RESEARCH IN LABOR ECONOMICS

Editor: SOLOMON W. POLACHEK
Department of Economics
State University of New York at Binghamton

Associate Editor: JOHN ROBST
Department of Economics
State University of New York at Binghamton

VOLUME 17 • 1998

JAI PRESS INC.

Stamford, Connecticut *London, England*

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100 Prospect Street
Stamford, Connecticut 06901-1640

JAI PRESS LTD.
38 Tavistock Street
Covent Garden
London WC2E 7PB
England

ISBN: 0-7623-0570-3
ISSN: 0147-9121

Manufactured in the United States of America

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TECHNOLOGY AND THE WAGE STRUCTURE: HAS TECHNOLOGY'S IMPACT ACCELERATED SINCE THE 1970S?

Lawrence Mishel and Jared Bernstein

Virtually all of the literature on the causes of the increase in wage inequality has invoked skill-biased technological change as a central factor.[1] It is notable, however, that neither have the economic conditions necessary for this causal linkage been articulated, nor has the empirical evidence been shown. In this paper, we attempt to correct this omission.

We begin by clarifying the "technology story" commonly offered by both economists and the popular press and identifying its various implied conditions. We also explore the weaknesses in the empirical research. This discussion leads us to examine: (1) the impact of technology in particular time periods so as to assess whether its impact has accelerated over time; (2) technology's impact on several subgroups of the workforce rather than two categories, e.g., college and non-college educated (or production/non-production); and (3) the role of technology in overall wage inequality as well as in education differentials. Before describing our empiri-

Research in Labor Economics, Volume 17, pages 305–355.

ISBN: 0-7623-0570-3

cal results, however, we discuss a variety of ways in which the technology explanation does not fit the pattern of wage inequality, especially since the mid-1980s.

Both of these exercises lead us to believe that technology has not been a source of growing wage inequality in either the 1980s or the 1990s. Our estimates of technology's impact (the impact of technology on the skill composition of employment) show that:

- Technology's impact on the need for more college graduates (or reduced demand for high school equivalents) was not significantly greater either in statistical or economic terms, in the 1980s or 1990s (1989–94) than in the 1970s, for both men and women.
- Technology's impact was more (less) favorable to the bottom (top half) of the male wage structure in the 1980s than in the 1970s, meaning technology's skill bias lessened. In the 1990s technology has had a neutral impact on the male wage structure meaning it was far less favorable (adverse) to high (low) wage workers than in the 1970s.
- Technology's impact was more adverse for the lowest segments of the women's wage structure in the 1990s relative to the 1970s, our only finding that fits the general technology story. But technology was less favorable to the highest wage women and more favorable to middle wage women in the 1980s and 1990s.
- From the mid-1980s through 1995 there was a stable 50/10 wage differential among men and women, a slow growth in education premiums among men, flat or falling real wages of high-wage men (college graduates, white-collar, 90th percentile), but a continued rapid growth in the 90/50 differential. "Returns to skill" can therefore account for only a small portion of the growth of wage inequality in the 1990s and for 35%–40% of the growth of wage inequality over the 1973–95 period. These wage patterns do not easily support a predominant role for technology or skill demand.
- The pattern of employment growth over the last ten years does not readily correspond to the technology story either. The slowdown in the late 1980s and early 1990s in the shift to white-collar occupations and to nonproduction employment within manufacturing does not correspond to a continued or accelerated impact of technological change over the last 10 years. The actual shifts in employment composition toward college graduates and white-collar workers, whether technology-induced or not, have not been large enough to generate a substantial growth in wage inequality.
- Although the employment structure has shifted toward the utilization of more educated workers it has not necessarily shifted employment to more skilled workers, if wage levels are considered to correspond to skill. There has been no substantial growth in the employment of high-wage workers (particularly among men), but a large shrinkage in middle-wage employment and a large growth in low-wage employment.

I. CLARIFYING THE TECHNOLOGY STORY

The technology explanation for the increase in wage inequality starts from the presumption that we are in a new period of rapid technological change that is exemplified by the computer revolution. The consequence is that those with "more skills" and "more education" are faring well while the "less educated" and "unskilled workers" are falling behind. The policy correlate is that we need to upgrade the cognitive skills of the workforce through school-to-work programs, better K–12 schools, increased college graduation rates, and so on. The popular story thus links a new era of technological change to the growth of wage inequality and the need for upgrading the skills of the unskilled.

The economics literature on this topic begins with the notion that the recent (post-1979) growth in education differentials, particularly the college wage premium, *has occurred while there has been a significant growth of the share of the workforce with a college degree. The growth of the relative employment of those with more education while their relative price increased implies that demand for education was growing faster than the supply of education.*[2] Thus, the *first proposition in the technology story is that the explanation of rising education/skill* differentials must be found in the causes of the growth of the relative demand for education/skill.

The second proposition in the analysis is to note that the relative demand for education is primarily driven by changes within industries and not by changes in the composition of employment across industries (a factor equated with trade/deindustrialization). This leads to the third proposition, which is that the within-industry phenomenon of rising education differentials and increased utilization of more educated workers is the consequence of skill-biased technological change. In sum, technology driven shifts in relative demand for education/skill are causing education/skill differentials (and therefore wage inequality) to grow.

This paper's empirical work operates within this framework and examines three main issues:

1. If technology is the driving force behind the growing use of more educated workers within industries then one would expect the industries with the fastest, or most, technological change to be the industries with the greatest increase in the utilization of more educated workers. Is this so?
2. Since technological change has been a powerful force generating the need for more skills for many decades, it is important to know whether technology's impact was greater in the 1980s or 1990s relative to earlier periods. This is the issue of *acceleration*.

3. Does the technology story fit when one examines the growth of overall wage inequality rather than the growth of education differentials? This issue boils down to the role of "residual" or within-group wage inequality in overall wage inequality and the relationship of technological change to growing within-group wage inequality. Empirically, one wants to know if technological change is increasingly associated with the greatest increase (decrease) in the utilization of high-wage (low-wage) workers, since this approach examines the relationship between technological change and both within-group and educational premiums.

The definition of the "impact of technological change" adopted in this paper is based on what we estimate: the impact of equipment accumulation, computerization, and research and development, which captures the effect of capital deepening, capital upgrading, process innovation, computerization and any associated change in work organization. We believe this definition captures the forces at work when economists and the public discuss this issue. Broader definitions of technology are possible, the broadest being any change in the way goods and services are produced. Besides being difficult to quantify, a broader definition necessarily includes practices and processes which include speedup, imposition of unsafe working practices, temporary employment, and other practices that do not have the unambiguous progressive connotation associated with "technological change."

This paper examines the impact of technological change through only one channel: changes in employer's demand for different types of labor, that is, changes in the composition of skill demand. We believe this mechanism to be at the core of the technology story. Other mechanisms may be possible but we have not seen them elaborated. For instance, technological advances in communications have made it easier to locate production offshore or in rural areas, but this scenario lowers wages through an exogenous shift in the price of labor, possibly through lowered "rents." Note that this effect of technology would be one that lowers wages, but has no effect on the skill intensity of production (production *location* would change, not production processes). The technology effect that we seek to measure, and the one we believe is most relevant, is one that shifts the relative demand for skill.

The following discussion seeks to clarify the dimensions of the technology hypothesis and motivates the specific empirical strategy we have adopted.

A. Acceleration

For technology to be a central factor to the growth of wage inequality in the 1980s and 1990s requires that the growth in the relative demand for skill/education *accelerated* and that technological change played a major role in this acceleration of relative demand. Consequently, our empirical examination of technology's role in growing wage inequality focuses on whether technology's impact on the composition of demand by education/skill was greater in the 1980s and 1990s than in the 1970s. 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.[3] If so, then technology or trade are factors driving up relative demand for education 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.

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 is creating a qualitatively new situation in today's workplace along with 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

It is also useful to distinguish between the role of technology in the growth of wage inequality and the issue of "skill complementarity." The literature on skill complementarity finds a positive relationship between capital (e.g., computers) and skill in the cross-section. The wage inequality literature tries to separate out the growth in the relative supplies of and demand for education/skill. If, however, the issue is whether the growth of relative demand has accelerated, it is not enough to simply cite or demonstrate that skill complementarities exist to provide an explanation for growing wage inequality. Such complementarities have long been associated with the need for greater skills and education. They must have grown stronger (and/or capital accumulation accelerated) in order to provide evidence for a larger technology impact.

We do not question that technological change and capital accumulation have historically been associated with the need for greater skills and education. In fact, our first empirical task we undertake is to demonstrate that there are skill complementarities (with equipment and R&D levels) in our data. Clearly, technology and capital accumulation have been major forces driving the long-term growth of skill demand. 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.

It follows that any analysis of the effect of technology on skill demand in one year or one time period (i.e., the 1980s) can not draw *any* conclusion about the role of technology in the *growth* of wage inequality. The work by Lawrence and Slaughter (1993) illustrates this most clearly. They find a correspondence between total factor productivity and the share of the workforce that are nonproduction or supervisory workers in a set of manufacturing industries over the 1980s, leading them to conclude that technological change explains the growth of wage inequality. This is a conclusion, however, that can not be reached based on their analysis of the relationship between one indicator of technological change and one broad measure of occupation mix in one sector in *one* time period.

B. Disaggregating the Unskilled

Most of the discussion of wage inequality takes place assuming two kinds of workers, "skilled" and "unskilled" or "more skilled" and "less-skilled" or "more educated" and "less-educated." Such categories are both misleading and uninformative. This terminology is misleading because the "unskilled" category corresponds to groups representing either 75% (those with less than a four year college degree—the noncollege educated) or 80% (production or nonsupervisory workers) of the workforce.[4] It certainly cannot be accurate to lump those with two year college degrees, skilled technicians and craft workers into a category labeled "unskilled."

Lumping the bottom three-fourths or eighty % together is also 13 uninformative because it masks underlying trends. As Juhn (1994) points out, the trends within the bottom eighty % of white men differ by decade, with the 1980s characterized as a hollowing out of the middle. This motivates our effort to disaggregate the workforce when we examine technology's impact on the education and skill demand structure. In particular, we examine the effect of technology on four or five different education groups and five wage/skill groups.

C. Wage Inequality Versus Education Differentials

The discussion of wage inequality in academic as well as in policy, political, and media forums frequently equates the growth of wage inequality with the growth of education wage differentials such as the college/high school wage premium. In fact, growing education differentials are only a part, and over the long term, a lesser part, of the overall growth of wage inequality. Even the 1980s, a period where education differentials grew strongly, only about half the growth of wage inequality in the 1980s can be attributed to widening education premiums, the remainder being due to the growing inequality among workers with the same education and experience—within-group wage inequality (Juhn, Murphy, & Pierce, 1993).

