Chapter 6
SKILL DEMAND, INEQUALITY, AND COMPUTERIZATION: CONNECTING THE DOTS

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INTRODUCTION

Inequality has social costs: it may engender political divisions, aggravate crime, and lead low-income families into poverty from which they or their children may not emerge. Dramatic shifts in relative well-being therefore demand attention. In the late 1980s, economists discovered that the earnings of high- and low-wage workers were rapidly diverging (Levy and Murnane 1992). Chart 1 plots earnings inequality for the years 1963 to 1995, measured as the percentage difference in earnings between the 90th percentile worker and the 10th percentile worker.[1] Between 1963 and 1979, this difference in earnings hovered steadily at approximately 220 percent among men and 190 percent among women. Over the next ten years, these gaps grew into fissures. The 90-10 weekly earnings differential expanded by 110 percentage points for both genders between 1979 and 1989 and then edged slowly upward throughout the 1990s. Mirroring these trends, educational earnings inequality—the earnings gap between college and high school educated workers—increased by two-thirds in the same decades (Chart 2). By 1999, educational inequality easily exceeded its high set in 1940, the earliest year for which consistent data are available.

What forces caused this remarkable divergence? Naturally, economists suspected factors influencing supply and demand, in particular skill-biased technical change (SBTC) (see Bound and Johnson 1992; Katz and Murphy 1992;

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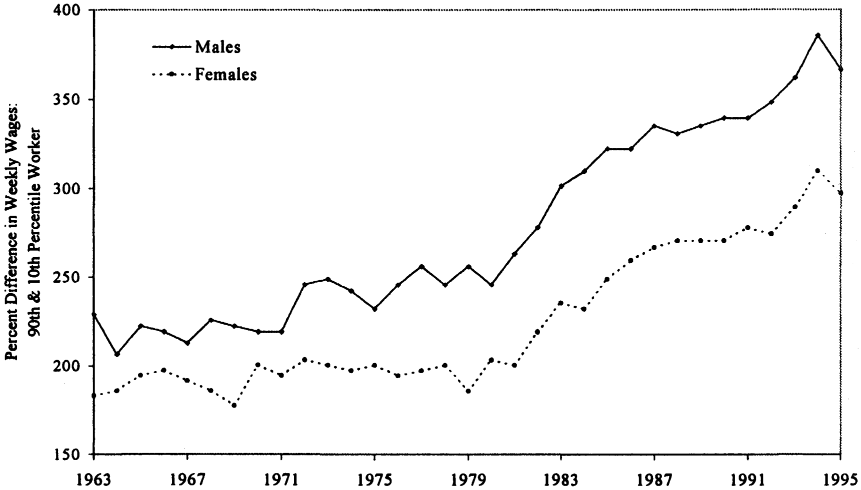
1. That is, the worker earning more than 90 percent of the employed population and the worker earning less than 90 percent of the employed population.

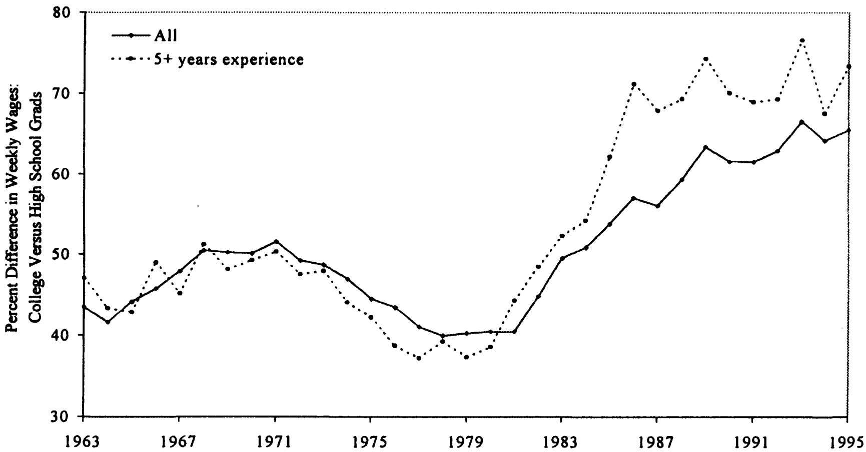
D. K. Ginther et al. (eds.), *Technology, Growth, and the Labor Market*

Chart 1. Overall U.S. Wage Inequality, 1963–95



Source: Katz and Autor (1999)

Chart 2. College/High School Weekly Wage Differential, 1963–95



Source: Katz and Autor (1999)

and Levy and Murnane 1992). To define terms, SBTC is a change in how work is accomplished that raises the productivity of high-skilled workers relative to that of workers with fewer skills. Gains in relative productivity increase demand for skilled workers' services, enhance their earnings power, and thereby increase earnings inequality. It is easy to see the SBTC hypothesis's appeal. Because inequality's rapid advance coincided with the advent of the era of desktop computing, many economists posited that *something* about computerization had made skilled workers relatively more productive.

