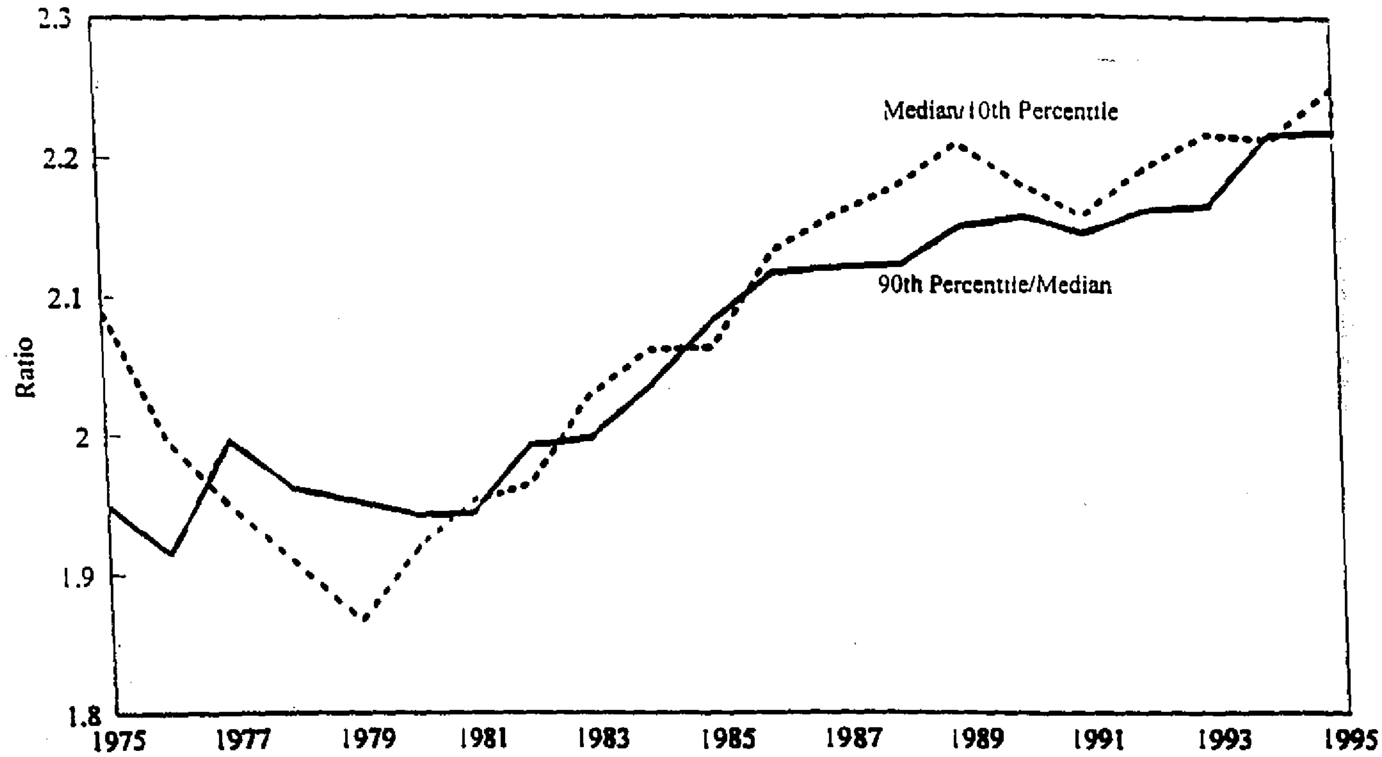
Men's Wage Inequality, 1975-95



Source: Economic Policy Institute analysis of March CPS data.