It is especially misleading to equate wage inequality and wider education differentials when discussing the long-term growth of wage inequality. For instance, since regression-adjusted education differentials fell during the 1970s and grew modestly in the 1989–1995 period the majority of the growth of wage inequality over the 1973–1994 period takes place within education and experience groups. Burtless (1995) notes that increased education premiums can explain only a third of the growth of wage inequality from 1969 to 1993. The decomposition by Mishel, Bernstein, and Schmitt (1996) shows changes in the returns to "skill" accounting for between 35% and 40% of the overall growth in wage inequality over the 1973–1995 period. It is therefore important for empirical analysis to distinguish the growth in education returns from the growth in overall wage inequality.

Nor can it easily be said that the two dimensions of wage inequality—between and within education groups—respond to the same factors. After all, the 1970s was

a period when education differentials grew smaller while within-group differentials either grew at a strong secular rate or were stable.[5] Similarly, as we discuss below, education differentials have been relatively flat in the 1990s while within-group wage inequality has grown strongly.

D. Wage Levels Versus Education Levels

The focus on education supply and education wage premiums leads the conventional formulation of the technology story to begin with an empirically flawed premise. Recall that a basic stylized fact of the technology story is that there has been an increase in the use of more educated/skilled (read college graduate) workers even though their relative price has risen and this phenomenon has occurred primarily within industries. Technological change is said to be the factor leading employers to increase their utilization of skilled/educated workers. This stylized fact is true, however, only when one focuses on the use of college graduates and the widening value of the education premium. A more complete analysis might equate skill with wage level (as in Juhn et al., 1993; Juhn & Murphy, 1995) and examine whether employers are increasing their use of high-wage workers and decreasing their use of low-wage workers.

Table 1 presents the relevant trends over the 1973–1994 period. This table uses data from the CPS (described below) to describe the wage structure by examining the share of workers between various real dollar cutoffs.[6] While it is true that the male workforce has become increasingly better educated—fewer high-school dropouts, more college graduates—it is also true that a greater proportion of men are working at low wages (paying less than the 1979 20th percentile in 1989 dollars, about $7.00/hour), with proportionately fewer at middle-paying jobs, and a very slight (0.05 points/year) shift towards high-paying jobs. The middle of the distribution hollowed for women as well in the 1980s, but there was a greater shift upward. In the most recent period, however, both men and women experienced a negative shift in the wage distribution. These adverse wage trends in the post-1979 period imply that the shift towards low pay within education groups has overwhelmed the shift into higher paid education categories. Our data on within-industry trends, presented below, show that there was a strong shift from middle-wage to low-wage employment within-industries.[7]

These results imply that an assessment of the impact of technology on the wage structure must go beyond examining employers' increasing use of more educated workers despite the increase in their relative price. The relevant empirical question is "What explains the loss of middle-wage jobs and the growth of low-wage employment overall and within industries?"

E. Within-Group Wage Inequality

The difference between the growth of overall wage inequality and education differentials is, of course, the growth of within-group wage inequality. The major

Table 1. Educational Upgrading and Changes in the Wage Structure, 1973–95

	Share of Employment				*Percentage Point Change*		
	1973	*1979*	*1989*	*1994*	*1973–79*	*1979–89*	*1989–94*
Education*							
Men							
Less Than High Scool	30.6%	22.4%	15.9%	n.a.	–8.2	–6.5	n.a.
High School	38.1	38.6	38.7	n.a.	0.5	0.1	n.a.
Some College	15.6	18.7	21.0	n.a.	3.1	2.3	n.a.
College	8.9	11.5	14.2	n.a.	2.6	2.7	n.a.
More Than College	4.5	6.1	7.8	n.a.	1.6	1.7	n.a.
Women							
Less Than High School	25.4%	17.2%	11.2%	n.a.	–8.2	–5.0	n.a.
High School	47.2	46.8	42.7	n.a.	–0.6	–4.1	n.a.
Some College	14.5	19.6	23.9	n.a.	5.1	4.3	n.a.
College	8.8	10.4	13.9	n.a.	1.6	3.5	n.a.
More Than College	2.3	3.5	5.8	n.a.	1.2	2.3	n.a.
Percentile Wage Range**							
Men							
1 to 20	18.9%	20.0%	26.1%	31.7%	1.1	6.1	5.6
21 to 50	34.6	30.0	30.0	28.3	–4.6	0.0	–1.7
51 to 75	26.1	25.8	20.9	18.2	–0.3	–4.9	–2.7
76 to 90	11.7	15.0	13.2	11.6	3.3	–1.8	–1.6
91 to 100	8.6	9.3	9.8	10.3	0.7	0.5	0.5
Women							
1 to 20	23.3%	20.6%	25.6%	24.8%	–2.7	5.0	–0.8
21 to 50	28.1	29.4	17.3	20.3	1.3	–12.1	3.0
51 to 75	26.7	25.1	22.6	20.2	–1.6	–2.5	–2.4
76 to 90	14.4	14.9	16.1	15.9	.5	1.2	–0.2
91 to 100	7.5	10.0	18.3	18.8	2.5	8.3	0.5

Notes: *Excludes those with 17 years of schooling.
**Wage ranges defined relative to 1979 wage distribution. For men, the wage ranges (in 1989 dollars) correspond to: $1.00–$6.98, $6.98–$11.06, $11.06–$15.08, $15.08–$20.11, and $20.11–$100.00. For women, the wage ranges (in 1989 dollars) correspond to: $1.00–$5.03, $5.03–$6.74, $6.74–$9.22, $9.22–$12.32, and $12.32–$100.00.

Source: Education shares from Mishel and Bernstein (1995), Tables 3.10 and 3.19. Wage shares from analysis of ORG CPS.

unexamined and unasked question in the wage inequality literature is what is the nature of within-group wage inequality. Sometimes it is simply labeled a growing return to unobservable skills, as in Juhn and colleagues (1993). If it is to be accepted, however, that technology is driving this growth in the wage premium for unobserved skills then at minimum one would want to examine the growth pattern of within-group wage inequality and show its correspondence to some technology factors. For instance, if technological change is a factor driving the growth of within- group wave inequality, which type of workers would we expect to be most affected?[8]

F. What is the Metric?

It is important to be clear about what evidence might be brought to bear to support the claim that technological change is a source of the growth in wage inequality since 1979. As argued earlier, evidence of the *presence* of skill-biased technological change does not provide evidence that technological change is responsible for an *increase* in wage inequality. That is, the fact that technological change (as proxied by capital accumulation and R&D) may be associated with the use of more educated or skilled workers is evidence of capital-skill complementarity and not necessarily of a role for technological change in generating increased wage inequality (after all, skill supply has continuously increased). Capital-skill complementarity has been evident for decades, but this fact provides no evidence of an *accelerated or larger* impact of technology in the 1980s or 1990s. To capture an acceleration of technology's impact requires information on at least two points in time.

Even a growth of capital-skill complementarity over several time periods is not always sufficient evidence of a greater technology impact. It is possible for complementarities to accelerate, but for capital growth to falter. In this case, the question becomes whether the impact of rising complementarities in a climate of flat or falling capital deepening is sufficient to drive changes in the wage structure. This question calls for an empirical estimate of technology's impact that incorporates the effect of changes in skill complementarities *and* the trends in capital accumulation and other indicators of technology. In this framework, analyses which focus only one time period, or fail to test for acceleration over multiple time periods, by design cannot provide information on a change in technology's impact. Likewise, analyses which only examine changes in complementarity across time periods provide only part of the needed information (Goldin & Katz, 1996).

Many studies that address technology's role use models which explain shifts in the occupational distribution of employment, usually the nonproduction worker share of manufacturing employment (or its proxy, the nonproduction worker share of the wage bill) (e.g., Auter, Krueger, & Katz, 1996; Berman, Bound, & Griliches, 1993; Berman, Machin, & Bound 1998; Machin, Ryan, & Van Reenan, 1996). These papers all show evidence that technology (has had an effect on employment shares (capital-skill complementarity), but only one explicitly tests for acceleration (Machin et al., 1996). In a test of whether the impact of technology (proxied by a measure of R&D) on the non-production share of the wage bill accelerated in four countries, the authors find no evidence of acceleration.[9]

What is needed is evidence that technology's impact on employment shares became larger in the 1980s and 1990s *and* that these larger employment shares were sizeable enough to substantially alter the wage structure. That is, the appropriate computation estimates an employment impact and then translates this employment impact into a wage effect using an estimated elasticity. Such an analysis of technology's impact on wage differentials parallels that of trade's impact based on a factor content methodology—estimate the employment composition effect and then translate it into a wage effect (Borjas, Freeman, & Katz, 1992; 1996).

This clarification of the technology story motivates our empirical work. We examine the impact of technological change on the demand for workers at various wage levels as well as various education levels, we attempt to directly relate technological change to within-group wage inequality. Estimates of technology's impact for each subgroup are made for specific time periods so that there can be tests for any acceleration of technology's impact.

II. DOES THE TECHNOLOGY STORY CORRESPOND TO THE BASIC TRENDS IN WAGE DIFFERENTIALS?

There are a variety of ways in which the technology story does not fit labor market trends since the mid-1980s. This is especially the case if the technology story is one where a seemingly small group of "unskilled" or "disadvantaged" workers are not able to keen up with the demands of the information age.

A. Wage Levels and Gaps

We first review the basic trends in real wages and wage differentials since 1973, focusing on the last ten years.[10] These trends are computed from the CPS ORG files, as reported in Mishel et al. (1996). As Figure 1 shows, male wages have both fallen (for the bottom 80%) and become much more dispersed. While most of the literature has focused on relative wages (or shares), this absolute wage decline among the bottom 80% of men—a group too high up the wage scale to credibly be labeled "unskilled" or "disadvantaged"—seems inconsistent with the technology story which argues that technology has bid up the wages of the skilled. Even the wage at the 90th percentile for men has been stable or falling for the last 10 years.

A complementary counterpart to this same pattern comes from examining wages by education, with non-college educated wages falling steadily and the male college wage stagnant or falling from the mid-1980s through 1995 (Mishel et al., 1996). Especially worrisome for the technology story is the precipitous decline from 1989 to 1995 in the wages earned by new (one-five years of experience) college graduates, which fell 9.5% and 7.7%, respectively, for new men and women college graduates. That is, how can an era of information-age technology be leading to ever-increasing need for skills when the wages paid for new college graduates—presumably the most computer-literate and technologically flexible component of the workforce—are falling? And note that this decline is occurring absent of any supply acceleration.