While loosely fitting the facts, three steps are needed to make this argument convincing. First, the SBTC hypothesis places the blame for rising inequality at the feet of shifting labor demand. Yet, since wages—and hence inequality—are (in some large part) determined by the interaction of supply and demand, a cogent model of inequality must consider both forces simultaneously. Second, a supply and demand framework needs historical context. Were similar demand shifts present prior to the 1980s when inequality did *not* grow? If so, the SBTC explanation would appear less promising. Finally, even if demand shifts explain rising inequality, it is a further leap to assert that computerization explains these shifts. To understand whether and why computers are responsible for SBTC, we must understand what computers do—or what it is that people do with computers—that increases the demand for more-educated workers relative to less-educated workers.

Culling from research conducted by us and others, this article explores these three missing links.[2] We offer a simple supply and demand framework for analyzing changes in inequality and use this framework to explore the contributions of both factors to inequality over the last six decades. After establishing that demand shifts do appear quite important to explaining recent trends in inequality, we offer a conceptual model for understanding how computerization may have stimulated these shifts. We offer initial evidence that confirms the relevance of this model and close by considering how research could more convincingly establish the causal connection between computerization and increased relative demand for educated workers.

1. THE DETERMINANTS OF EARNINGS INEQUALITY

What drives inequality? Without denying the potential impacts of institutional factors such as minimum wages, labor unions, and international

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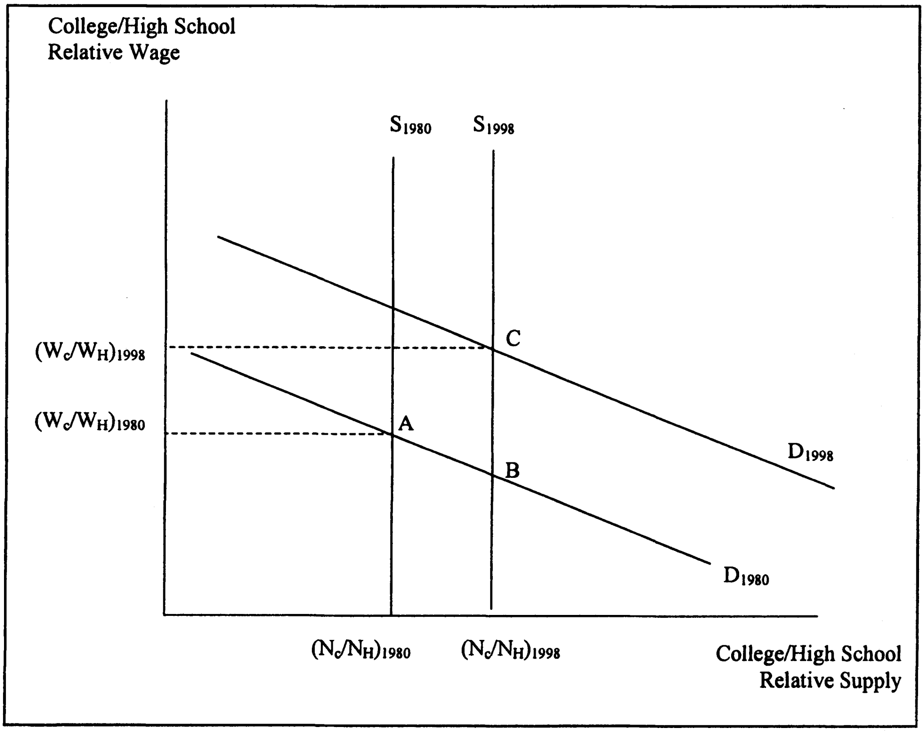
2. Key sources for our discussion are Bound and Johnson (1992), Katz and Murphy (1992), Juhn, Murphy and Pierce (1993), Johnson (1997), Autor, Katz, and Krueger (1998), Katz and Autor (1999), Autor, Levy, and Murnane (2001), and Acemoglu (2002).

trade, we focus on a model of the supply of and demand for skill.[3] Consider a model of wage setting for high- and low-skilled workers depicted by Chart 3. Call these groups college and high school graduates. The X-axis in the chart measures the relative supply of college versus high school graduates, and the Y-axis measures their relative wages (that is, the level of earnings inequality between college and high school graduates). The downward sloping (relative) demand curve for college versus high school graduates (D_{1980}, D_{1998}) indicates that when the relative supply of college graduates increases, their relative wages drop—hence educational earnings inequality falls.