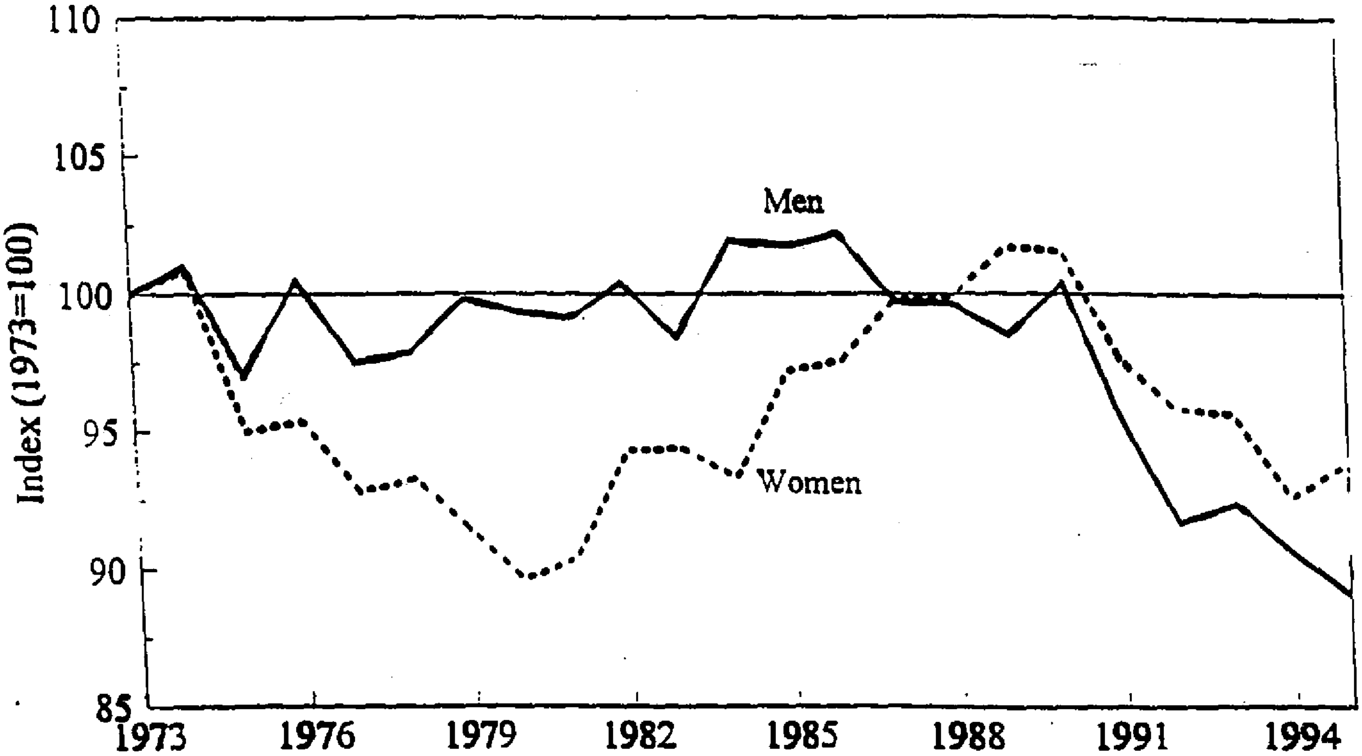
Figure 4

Women's Wage Inequality, 1975-95



Source: Economic Policy Institute analysis of March CPS data.

FIGURE 5
College Entry Level Wages, 1973-95



Source: Mishel, Bernstein, & Schmitt (1996).

FIGURE 6
Nonproduction Worker Share of Total Manufacturing Employment
1949-94

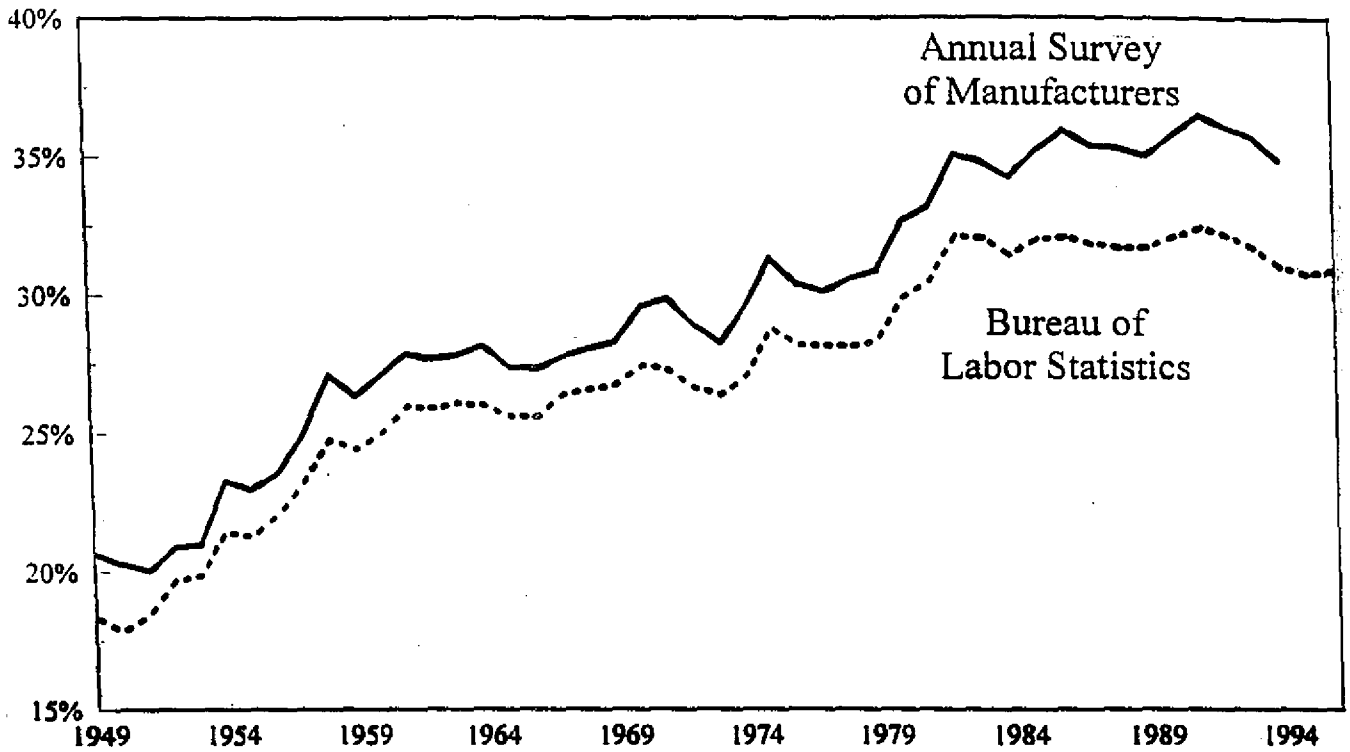


Figure 7

Trends in Nonproduction Worker Relative Wage and Employment, 1949-94

FIGURE 8
AKK Relative Demand
Annual Trend at Sigma=1.4,
1940-95