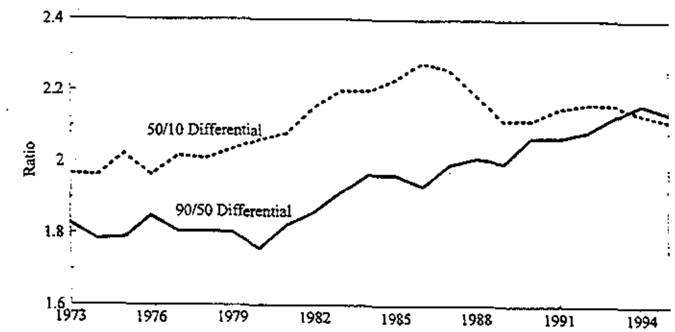
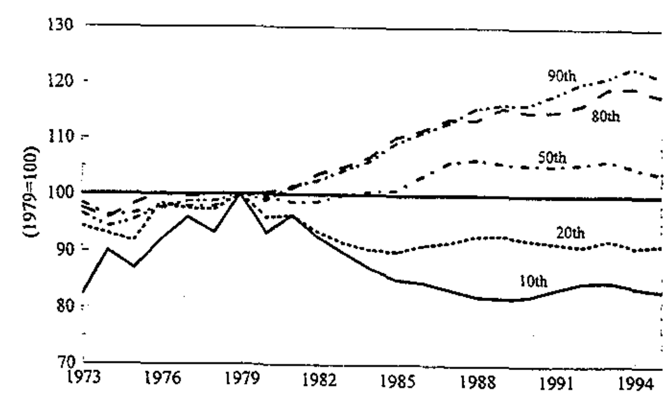


Figure 1. Hourly Wages for Men by Decile, 1973–1995

Among women (Figure 2) wage stagnation has broadened over time such that wages have been stagnant or falling for the bottom 50% since 1989. High wage women, however, have seen their wages steadily rise.

The growth in the 90/50 and 50/10 differentials (i.e., the ratio of the hourly wages at these quartiles) are shown in Figures 3 and 4. Since the mid-1980s there has been no expansion of the 50/10 wage gap among either men or women (starting in 1988) whereas the 90/50 wage gap grows steadily throughout the 1980s and 1990s. It appears that the least skilled, or the lowest-paid, have fared the same as the median



Source: Mishel, Bernstein, and Schmitt (1996)

Figure 2. Hourly Wages for Women by Decile, 1973–1995

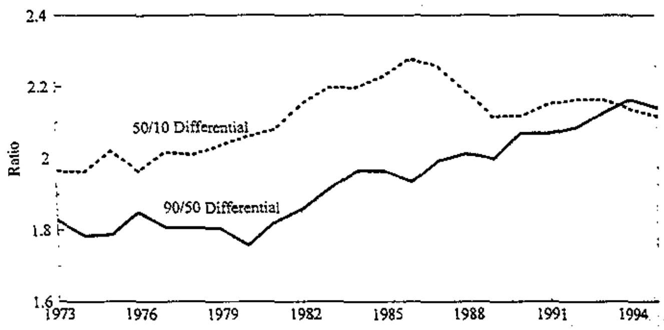
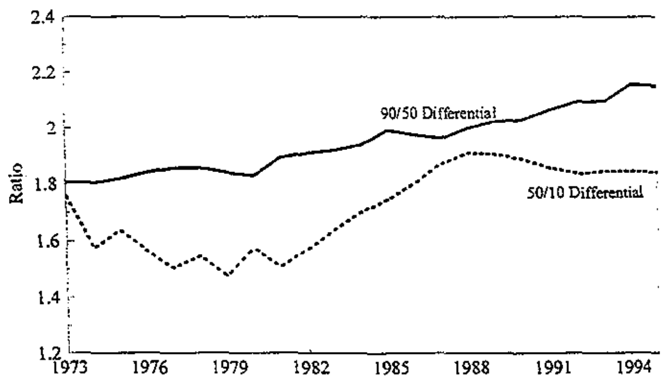


Figure 3. Men's Wage Inequality, 1973–1995

worker for almost 10 years.[11] Rather than the bottom being left behind, we have the top pulling away (in *relative* terms) from the remainder of the workforce.

Unless we accept that technology's impact is exclusively complimentary with the highest paid workers, this pattern seems to challenge the usual imagery of technology's impact. The more conventional wisdom would expect the impact of technological change to become more negative as we move down the wage scale, generating a pattern wherein the top *and* middle pull away from the bottom; here, however, we see this is not the case. We find it difficult to believe that middle-wage workers (an unskilled group) are being left behind by an information age to the same extent as those in the bottom of the skill distribution (i.e., at the 10th percentile).



Source: Mishel, Bernstein, and Schmitt (1996)

Figure 4. Women's Wage Inequality, 1973–1995

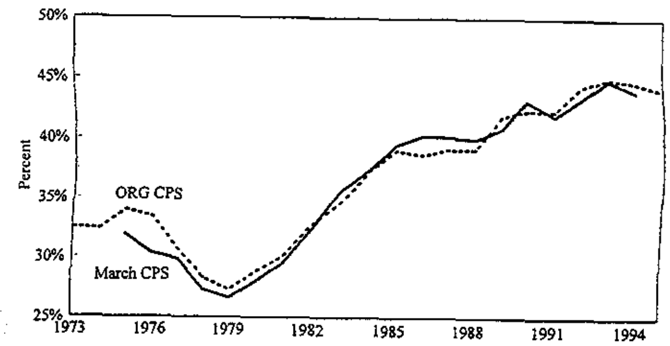
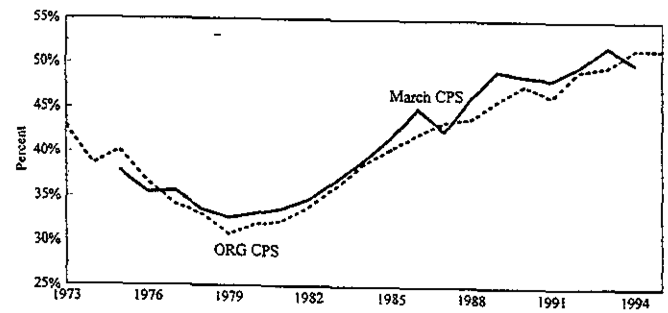


Figure 5. Male College-High School Wage Premium, 1973–1995

B. Education Differentials

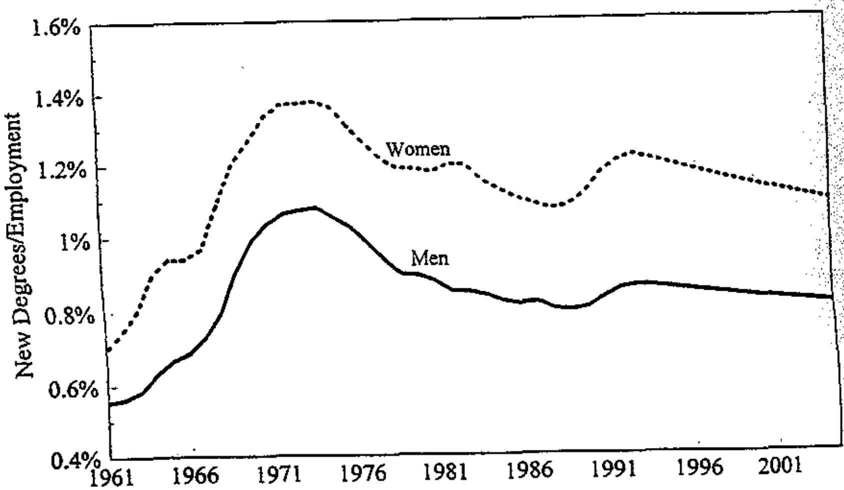
There is every reason to believe technological change has been as great in the late-1980s and in the 1990s as in the early 1980s. In fact, the business press has included many stories about an accelerated technological change in the 1990s that has led us to a new, higher trajectory of productivity growth (see, for example, Shepard, 1997). One key indicator of technological change, the share of the workforce using computers, has continued its rapid growth into the 1990s (Auter et al. 1996). Our data, discussed below, show an acceleration of R&D spending (as proxied by the growth of share of scientists and engineers within industries, as in Allen, 1993, 1996) and computerization (but not of equipment accumulation).

If the 1980s technology trends have continued or accelerated in the 1990s, and if such trends are driving increased education differentials, then one would expect



Source: Mishel, Bernstein, and Schmitt (1996)

Figure 6. Female College-High School Wage Premium, 1973–1995



Note: *1994–2005 Projected
Source: Mishel, Bernstein, and Schmitt (1996)

Figure 7. College Degrees as a Share of Employment, 1961–2005*

that these 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, as Figure 7 shows, there has been no significant acceleration of the supply of college graduates (relative to employment), except perhaps among women.[12] Yet, the male college-high school wage premium grew rapidly in the early 1980s, but has grown slowly in the late 1980s and in the 1990s. This can be seen in the estimates of the regression-adjusted college-high school wage premium (using both the March and ORG CPS data) presented in Table 2 and shown in Figures 5 and 6.[13] For instance, the college wage premium among men grew at an annual rate of 3.3% from 1979 to 1989 (model 2, ORG) but grew at an annual rate of 0.8% between 1989 and 1995. These data suggest that the relative demand for education among men has grown *more slowly* in the late 1980s and in the 1990s than in the early 1980s, in other words, technology's impact decelerated in the 1990s. 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 1979–1995 period, even though there was a stronger growth in the relative supply of women college graduates. This implies an acceleration of relative demand for education among women. Can technology trends explain this faster growth in relative demand for education among women compared to men?

Table 2. Estimated College-High School Wage Premium, 1973–1995

	Org CPS				*March CPS*			
	Men		*Woman*		*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	44.4	44.6	49.4	43.8	43.4	43.4	49.9	45.7
1993	45.1	45.0	49.9	44.2	45.0	44.7	52.1	47.9
1994	44.8	44.7	51.9	46.5	44.0	44.4	50.3	45.6
1995	44.1	44.4	51.8	46.0				
New Coding								
1992	36.9%	38.3%	43.7%	39.6%	33.8%	35.4%	42.5%	40.1%
1993	37.6	38.7	44.3	40.0	35.4	36.7	44.1	41.1
1994	37.5	38.5	46.3	42.2	36.8	37.8	46.7	43.7
1995	37.3	38.5	46.7	42.1	36.8	38.4	45.5	42.0

Notes: *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.
**Adds 12 industry controls to the simple model.

C. Decompositions of Wage Inequality

The primary mechanism by which technology is said to affect wage inequality is by increasing the demand for education and, thereby, raising education premiums. As pointed out above, however, increased returns to education and experience can explain less than forty % of the long-term growth in overall wage inequality. This is even more the case in the 1989–1995 period, where increased "returns to skill" can account for less than twenty % of the growth of the 90/50 wage gap among men and women (Mishel et al., 1996). That education differentials are playing a modest role (absolutely and relative to the 1979–1989 period) in the continued rapid growth of wage inequality at the top of the wage structure seems inconsistent with a continued strong or faster growth in skill-biased technological change in the 1990s.

The counterpart to the education differential trends is that within-group wage inequality grew faster in the late 1980s and the 1990s. This result is implied by the fact that while the educational differentials flattened (at least for men), the 90/50 differential (which reflects both the within and the between growth in inequality) continued to rise at a relatively constant rate. As discussed above, there has not been any research or analysis that connects technological change to a growth in within-group wage inequality, let alone to an acceleration of within group wage inequality as education premiums rise more slowly.