Chart 3. Impact of Demand and Supply Shifts on the Relative Earnings of College vs. High School Graduates



Although the demand curve is a central feature of this diagram, it is purely notional—we never observe it. What we do observe is the number of college and high school graduates employed and their relative earnings at a given time. We can therefore plot the point $(N_C/N_H)_{1980}$ on the horizontal axis depicting the relative supply of college graduates in 1980, and the point

3. On these topics, see Freeman (1995), DiNardo, Fortin, and Lemieux (1996), Feenstra and Hanson (1999), Lee (1998), and Black and Strahan (2001).

$(W_C/W_H)_{1980}$ on the vertical axis, depicting their relative wages. We draw the supply curve of college versus high school graduates, S_{1980}, as extending directly upward from $(N_C/N_H)_{1980}$, embodying the assumption that the ratio of college to high school graduates available to work is approximately fixed (inelastic) in a given year.[4] Using these two data points, we infer that the relative supply curve S_{1980} intersected the relative demand curve D_{1980} at the point A in 1980, yielding the level of inequality $(W_C/W_H)_{1980}$.

Now consider the analogous exercise for the year 1998. The point $(N_C/N_H)_{1998}$ lies to the right of $(N_C/N_H)_{1980}$; relative supply of college graduates increased between 1980 and 1998. If the demand curve in 1998 were still in its 1980 position, this increase in supply would have reduced educational inequality. In fact, this did not occur. The point $(W_C/W_H)_{1998}$ lies above $(W_C/W_H)_{1980}$; wage inequality rose during 1980 to 1998 even as the relative supply of college graduates increased. We infer that relative demand for college graduates must have shifted outward simultaneously.

By how much did it shift? We need to know the slope of the relative demand curve for college versus high school graduates to answer this question. If the demand curve is relatively flat (elastic), it would have to shift quite far to the right to cause wages to rise from $(W_C/W_H)_{1980}$ to $(W_C/W_H)_{1998}$. If instead the demand curve were steeply downward sloping (inelastic), a small outward shift would raise wages considerably. The term for the (inverse of the) slope of the demand curve is the elasticity of substitution between college and high school graduates, denoted here as σ. The shallower this slope, the more elastic demand and the less a change in relative supply translates into a change in relative wages. A number of careful studies estimate the elasticity of substitution between college and high school graduates at between -1 and -2, with a preferred estimate of -1.4. Using $\sigma = 2$, for example, a 1 percent increase in the relative supply of college graduates would translate into a reduction of the college/high school relative wage differential by 0.5 percentage points ($0.5 = 2^{-1}$).[5]

To bring this supply and demand framework to the data, we enumerate in Table 1 employment shares of high school graduates and college equivalents in each decade from 1940 to 1998 alongside the contemporaneous

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4. This is an approximation. An increase in the relative wage is likely to increase relative supply, and hence the relative supply curve should be upward sloping. This modification would not change the essence of our analysis.
5. Katz and Murphy (1992), Hamermesh (1993), Heckman, Lochner and Taber (1998). Note that if this elasticity were infinite (that is, if college and high school graduates were perfect substitutes), shifts in relative supply would not impact relative wages since employers would substitute costlessly between education groups rather than paying either group higher wages.

percentage differential in college/high school hourly earnings.[6] Between 1980 and 1998, our measure of earnings inequality, the college/high school wage differential, rose from 48 to 75 percentage points, a 56 percent gain. Simultaneously, the college share of employment rose from 39 to 43 percent, and the high school share declined from 36 to 33 percent. This pattern of rising college/high school wages in the face of increasing college/high school labor supply provides first order evidence of a demand shift. Using elasticity estimates of 1.0, 1.4, and 2.0, we calculate that relative demand for college versus high school graduates shifted outward at 3.4 to 4.4 percentage points annually during the period 1980 to 1998 (see Table 2).[7] Hence, substantial demand shifts were underway precisely during the period when earnings inequality expanded.

Does this imply that the explosion of earnings inequality was caused by a sudden rise in relative demand for college workers? Not necessarily. Answering this question requires some historical perspective. Observe from Table 1 that in 1940, less than 10 percent of the workforce held a college degree. By 1998, this share exceeded 40 percent.[8] Yet, despite the quadrupling of their supply, college graduates' wages remained 37 to 75 percent above those of high school graduates in all six decades. In fact, their relative wages rose in every decade save for the 1940s and 1970s. Apparently,

Table 1. Full Time Equivalent Employment Shares and Relative Wages of College and High-School Graduates, 1940–98 (Percent)

	High school graduates	College equivalents	College/high-school wage differential
1940	19.1	9.3	64.6
1950	24.3	12.4	36.7
1960	27.4	16.4	48.6
1970	34.1	21.5	59.3
1980	35.8	31.3	47.8
1990	37.0	38.0	66.1
1998	33.3	43.2	75.4

Source: Autor, Katz and Krueger (1998, updated to 1998 data). Data source for 1940–80 is Census Public Use Micro Samples. Data source for 1990–98 is Current Population Survey.