III. DOES THE TECHNOLOGY STORY CORRESPOND TO THE BASIC TRENDS IN EMPLOYMENT COMPOSITION?

This section reviews some employment patterns that are inconsistent with the general technology story.

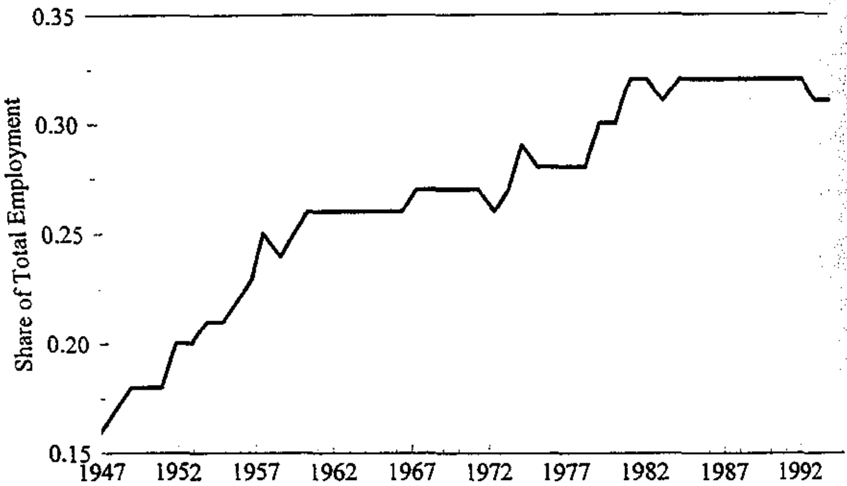
The shifts in occupational composition also seem inconsistent with a technology story that presumes skill-biased technology change grew strongly, or even more strongly, in the late 1980s and 1990s as in the 1970s or early 1980s.[14] First, consider the shift to white-collar and higher-paying occupations. Table 3 presents an index of occupational upgrading for each year over the 1972–1995 period using employment data on thirteen major occupations and the relative wage and compensation structure. This index captures the degree to which there has been a shift toward high-wage, and presumably high skill, occupations. Again, there has been very modest occupational upgrading in the 1989–1995 period (0.14% annually) relative to the occupational upgrading over the 1979–1989 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 employment in the "information age."

The trends in manufacturing seem even less hospitable to a technology story. The basic (much studied) shift towards the increased utilization of nonproduction workers in manufacturing seem to have only taken place in the early 1980s, with no shift occurring in the late 1980s and early 1990s and an actual decline in the share of nonproduction workers in the last few years (see Figure 8).

Table 3. Effects of Shifts in Composition of Employment by Occupation on Wages and Compensation, 1972–95

	Wage Impact		*Compensation*	
Year	*Index**	*Annual Effect*	*Index**	*Annual Effect*
1972	100.00		100.00	
1973	100.29	0.29%	100.29	0.29%
1974	100.63	0.34	100.56	0.27
1975	100.62	–0.01	100.41	–0.15
1976	101.02	0.39	100.79	0.37
1977	101.02	0.01	100.80	0.01
1978	101.09	0.07	100.87	0.07
1979	101.51	0.42	101.25	0.38
1980	102.05	0.53	101.67	0.41
1981	102.19	0.14	101.74	0.08
1982	102.35	0.16	101.77	0.03
1983	102.70	0.34	102.08	0.31
1984	103.07	0.36	102.43	0.34
1985	103.39	0.32	102.71	0.27
1986	103.48	0.08	102.76	0.05
1987	103.71	0.22	102.95	0.18
1988	104.16	0.43	103.34	0.38
1989	104.48	0.31	103.61	0.27
1990	104.53	0.05	103.63	0.01
1991	104.69	0.15	103.72	0.10
1992	104.77	0.07	103.78	0.05
1993	105.02	0.23	103.98	0.19
1994	105.14	0.12	104.08	0.10
1995	105.59	0.43	104.48	0.38
Annual Growth				
1972–79	0.21%		0.18%	
1979–89	0.29		0.23	
1989–95	0.18		0.14	

Note: *Based on shift share analysis of 13 occupational employment categories with relative wages and compensation equal to the average over the 1979–95 period.



Source: Bureau of Labor Statistics (1996)

Figure 8. Nonproduction Employment Share in Manufacturing, 1947–1995.

IV. 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, Bound, and Griliches (1993), Berman, Machin, and Bound (1998), Goldin and Katz (1996) and others (Machin et al. 1996, Berndt, Morrison & Rosenblum 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:

$$SK_{it} = \alpha_{it} + \beta_1 \log Y_{it} + \beta_2 TECH_{it} + \beta_3 (W_{sk}/W_{un})_{it} \tag{1}$$

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 complimentarity, 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. Industry-specific relative wages, however, are widely considered endogenous, and so this term typically dropped. The underlying assumption is that 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 examining the change in complementarity across time. Differencing (1) accomplishes this plus removes the fixed effects. In this case, the coefficient on ΔTECH (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., 1996). 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, that is, it can 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 tests for changes in complementarity:

$$\Delta SK_{it} = \alpha_1 T_2 + \alpha_2 T_3 + \beta_1 \Delta \log Y_{it} + \beta_2 \Delta TECH_{it} + \lambda_1(\Delta TECH_{it} {}^*T_2) + \lambda_2(\Delta TECH^*_{it} T_3) \tag{2}$$

In (2), which examines changes in complementarity over three time periods (the reference period, T_1, is omitted), skill shares, value added, and technology are all measured as first differences. The two interaction terms measure 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; $\lambda_2 - \lambda_1 > 0$ implies the same for period 3 over period 2.

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).

In our empirical model, we estimate the skill bias for specific technological indicators in specific time periods by regressing within-industry changes in the composition of employment on changes in technology indicators. We then combine these two sources of information—shifts in skill bias and rate of technological change—to obtain period-specific estimates of technology's impact for employment subgroups. These estimates provide the basis for examining the way that technology shapes demand (e.g., the need for college graduates) and how the pattern has shifted over time. We are particularly interested in whether technology's impact on reducing the demand for "unskilled" workers was greater in the 1980s or the 1990s than in the 1970s.

Specifically, we estimate variations of the following model:

$$\Delta y_{it} = \alpha + \beta_2\, 80s + \beta_3 90s + \sum_{k=1}^{3} \beta_k\, \Delta TECH_{it} + \sum_{j=1}^{3} \beta_j\, \Delta TECH^{*}_{it}\, 80s$$

$$+ \sum_{n=1}^{3} \beta_n \Delta TECH^{*}_{it}\, 90s + \varepsilon_{it} \tag{3}$$

All non-dummy variables are measured as annualized changes. The subscript i denotes the unit of observation, that is, the industry; we observe changes within 34 (15 manufacturing, 19 non-manufacturing) private sector industries over three time periods (1973–79, 1979–89, 1989–94), resulting in 102 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. 1943, 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 three time periods noted above; α is the constant term; 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 (3) as a reduced form model with the technology indicators shifting demand and supply shifts captured by the time period dummies.

The parameters in (3) 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 1980s over the 1970s; likewise, the coefficients in B_m represent the change in skill complementarities in the 1990s 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 the β_j to β_m.

An example of how we use equation (3) may be helpful. Consider a variation of (3) with the change in the share of college graduates as the dependent variable and with only one technology indicator, the change in equipment accumulation per worker

$$\hat{y} = \hat{a} + \hat{B}_1\, 80s + \hat{B}_2\, 90s + \hat{B}_3\, EQP + \hat{B}_4\, EQP * 80s + \hat{B}_5\, EQP * 90s$$

In this example, B_3 represents the growth of complementarity of equipment accumulation with college-educated workers over the 1970s; $B_3 + B_4$ is the same for the 1980s, and $B_3 + B_5$ is the same for the 1990s. Thus, a test for whether equipment investment is skill-biased for college graduates in the 1980s relative to the 1970s asks whether B_4 is significantly greater than zero.

The impact of technology on demand for different types of labor may occur through either an increase in complementarities holding technology constant, an increase in technological change with constant complementarities, or some combination of these two effects. In order to test the different impact of these effects by time period, we develop a set of estimates of the impact of technology on the composition of employment in the 1970s, 80s, and 90s by multiplying the complementarities specific to each period by the average within-industry change in the appropriate technology indicator for the time period. This produces an estimate of technology's impact in each time period for each dependent variable and allows us to determine if technology, as proxied by our three indicators, had a statistically significant impact in particular time periods. Most important, by differencing this result between time periods, (e.g., the 1980s effect minus the 1970s effect), we can determine whether technology's effect accelerated between two time periods.

Specifically, we compute:

$$TI = \Sigma\, B * \Delta\overline{TECH} \tag{4}$$

TI is the impact of technology on a dependent variable in one of three time periods (i.e., t = 70s, 80s, or 90s). The coefficients used in (4) are those relevant to the particular time period and the variables of interest. We generate predictions for each of the three time periods 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. 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.

A. 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, y_{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 separate 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 to 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 1979 private sector wage distribution. 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 (gender-specific) 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:

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

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. The y's in each summation are wage cutoffs at the given percentile taken from the entire 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 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).[16]

"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.[17]

With two exceptions, the dependent variables come exclusively from the annual Outgoing Rotation Group (ORGs) files of the CPS. The two exceptions are (1) for 1973 we use the May CPS, since the ORGs do not begin until 1979, and (2) we use the 1990 PUMS file to compute education shares for 1989 when we make comparisons with 1994.

Due to various changes in the CPS over the past 20 years, the development of a consistent series requires various data adjustments. Since the 1973 data use no imputations (or, in census terminology, "allocations") in the wage data (later CPSs 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 differentiate with 1989.

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).

B. 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.[18] "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.[19]

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.[20]

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 & Bernstein, 1996).

One final addition to equation (3) 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.

V. DESCRIPTIVE TRENDS

The impact of technological change in a time period in our analysis depends on two factors: (1) The rate of introduction of new technologies reflected in the growth of various "technology indicators"; and (2) the relationship, or complementarity, between particular technology indicators and changes in the skill/wage/education composition of the workforce reflected in the coefficients in our regressions. This section provides the descriptive trends for the technology indicators which give us the first possible clues about possible acceleration. We also review the trends in the dependent variables.

Table 4 presents the overall trends in technology indicators (in annual growth rates) while Tables 5 and 6 present the basic descriptive data on within-industry trends weighted by gender-specific employment counts by industry. This weighting scheme allows the same within-industry trends to affect men and women differently depending upon the industrial composition of the trends.

The overall technology indicators (Table 4) reveal a slowing of the annualized growth rate of equipment accumulation per worker, although computer accumulation (a subset of equipment) accelerated in the 1980s, and slowed in the 1990s. R&D slowed in the 1980s, but picked up in the 1990s.[21] We also present the growth rate in two measures of productivity, both compiled by the BLS. Labor productivity, the ratio of private, non-farm output to hours, shows no acceleration over the three time periods. Multifactor productivity, which includes capital services as an input measure, rose 0.3% annually in the 1970s, decelerated and failed to increase at all in the 1980s, then accelerated slightly in the 1989–1994 period. At this aggregate

Table 4. Technology Indicators, 1973–94

	Log Annual Growth		
	1973–79	*1979–89*	*1989–94*
R&D Capital Stock Per Worker			
Total	–0.01%	0.85%	n.a.
Total Civilian	0.64	0.44	0.81%
Capital Accumulation*			
Equipment Per Worker	3.57%	2.53%	0.48%
Computer Equipment Per Worker	24.05	25.71	12.06
Productivity**			
Labor	1.1%	1.0%	1.0%
Multifactor	0.3	0.0	0.2

Notes: *Per private sector FTE.
**Private nonfarm business sector.

Table 5. Within-Industry Trends among Men, 1973–94

	1973–79	*1979–89*	*1989–94*
Capital Accumulation			
(Annual Change)			
Equipment Per Worker ($000)	$1.61	$1.62	$0.33
Computerization Per Worker ($000)	0.25	0.26	0.50
R&D			
(Annual Percentage Point Change)			
Share of Science and Engineers	0.069	0.079	0.107
Education			
(Annual Percentage Point Change)			
Less Than High School	–1.116	–0.668	–1.159
High School (H.S.)	0.168	0.137	0.932
Some College	0.466	0.197	–0.194
College Only	0.323	0.233	0.387
Advanced	0.160	0.101	0.032
High School Equivalent	–0.679	–0.420	–0.393
Wage Quantities			
(Annual Percentage Point Change)			
0–20	0.206	0.513	1.334
20–50	–0.636	0.113	–0.407
50–75	–0.365	–0.423	–0.550
75–90	0.690	–0.211	–0.427
90–100	0.105	0.009	0.049
Residual Wage Quantities			
(Annual Percentage Point Change)			
0–20	–0.033	0.092	–0.249
20–50	–0.259	–0.275	0.289
50–75	–0.060	–0.149	0.034
75–90	0.360	0.088	–0.090
90–100	–0.009	0.244	0.015

level, there is little evidence of technology-induced acceleration in productivity growth.

The within-industry trends suggest a greater growth in technology in the 1980s, and perhaps a greater associated impact on the wage/skill/education structure of demand. Equipment and computer accumulation per worker grew similarly in the 1970s and 1980s in industries where men were concentrated but R&D grew more strongly. There was a decline in R&D but a larger growth in equipment and computer accumulation in women's industries in the 1980s. In the 1990s there was a slowdown in equipment and computer accumulation facing both men and women, but a growth in R&D. Overall, this suggests that if skill complementarities were as large in the 1980s as in the 1970s, then technology's impact probably accelerated. On the other hand, the slowdown in capital accumulation in the 1990s mitigates against finding an acceleration in this period relative to the 1980s or 1970s.

The within-industry trends in education shares provide no surprises. There was rapid education upgrading in the 1970s (fewer "less than high school" and more with at least some college) which continued in the 1980s but at a slower rate. The

Table 6. Within-Industry Trends among Women, 1973–94

	1973–79	*1979–89*	*1989–94*
Capital Accumulation			
(Annual Change)			
Equipment Per Worker ($000)	$1.08	$1.38	$0.59
Computerization Per Worker ($000)	0.03	0.27	$0.49
R&D			
(Annual Percentage Point Change)			
Share of Science and Engineers	0.051	0.045	0.111
Education			
(Annual Percentage Point Change)			
Less Than High School	–1.027	–0.507	–1.078
High School (H.S.)	–0.202	–0.420	0.621
Some College	0.675	0.363	–0.170
College Only	0.412	0.363	0.597
Advanced	0.142	0.201	0.030
High School Equivalent	–0.813	–0.700	–0.609
Wage Quantities			
(Annual Percentage Point Change)			
0–20	–1.344	0.672	0.194
20–50	1.387	–1.103	0.439
50–75	–0.447	–0.207	–0.476
75–90	0.130	0.033	–0.327
90–100	0.274	0.606	0.172
Residual Wage Quantities			
(Annual Percentage Point Change)			
0–20	–0.296	0.475	–0.087
20–50	0.569	–0.822	0.166
50–75	–0.090	–0.193	0.052
75–90	–0.192	0.177	–0.046
90–100	0.009	0.362	–0.085

early 1990s continued the process of education upgrading although the character changed. We suspect, however, that the large shift to high school and the negative shift out of some college is due to inconsistencies in coding in the data (we attempt to account for this change as we describe in the data section). The summary measure—high-school equivalents—appears to provide a reasonable aggregated category.[22]

Although the workforce has steadily shifted into higher education categories there has been no corresponding steady shift into higher wage groups. Among men in the 1970s, there was a small shift towards low-wage work but a more sizeable growth in higher wage employment. Since 1979, however, there has been an erosion of upper middle wage jobs (the 50–75 and 75–90 categories) and a growth of low-wage jobs with very little growth of the highest wage jobs. This downward trajectory for men accelerated in the 1990s. Among women, there was a consistent "wage upgrading" in the 1970s but polarized shifts in the 1980s and 1990s as employment declined in the upper-middle but grew at both the bottom and the top. Again, the downward wage shift was stronger in the 1990s than in the 1980s.

VI. RESULTS

As a first step we estimate the complementarities between our technology indicators and skill measures using our data as a pooled cross-section for 1973, 1979, 1989 and 1994. Table 7 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 generally show highly significant levels 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 and fewer middle- and low-wage workers. The exception is the lack of an association between R&D and "skill" among women.

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. Only in the male high-school equivalent model is this the case, suggesting significant cross-sectional complementarity between investment in computer equipment and college-equivalent employment for males.[23] In other models, however, including those with male wage quantities as the dependent variable, the coefficient on computer equipment is not statistically significant. This suggests that in these cases computer equipment is neither more nor less of a complement with skill than other types of equipment. It is interesting to note that in models (unreported) which predict high school equivalents we do not find equipment complementary with more education unless

Table 7. Relationship Between Technology Indicators and Skill and Education in Pooled Cross-Section (1)

	% H.S. Equivalents				% Wage 0–75%			
Variable	*Men*		*Women*		*Men*		*Women*	
Equipment Per FTE	−0.334**	−.133	−.673**	−.525**	−.621**	−.737**	−.763**	−.608**
($000)	(.129)	(.158)	(.134)	(.191)	(.189)	(.234)	(.210)	(.298)
Share of Scientists and Engineers	−.665**	−.598**	−.054	−.043	−1.68**	−1.722**	.316	.327
	(.246)	(.244)	(.290)	(.290)	(.359)	(.362)	(.452)	(.454)
Computer Equipment Per FTE ($000)		−2.499**		−1.048		1.438		−1.100
		(1.154)		(.960)		(1.711)		(1.503)
Industry Effects (33)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects (3)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	.971	.972	.968	.968	.849	.849	.948	.948
N	136	136	136	136	136	136	136	136

Notes: (1) Pooling 1973, 1979 (with imputations), 1989 and 1994.
* $p < 0.10$
** $p < 0.05$

there are industry effects included, underscoring the within-industry nature of technology's impact.

These results show skill complementarity, as have others, but do not address whether technology's impact on skill demand 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 (3), which measures whether the rate of complementarity between specific technology indicators and the dependent variables has accelerated over time across the three time periods 1973–79, 1979–89 and 1989–94 (Tables 8, 9, 12, 13).

We also present estimates of technology's impact on education and wage upgrading (Table 10 and 13) based on equation (4). 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 the 1980s than the 1970s and allow us to explore the character of technological change in the 1990s.

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.

A. Education Upgrading—Men

The estimated coefficients in Table 8 allow us to assess the relationship between technological change and within-industry shifts in the composition of the male workforce by education level. These estimates provide no simple story. Because most of the interaction terms between a time period (T80 or T90) and a technology indicator are not statistically significant there is little basis for saying that complementarities shifted over time—technology becoming more or less skill biased.

The story does not become simpler even if we ignore statistical significance because the shifts in complementarity vary according to indicator. Consider the estimates of model (1) for high school graduates. For instance, equipment accumulation became more skill-neutral between the 1970s and 1980s, as seen in the positive sign on the equipment interaction in the 1980s for high school graduates. On the other hand, R&D became more of a substitute for high school graduate men in the 1980s and 1990s, as the negative interaction terms shows. A more consistent pattern is seen in model (1) estimates of the summary measure, high school equivalents, which show movement towards greater complementarity of both equipment and R&D in the 1980s.

The model (2) estimates provide information on the role of computerization. Although computerization is associated with greater within-industry employment of college graduates and lesser employment of high school graduates, this was less the case in the 1980s than the 1970s. This can be seen in the positive coefficient on

the 1980s interaction term for high school graduates and equivalents and the corresponding negative coefficient for the most educated groups.

Table 10 presents the estimates of the "technology impact" on educational upgrading and the associated standard errors for each period and the shifts across time periods. The technology impact estimates represent the effect on the annual growth of the employment share of each education group. Like others who have run similar models, we find significant complimentarity between education and capital deepening over the periods we examine. But, most importantly, 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.

The results for high school equivalents aptly summarize the results for the specific education groups. Using model (1) for men, technology's impact was to shrink the employment share of high school equivalent workers by 0.164 percentage points per year in the 1980s, a rate .086 faster than the .077 rate in the 1970s. However, the difference between the 1970s and 1980s technology impact was not significantly different (see line (4)). Equally important, the magnitude of the acceleration, –.086 percentage points a year, implies an additional 0.86 percentage point shrinkage in the relative employment of high school equivalent workers over the entire 1979–1989 period. Using the Katz and Murphy elasticity of –.709 employed in Borjas, Freeman, and Katz (1996), an 0.86 percentage point employment effect implies technology's effect in the 1980s was to reduce the relative wage of male high school equivalents by 2.8%.[24] 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 roughly three-percentage point technology-induced decline in relative wages is not a "small" effect. It does serve, however, to deflate the elevated role of technology in the wage inequality debate, putting technological change (at best) on par with other factors which explain the growth of education premiums such as industry shifts, international trade, unions and a lower minimum wage.

B. Education Upgrading—Women

Table 9 presents the estimates of complementarities between the technology indicators and educational upgrading among women. Again, the change in complementarities in the 1980s does not support any simple story of a growing skill bias since the shifts for particular indicators do not necessarily move in the same direction. Thus, for high school dropout women the effects of equipment accumulation and computerization were less favorable in the 1980s while R&D growth became more favorable. Equipment accumulation and computerization were less biased against female high-school graduates in the 1980s, but R&D became more biased against them. As with men, the estimates for high school equivalents do show

Table 8. The Effect of Technology Indicators on Male Educational Upgrading, 1973–94[1]

Independent Variable[2]	*Percent Less Than High School*		*Percent High School (H.S.)*		*Percent Some College*		*Percent College Only*		*Percent Advanced Degree*		*Percent High School Equivalent*	
	(1)	*(2)*	*(1)*	*(2)*	*(1)*	*(2)*	*(1)*	*(2)*	*(1)*	*(2)*	*(1)*	*(2)*
Equip/N ($000)	0.030	0.028	–0.066	–0.060	0.002	0.003	0.019	0.017	0.015	0.013	–0.034	–0.030
	(0.042)	(0.042)	(0.042)	(0.040)	(0.033)	(0.033)	(0.029)	(0.028)	(0.018)	(0.018)	(0.033)	(0.031)
Equip * T80	–0.013	–0.007	0.002	0.016	–0.019	–0.012	0.020	0.003	0.009	–0.001	–0.024	0.002
	(0.048)	(0.052)	(0.048)	(0.049)	(0.038)	(0.041)	(0.034)	(0.035)	(0.021)	(0.022)	(0.037)	(0.038)
Equip * T90	0.053	0.069	0.035	0.056	–0.058	–0.040	–0.020	–0.069*	–0.009	–0.015	0.051	0.100
	(0.050)	(0.056)	(0.050)	(0.054)	(0.039)	(0.045)	(0.035)	(0.038)	(0.021)	(0.024)	(0.039)	(0.041)
SciShare (Sci)	0.275	–0.122	–0.412	0.670	–0.813	–0.762	0.285	0.102	0.293	0.110	–0.330	–0.000
	(0.947)	(0.979)	(0.949)	(0.937)	(0.751)	(0.784)	(0.668)	(0.658)	(0.409)	(0.415)	(0.740)	(0.717)
Sci * T80	–0.690	–0.274	–0.678	–1.301	1.188	1.174	0.181	0.277	–0.001	0.125	–0.566	–0.763
	(1.059)	(1.094)	(1.061)	(1.047)	(0.839)	(0.876)	(0.747)	(0.736)	(0.457)	(0.464)	(0.827)	(0.801)
Sci * T90	0.663	1.086	–1.195	–1.856*	0.158	0.143	–0.029	0.056	0.403	0.571	–0.383	–0.611
	(1.035)	(1.065)	(1.037)	(1.020)	(0.820)	(0.853)	(0.730)	(0.716)	(0.446)	(0.452)	(0.808)	(0.780)
Comp/N ($000)		3.590		–6.647**		–0.523		1.793		1.787*		–3.240**
		(2.231)		(2.136)		(1.786)		(1.500)		(0.947)		(1.634)
Comp * T80		–3.652		6.354**		0.401		–1.505		–1.599*		2.798*
		(2.253)		(2.157)		(1.804)		(1.515)		(0.956)		(1.650)
Comp * T90		–3.672		6.491**		0.410		–1.486		–1.745*		2.924*
		(2.237)		(2.141)		(1.791)		(1.504)		(0.949)		(1.638)
N Growth	0.064**	0.064**	–0.058**	–0.055**	0.033**	–0.032**	0.032**	0.030**	–0.005	0.007	–0.013	–0.009
	(0.018)	(0.019)	(0.018)	(0.018)	(0.014)	(0.015)	(0.013)	(0.012)	(0.008)	(0.008)	(0.014)	(0.014)
Adj R2	0.31	0.31	0.51	0.55	0.43	0.42	0.08	0.16	0.21	0.24	0.22	0.32
N	102	102	102	102	102	102	102	102	102	102	102	102

Notes: *p < 0.10
**p < 0.05
[1]Weighted by industry shares of male employment.
[2]All models were estimated with a constant term and time dummies for the 1980s and 1990s (not shown).

Table 9. The Effect of Technology Indicators on Female Educational Upgrading, 1973–94[1]

Independent Variable[2]	*Percent Less Than High School* (1)	(2)	*Percent High School (H.S.)* (1)	(2)	*Percent Some College* (1)	(2)	*Percent College Only* (1)	(2)	*Percent College or More* (1)	(2)	*Percent High School Equivalent* (1)	(2)
Equip/N ($000)	0.149**	0.109**	–0.188**	–0.151 **	0.001	0.007	0.038	0.032	0.001	0.003	–0.029	–0.030
	(0.049)	(0.048)	(0.064)	(0.066)	(0.047)	(0.049)	(0.038)	(0.040)	(0.024)	(0.026)	(0.045)	(0.048)
Equip * T80	–0.084	–0.036	0.042	0.022	0.012	–0.019	0.018	0.023	0.012	0.010	–0.040	–0.032
	(0.055)	(0.058)	(0.071)	(0.079)	(0.052)	(0.059)	(0.043)	(0.048)	(0.027)	(0.031)	(0.050)	(0.058)
Equip * T90	–0.092*	–0.144**	0.168**	0.220**	–0.045	0.013	–0.041	–0.093*	0.010	0.005	0.038	0.076
	(0.056)	(0.061)	(0.073)	(0.083)	(0.053)	(0.062)	(0.044)	(0.051)	(0.027)	(0.033)	(0.051)	(0.061)
SciShare (Sci)	–1.261	–1.172	0.896	0.796	–0.139	–0.116	0.462	0.459	0.042	0.033	–0.581	–0.571
	(1.086)	(1.004)	(1.142)	(1.375)	(1.039)	(1.022)	(0.851)	(0.837)	(0.535)	(0.545)	(0.993)	(1.001)
Sci * T80	0.970	0.907	–1.442	–1.305	0.514	0.421	–0.331	–0.326	0.290	0.303	–0.012	–0.005
	(1.228)	(1.139)	(1.600)	(1.560)	(1.176)	(1.160)	(0.962)	(0.949)	(0.605)	(0.618)	(1.124)	(1.136)
Sci * T90	1.877	1.544	–1.400	–1.069	–1.438	–1.289	0.337	0.187	0.623	0.625	–0.360	–0.271
	(1.158)	(1.072)	(1.509)	(1.468)	(1.108)	(1.091)	(0.907)	(0.893)	(0.571)	(0.581)	(1.059)	(1.068)
Comp/N ($000)		4.076**		–3.593*		–0.939		0.655		–0.199		0.041
		(1.452)		(1.987)		(1.478)		(1.210)		(0.787)		(1.447)
Comp * T80		–4.132**		3.447*		1.142		–0.645		0.189		–0.107
		(1.457)		(2.010)		(1.495)		(1.223)		(0.796)		(1.463)
Comp * T90		–3.691**		3.227		0.668		–0.415		0.212		–0.198
		(1.457)		(1.994)		(1.483)		(1.213)		(0.790)		(1.452)
N Growth	0.097**	0.101**	–0.134**	–0.135**	0.005	0.001	0.017	0.019	0.015**	0.015*	–0.028**	–0.029**
	(0.015)	(0.014)	(0.019)	(0.019)	(0.014)	(0.014)	(0.012)	(0.012)	(0.007)	(0.008)	(0.013)	(0.014)
Adj R2	0.51	0.58	0.63	0.65	0.55	0.57	0.20	0.23	0.22	0.20	0.16	0.15
N	102	102	102	102	102	102	102	102	102	102	102	102

Notes: *p < 0.10
**p < 0.05
[1]Weighted by industry shares of female employment.
[2]All models were estimated with a constant term and time dummies for the 1980s and 1990s (not shown).

stronger skill complementarities in the 1980s (except for computerization), but the changes are statistically indistinguishable from zero.

The estimates of technology's impact on the educational composition of employment among women (Table 10) do show some acceleration in the 1980s over the 1970s, but the changes are generally insignificant. For example, technology-induced demand shift against high-school equivalent females led to an accelerated decrease of their utilization of 0.8 percentage points over the 1980s (again, ignoring significance). The impact of this quantity shift on female relative wages is about the same as males, a lowering of relative wages by slightly less than 3%.

C. Wage Quantities—Men

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. The estimated complementarities for men are presented in Table 11.

The data do tell a technology story but it is not the conventional one. The shifts in complementarity in the 1980s for the two lowest wage groups, 0–20% and 21–50%, were favorable to them (except computers for the 21–50% group), indicating a decline in the technology bias against the bottom half. The corresponding trend is that equipment accumulation became less associated with the use of high wage workers, the 76–90% and the 91–100% groups, in the 1980s than in the 1970s. Computerization was also less favorable to the highest wage men (the 91–100% group) in the 1980s than in the 1970s.[25] R&D complementarities, on the other hand, became less favorable to the upper-middle (51–75%) and lower-upper (76–90%) wage groups while more favorable to the highest earners. Changes in the complementarity of computerization reveal no consistent monotonic pattern as one moves up the wage scale.

The estimated technology impacts presented in Table 13 reinforce this new technology story. Technological change was less biased in the 1980s than the 1970s for the bottom half (see line (4)), with a lessening of the skill bias being statistically significant for the 21–50% group in both models (1) and (2). *There is definitely no support for an accelerated technology effect working against the bottom half in the 1980s.* Note that the line (4) estimate is positive for the two lowest wage groups in both models. Again, the corresponding effect is a weaker association between technological change and the use of high wage workers (the 76–90% and 91–100% groups) in the 1980s, a shift which is statistically significant for the 76–90% group. That is, *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.* The middle wage group (51–75%), corresponding to the better paid noncollege-educated workforce, were equally and adversely affected by technology in both the 1970s and 1980s. Technological change in the 1980s, therefore, was, if anything, less adverse for the bottom 75% of the male wage structure in the 1980s relative to the 1970s. The conventional story of a 1980s technology shock helping higher-skilled workers and hurting lower-skilled male workers definitely does not fit with the estimates in Table 13 if one substitutes "paid" for "skilled." In fact, these estimates suggest the opposite as the shift between the 1970s and 1980s was *against* the two highest paid groups in the male wage structure.

The estimates of technology's impact in the 1990s is even less consistent with the technology story. Technology's impact in the 1990s was nearly neutral, as indicated by the small impacts shown on line (3) for every wage group. Since this neutrality in the 1990s represents a shift from technology disemploying workers in the bottom three-fourths and favoring the employment of high wage workers in the 1970s (line (1)), deceleration of skill-biased change is evident in line 5.

These results are consistent with the slowdown in the growth of white-collar employment and the slower growth of the relative demand for college-educated men in the 1990s. In contrast, the estimate of technology's impact does not help explain the reduction of middle-wage employment and the expansion of low-wage employment in the 1980s and 1990s.

D. Wage Quantities—Women

The estimated relationships between technology indicators and shifts in female wage quantities are presented in Table 12. Complementarity shifts for women appear to favor the employment of middle-wage women. R&D deepening was clearly biased against middle-wage (21–75%) women in the 1970s, but this pattern reversed in the two later periods. Thus, the skill-bias shifts for R&D in the 1980s and 1990s strongly favored the broad middle-wage group (the 21% to 75% group) yet were adverse for both the lowest and highest-wage women. The coefficients on equipment accumulation also imply a favorable shift for middle-wage women as equipment accumulation was less adverse in the 1980s and 1990s relative to the 1970s. Computerization, was also more favorable to lower-middle (21–50%) and upper-middle wage (51–75%) women in the 1980s and 1990s than in the 1970s.

Shifts in complementarity were consistently adverse for low-wage women workers in both the 1980s and 1990s. For high-wage women the results are mixed, as equipment accumulation and R&D became less favorable to their increased employment, but computerization was more favorable.

The estimated technology impacts for female wage quantities tells yet another technology story (Table 13). Using either model (1) or model (2), technology's impact in the 1980s was less favorable to the lowest wage women workers (line (4) is negative) and to the highest wage workers (76–90% and 91–100%). In contrast, technology was more favorable to the two middle-wage groups in the 1980s than in the 1970s. This pattern suggests a "filling out" of the middle led by technology. Note that the shifts from the 1970s to the 1980s are statistically significantly for four of the five wage quantity groups. *There is no support for an accelerated technology impact hurting the bottom half or three-fourths and helping the top half,*

Table 10. Technology Impact on Annual Change Education Shares, 1973–94

	Men				Women			
	Without Computers (1)		With Computers (2)		Without Computers (1)		With Computers (2)	
Dependent Variable	*Tech Impact*	*Std Error*	*Tech Impact*	*Std Error*	*Tech Impact*	*Std Error*	*Tech Impact*	*Std Error*
% Less Than H.S.								
1. 1973–79	0.067	0.065	0.126*	0.075	0.075	0.058	0.144**	0.059
2. 1979–89	–0.006	0.054	–0.014	0.067	0.066	0.054	0.064	0.053
3. 1989–94	0.127**	0.045	0.093	0.078	0.099**	0.045	0.208**	0.053
4. 80s Less 70s	–0.073	0.084	–0.140	0.100	–0.009	0.079	–0.080	0.079
5. 90s Less 70s	0.060	0.079	–0.033	0.108	0.024	0.074	0.064	0.080
6. 90s Less 80s	0.133*	0.070	0.107	0.103	0.033	0.070	0.144*	0.075
% High School (H.S.)								
1. 1973–79	–0.109*	0.065	–0.218**	0.072	–0.143*	0.076	–0.204**	0.081
2. 1979–89	–0.159**	0.054	–0.197**	0.064	–0.245**	0.070	–0.258**	0.072
3. 1989–94	–0.142**	0.045	–0.206**	0.075	–0.066	0.059	–0.169**	0.073
4. 80s Less 70s	–0.050	0.084	0.021	0.096	–0.101	0.103	–0.054	0.108
5. 90s Less 70s	–0.033	0.079	0.012	0.104	0.078	0.096	0.035	0.109
6. 90s Less 80s	0.017	0.070	–0.009	0.098	0.179**	0.091	0.089	0.102
% Some College								
1. 1973–79	–0.053	0.052	–0.061	0.060	–0.008	0.056	–0.024	0.060
2. 1979–89	0.002	0.042	–0.013	0.053	0.048	0.051	0.062**	0.054
3. 1989–94	–0.088**	0.036	–0.134**	0.063	–0.194**	0.043	–0.271	0.054
4. 80s Less 70s	0.055	0.066	0.048	0.080	0.056	0.076	0.087	0.081
5. 90s Less 70s	–0.036	0.063	–0.073	0.087	–0.185**	0.071	–0.247**	0.081
6. 90s Less 80s	–0.091	0.055	–0.121	0.082	–0.242**	0.067	–0.333**	0.076
% College Only								
1. 1973–79	0.050	0.046	0.079	0.050	0.073	0.046	0.084*	0.049
2. 1979–89	0.100**	0.038	0.137**	0.045	0.088**	0.042	0.090**	0.044
3. 1989–94	0.027	0.032	0.153	0.053	0.083**	0.036	0.151**	0.044
4. 80s Less 70s	0.050	0.059	0.058	0.067	0.015	0.062	0.006	0.066
5. 90s Less 70s	–0.023	0.056	0.074	0.073	0.010	0.058	0.067	0.066
6. 90s Less 80s	–0.073	0.049	0.016	0.069	–0.005	0.055	0.061	0.062
% Advanced Degree								
1. 1973–79	0.045	0.028	0.074**	0.032	0.004	0.029	0.000	0.032
2. 1979–89	0.063**	0.023	0.087**	0.028	0.043	0.027	0.042	0.029
3. 1989–94	0.076**	0.020	0.093**	0.033	0.077**	0.022	0.081 **	0.029
4. 80s Less 70s	0.018	0.036	0.013	0.042	0.039	0.039	0.042	0.043
5. 90s Less 70s	0.031	0.034	0.020	0.046	0.074**	0.036	0.080*	0.043
6. 90s Less 80s	0.013	0.030	0.006	0.044	0.034	0.035	0.038	0.040
% High School Equivalent								
1. 1973–79	–0.077	0.051	–0.130**	0.055	–0.072	0.053	–0.071	0.059
2. 1979–89	–0.164**	0.042	–0.221 **	0.049	–0.142**	0.049	–0.148**	0.053
3. 1989–94	–0.070**	0.035	–0.200**	0.057	–0.095**	0.041	–0.140*	0.053
4. 80s Less 70s	–0.086	0.065	–0.091	0.073	–0.070	0.073	–0.077	0.079
5. 90s Less 70s	0.007	0.062	–0.070	0.079	–0.023	0.068	–0.068	0.079
6. 90s Less 80s	0.093*	0.054	0.021	0.075	0.047	0.064	0.009	0.074

Notes: $*p < 0.10$
$**p < 0.05$

Table 11. The Effect of Technology Indicators on Male Wage Quantities, 1973–94[1]

Independent Variable[2]	*Share 0–20%*		*Share 21–50%*		*Share 51–75%*		*Share 76–90%*		*Share 91–100%*	
	(1)	*(2)*	*(1)*	*(2)*	*(1)*	*(2)*	*(1)*	*(2)*	*(1)*	*(2)*
Equip/N ($000)	–0.073	–0.073	–0.116**	–0.114*	–0.099*	–0.100*	0.193**	0.194**	0.096**	0.093**
	(0.047)	(0.047)	(0.062))	(0.061)	(0.051)	(0.052)	(0.049)	(0.048)	(0.029)	(0.028)
Equip * T80	0.018	0.021	0.127*	0.152*	0.076	0.063	–0.172**	–0.181 **	–0.049	–0.055
	(0.053)	(0.059)	(0.071)	(0.075)	(0.055)	(0.064)	(0.056)	(0.060)	(0.033)	(0.034)
Equip * T90	0.025	0.021	0.106	0.013	0.142**	0.143**	–0.157**	–0.107*	–0.115**	–0.069*
	(0.055)	(0.064)	(0.074)	(0.082)	(0.061)	(0.070)	(0.058)	(0.065)	(0.034)	(0.037)
SciShare (Sci)	–0.840	–0.822	–1.839	–1.993	0.798	0.847	1.626	2.041 *	0.255	–0.073
	(1.058)	(1.111)	(1.409)	(1.426)	(1.159)	(1.215)	(1.110)	(1.134)	(0.654)	(0.647)
Sci * T80	0.169	0.162	2.129	2.409	–1.897	–2.009	–0.907	–1.355.	0.507	0.793
	(1.182)	(1.241)	(1.575)	(1.593)	(1.295)	(1.358)	(1.241)	(1.267)	(0.732)	(0.723)
Sci * T90	0.067	0.042	2.484	2.471	–1.083	–1.133	–1.319	–1.638	–0.150	0.258
	(1.156)	(1.209)	(1.539)	(1.551)	(1.266)	(1.322)	(1.213)	(1.234)	(0.715)	(0.704)
Comp/N ($000)		–0.198		1.002		–0.300		–3.641		–3.137**
		(2.532)		(3.249)		(2.770)		(2.584)		(1.474)
Comp * T80		0.162		–1.402		0.507		3.740		–3.008**
		(2.556)		(3.281)		(2.797)		(2.609)		(1.488)
Comp * T90		0.220		–0.446		0.301		3.327		–3.401**
		(2.538)		(3.257)		(2.776)		(2.590)		(1.478)
N Growth	–0.058**	–0.057**	–0.019	–0.012	0.031	0.029	0.005	0.003	0.040	0.038**
	(0.020)	(0.021)	(0.027)	(0.027)	(0.022)	(0.023)	(0.021)	(0.021)	(0.126)	(0.012)
Adj R2	0.55	0.53	0.23	0.26	0.07	0.04	0.55	0.56	0.22	0.29
N	102	102	102	102	102	102	102	102	102	102

Notes: *$p < 0.10$
**$p < 0.05$
[1]Weighted by industry shares of female employment.
[2]All models were estimated with a constant term and time dummies for the 1980s and 1990s (not shown).

Table 12. The Effect of Technology Indicators on Female Wage Quantities, 1973–94[1]

Independent Variable[2]	*Share 0–20%* (1)	*Share 0–20%* (2)	*Share 21–50%* (1)	*Share 21–50%* (2)	*Share 51–75%* (1)	*Share 51–75%* (2)	*Share 76–90%* (1)	*Share 76–90%* (2)	*Share 91–100%* (1)	*Share 91–100%* (2)
Equip/N ($000)	0.161**	0.107	–0.125	–0.101	–0.151 **	–0.138**	–0.100*	–0.097*	0.216**	0.229**
	(0.072)	(0.075)	(0.078)	(0.082)	(0.066)	(0.069)	(0.056)	(0.058)	(0.070)	(0.070)
Equip * T80	–0.223**	–0.134	0.157*	0.190*	0.083	0.068	0.109*	0.039	–0.126	–0.163*
	(0.080)	(0.090)	(0.086)	(0.099)	(0.074)	(0.084)	(0.062)	(0.070)	(0.078)	(0.085)
Equip * T90	–0.188**	–0.150	0.123	0.056	0.177**	0.078	0.131**	.122	–0.243**	–0.106
	(0.082)	(0.095)	(0.088)	(0.104)	(0.075)	(0.088)	(0.063)	(0.074)	(0.080)	(0.089)
SciShare (Sci)	3.078*	3.211 **	–4.658**	–4.795**	–3.322**	–3.392**	3.796**	3.841 **	1.106	–1.134
	(1.592)	(1.566)	(1.716)	(1.720)	(1.467)	(1.456)	(1.233)	(1.225)	(1.557)	(1.468)
Sci * T80	–3.409*	–3.449*	5.379**	5.670**	3.184*	3.258**	–4.026**	–4.250**	–1.128	–1.230
	(1.800)	(1.776)	(1.941)	(1.951)	(1.659)	(1.652)	(1.395)	(1.389)	(1.761)	(1.664)
Sci * T90	–3.040*	–3.219*	4.831 **	4.846**	3.424**	3.270**	–4.596**	–4.650**	–0.619	–0.247
	(1.697)	(1.671)	(1.830)	(1.836)	(1.564)	(1.554)	(1.315)	(1.307)	(1.660)	(1.567)
Comp/N ($000)		5.306**		–1.725		–1.031		–0.712		–1.837
		(2.263)		(2.486)		(2.105)		(1.770)		(2.121)
Comp * T80		–5.607**		1.248		1.049		1.287		2.002
		(2.289)		(2.515)		(2.129)		(1.790)		(2.146)
Comp * T90		–5.235**		1.915		1.388		0.729		1.204
		(2.271)		(2.495)		(2.112)		(1.776)		(2.128)
N Growth	0.015	0.018	–0.006	0.001	–0.020	–0.017	–0.028	–0.034**	0.039*	0.032
	(0.022)	(0.022)	(0.023)	(0.024)	(0.020)	(0.020)	(0.017)	(0.017)	(0.021)	(0.020)
Adj R2	0.73	0.74	0.78	0.78	0.23	0.25	0.25	0.26	0.26	0.35
N	102	102	102	102	102	102	102	102	102	102

Notes: * $p < 0.10$
** $p < 0.05$
[1] Weighted by industry shares of female employment.
[2] All models were estimated with a constant term and time dummies for the 1980s and 1990s (not shown).

Table 13. Technology Impact on Annual Change in Wage Quantities, 1973–94

Dependent Variable	*Men*				*Women*			
	Without Computers (1)		*With Computers (2)*		*Without Computers (3)*		*With Computers (4)*	
	Tech Impact	*Std Error*	*Tech Impact*	*Std Error*	*Tech Impact*	*Std Error*	*Tech Impact*	*Std Error*
% 0–20								
1. 1973–79	–0.176**	0.073	–0.175**	0.085	0.387**	0.086	0.477**	0.092
2. 1979–89	–0.142**	0.060	–0.146*	0.076	–0.112	0.079	–0.136*	0.082*
3. 1989–94	–0.098*	0.051	–0.089	0.089	–0.012	0.066	0.009	0.083
4. 80s Less 70s	0.034	0.093	0.033	0.114	–0.500*	0.116	–0.613**	0.123
5. 90s Less 70s	0.078	0.088	0.090	0.123	–0.399**	0.108	–0.468**	0.124
6. 90s Less 80s	0.043	0.078	0.057	0.117	0.101	0.103	0.145	0.116
% 21–50								
1. 1973–79	–0.314**	0.097	–0.296**	0.109	–0.457*	0.092	–0.486**	0.101
2. 1979–89	0.040	0.080	–0.010	0.097	0.101	0.085	0.065	0.090
3. 1989–94	0.065	0.067	0.296**	0.114	0.017	0.072	0.072	0.091
4. 80s Less 70s	0.345**	0.124	0.286*	0.146	0.559**	0.125	0.551**	0.136
5. 90s Less 70s	0.379**	0.118	0.591**	0.158	0.474**	0.117	0.558**	0.136
6. 90s Less 80s	0.026	0.104	0.305**	0.150	–0.084	0.111	0.007	0.128
% 51–75								
1. 1973–79	–0.104	0.080	–0.110	0.093	–0.394**	0.079	–0.411 **	0.086
2. 1979–89	–0.123*	0.066	–0.097	0.083	–0.105	0.073	–0.102	0.076
3. 1989–94	–0.016	0.056	–0.016	0.097	0.026	0.061	0.127	0.077
4. 80s Less 70s	–0.019	0.102	0.013	0.124	0.289**	0.107	0.309**	0.115
5. 90s Less 70s	0.088	0.097	0.094	0.134	0.420**	0.100	0.538**	0.115
6. 90s Less 80s	0.107	0.085	0.080	0.128	0.131	0.095	0.229**	0.108
% 76–90								
1. 1973–79	0.423**	0.076	0.362**	0.087	0.153**	0.066	0.140*	0.072
2. 1979–89	0.090	0.063	0.102	0.077	–0.006	0.061	0.039	0.064
3. 1989–94	0.044	0.053	–0.086	0.091	–0.067	0.052	–0.063	0.065
4. 80s Less 70s	–0.333**	0.098	–0.260**	0.116	–0.159	0.900	–0.101	0.097
5. 90s Less 70s	–0.378**	0.093	–0.448**	0.125	–0.220**	0.084	–0.204**	0.097
6. 90s Less 80s	–0.045	0.082	–0.187	0.119	–0.061	0.080	–0.103	0.091
% 91–100								
1. 1973–79	0.172**	0.045	0.223**	0.049	0.311 **	0.084	0.280**	0.086
2. 1979–89	0.135**	0.037	0.151**	0.044	0.122	0.077	0.134*	0.077
3. 1989–94	0.005	0.031	–0.105**	0.052	0.036	0.065	–0.144*	0.078
4. 80s Less 70s	–0.037	0.058	–0.072	0.066	–0.189*	0.114	–0.147	0.116
5. 90s Less 70s	–0.167**	0.055	–0.327**	0.072	–0.276**	0.106	–0.424*	0.116
6. 90s Less 80s	–0.130**	0.048	–0.255**	0.068	–0.087	0.100	–0.277**	0.109

Notes: * $p < 0.10$
** $p < 0.05$

that is, the conventional technology story. The estimates for the 1990s also suggest a "filling out" of the middle relative to the 1970s with the quantitative impact being even larger (see line (5)).

VII. 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; examining both male and female trends; and, quantifying the relationship between technology and within-group wage inequality. This more complete analysis produces a technology story different from the conventional one. 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" (non-college graduates) or "less-skilled" (the bottom three-fourths) workers. Our estimates show that technology's impact on high school equivalent employment 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 men find a quantitatively large (0.3% or 0.4% a year, adding up the two highest wage groups) and statistically significant deceleration of technology's effect in the 1980s versus the 1970s or in the 1990s versus the 1970s (an 0.5% to 0.7% annual deceleration). There are comparable 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. Only among the lowest wage women was there any evidence of technology being more adverse in the 1980s and 1990s than in the 1970s. Among women, technology seems to be strengthening the broad middle while being less favorable to the top and to the bottom.

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.

ACKNOWLEDGMENT

This research was accomplished with the financial support of the Russell Sage Foundation and the Rockefeller Foundation. David Webster's research on this project was invaluable.

NOTES

1. See, for examples, Berman, Machin, and Bound 1998; Danziger and Gottschalk, 1995, chapter 7; Berman, Bound and Griliches, 1993; Bound and Johnson, 1992.

2. Some have argued that the increase in the college premium is a result not of the acceleration of relative demand but of the acceleration of relative supply (see Katz and Murphy, 1992; Auter, Katz, & Kreuger, 1996). This interpretation, however, undermines the technology explanation, which is predicated on technology-induced demand acceleration.

3. See note 2.

4. Berman and colleagues (1996) use a manufacturing data base that has both production/non-production and educational classifications. They show that, in 1989, 38% of production workers had at least some college (8% had at least a four-year college degree), while 24% of non-production workers have completed high school or less (54% had less than four-year college degree).

5. The two data sets that have been used to examine within group differentials—the March CPS and the CPS Outgoing Rotation Groups—show different trends. The March data rise steadily throughout the 1970s and 1980s, whereas the trend in the ORG is flat in the 1970s and increasing in the 1980s.

6. The percentile cutoffs are determined from the 1979 wage distribution and are given in the table in 1989 dollars. Separate cutoffs are calculated for men and women. In order to avoid "clumping" in the observed wage distribution, generated by reporting error, we smooth reported wages as described inMishel and Bernstein, (1993, p. 23). This procedure leads to "imperfect" cutoffs, in terms of generating slightly uneven categories in the base year (note, for example, that in 1979 there was 25.8% of the male workforce between the 50th and 75th percentile).

7. The shift out of the middle of the wage distribution to the bottom is primarily generated by within-industry trends, the arena most relevant to the role of technology (see Tables 5 and 6).

8. While it would be tempting to argue that "unobservable skills" correlate with observable skills, and thus assume that college-educated workers would be a likely group to examine here, recall that by construction unobservable skills are orthogonal to education (see Juhn et al., 1993).

9. The results are relegated to a note (number 9) in the paper. The test for acceleration of the 1980s over the 1970s was insignificant in all cases and had the "incorrect" sign in the US case.

10. The wage rates are deflated by the CPI-U-X1.

11. As noted, these data come from the CPS ORG files. We have also examined the trends in these same wage differentials in the March CPS. For men, the March data show a similar growth in the 90/50,

but show a decline in the 50/10 differential over the last 10 years. This pattern is even more contradictory to a technology explanation. The March CPS trends for women are somewhat more in keeping with the technology story, with both the 90/50 and the 50/10 continuing to grow into the 1990s. It is curious, however, that the wage gaps grow more slowly starting in the mid-1980s.

12. These data are drawn from the Department of Education series on new bachelors' degrees and are therefore not influenced by the coding changes introduced in the CPS in the early 1990s. More relevant data in this context would be college employment relative to non-college employment, but this cannot be computed from this data source. An analysis of the employment share of college graduates constructed from the CPS, however, shows the same result. The data are from the ORG series and are based on years of schooling (16 years) for 1973–1991. The trend between 1991–92 is based on the March 1992 and March 1993 surveys and extrapolates based on the percentage point share of those with college degrees as their highest degree. The 1992–94 trends are based on the ORG data and extrapolations based on highest degree attained. The series begins with the 1994 level and extrapolates backward.

13. The data in Figures E and F are the values of the coefficients on the college "dummy" from log wage regressions which include controls for education, experience, regions, marital status and race.

14. Wolff (1995) and Howell (1994) make these same arguments. Wolff's analysis of occupational/industry shifts and skill demands leads him to conclude that "the bias in technological change toward workers with cognitive skills was strongest in the 1960s but fell rather sharply in the 1970s and again in the 1980s." Note that this contradicts the finding in Auter et al.

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

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

18. 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.

19. 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.

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

21. In this table, we use gross R&D stock from the NIPA accounts; FTEs are from the BEA series.

22. We suspect that some portion of the education shifts in the 1990s reflects measurement error due to the coding changes in the surveys and the problems combining PUMs estimates and ORG estimates.

23. In similar models by Berndt and colleagues (though only for the manufacturing sector), the computer coefficient is insignificant in 5 out of 8 specifications, including all specifications for white collar workers (pp. 22–24). In Berman and colleagues (also only for manufacturing), the computer coefficient is significant. These models, however, omit the equipment term. In such models, it is impossible to discern whether the computer variable is "doing the work" of the more inclusive equipment variable.

24. 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.

25. Note that computers went from being adverse in the 1970s for the 76–90% groups to being essentially neutral in the 1980s, a shift towards greater complementarity.

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