6. College equivalents are defined as all workers with a college degree or greater plus one-half of those with some college. High school graduates are those with exactly a high school degree.
7. More precisely, these figures are one hundred times annual log changes and are weighted averages of the estimated demand shifts over the ten years from 1980 to 1990 and the eight years from 1990 to 1998.
8. High school graduates also increased their share of employment in this period, yet only by half as much.

Table 2. Changes in College Equivalent/Noncollege Log Relative Wages, Supply, and Estimated Demand, 1940–80

	Relative wage change	Relative supply change	Implied relative demand shift: College vs. high school grads. $\sigma = 1.0$	$\sigma = 1.4$	$\sigma = 2.0$
	A. 100 × Annual Log Changes by Decade				
1940–50	–1.86	2.35	0.50	–0.25	–1.35
1950–60	0.83	2.91	3.75	4.08	4.58
1960–70	0.69	2.55	3.25	3.52	3.94
1970–80	–0.74	4.99	4.25	3.95	3.50
1980–90	1.51	2.53	4.05	4.65	5.56
1990–98	0.36	2.25	2.61	2.76	2.98
	B. 100 × Annual Log Changes for Aggregated Time Periods				
1940–70	–0.11	2.61	2.50	2.45	2.39
1970–98	0.38	3.33	3.71	3.86	4.08

Source: Autor, Katz and Krueger (1998, updated to 1998 data). Data source for 1940–80 is Census Public Use Micro Samples. Data source for 1990–98 is Current Population Survey. σ is the assumed elasticity of substitution between college and high school equivalents.

demand for college graduates has been growing for at least as long as we can consistently measure it. Accordingly, the salient question for our analysis is not whether the demand for college graduates has risen since 1980. Instead, we must ask whether recent technological changes accelerated demand growth for college graduates beyond its prevailing postwar rate.

The answer to this refined question proves less clear cut. We begin with two certainties visible from Table 2. First, shifts in the growth rate of supply of college graduates exerted an important influence on earnings inequality throughout the past six decades. This pattern is most visible during the 1970s. In that decade, the growth rate of college graduates almost doubled from the prior decade while inequality contracted measurably. Conversely, the rise in inequality during the 1980s coincided with a sharp deceleration in the production of new college graduates. Therefore, an important source of recent fluctuations in inequality is fluctuating growth in supply overlaid on secularly increasing demand for college graduates.[9] Had the growth in supply of college graduates not accelerated in the 1970s and then slowed in the 1980s, fluctuations in inequality would certainly have been far less pronounced.

The second fact to which the data testify unambiguously is that relative demand for college graduates did accelerate in the most recent three decades (1970–98) in comparison to the prior three (1940–70). This result is

9. This observation is first offered by Katz and Murphy (1992).

visible in the lower panel of Table 2, which tabulates estimated demand shifts for the first and second halves of the 1940 to 1998 interval. Regardless of the elasticity assumed, we find a demand acceleration of at least 40 percent in the most recent three decades. Recent trends in inequality are therefore not entirely explained by fluctuations in supply overlaying steadily shifting demand. Demand growth accelerated sometime after 1970. Many would call this acceleration skill-biased technical change.[10]

When we look more closely at decade-by-decade comparisons, we find two ambiguities. First, the precise timing of the measured acceleration depends on the assumed elasticity. For low values of σ (1.0–1.4), we estimate that demand accelerated sharply in the 1970s and potentially accelerated further in the 1980s. For larger values of σ, we infer that demand decelerated in the 1970s and rebounded even more abruptly in the 1980s. Hence, although we can be confident that relative demand for college graduates accelerated after the 1960s, we cannot be certain whether this acceleration began in the 1970s or 1980s.

The second ambiguity is visible in the 1990s. We find a substantial deceleration in relative demand growth for college graduates during the most recent decade. This inference is also robust to the elasticity assumed, suggesting that either—quite counterintuitively—the "technology shock" that began in the 1970s or 1980s slowed considerably in the 1990s, or that other forces were operative in this decade.

We draw four conclusions from this analysis. Relative demand for skilled workers has grown secularly for at least six decades. Overlaid on these demand shifts, the fluctuating supply of new college graduates has influenced inequality trends. Augmenting the steady demand shifts visible since the 1940s, relative demand favoring college graduates accelerated during the 1970s or 1980s. The recent demand deceleration, however, poses an important puzzle for the SBTC hypothesis.

2. COMPUTERS AND SKILL-BIASED TECHNICAL CHANGE: CIRCUMSTANTIAL EVIDENCE

Was computerization responsible for the acceleration in the relative demand for college graduates during the last three decades? A variety of indirect evidence suggests that the answer is yes. Numerous studies document a strong association between the adoption of computers and computer-based

10. In an insightful recent paper, Card and Lemieux (2001) present evidence that the estimated demand acceleration during the 1980s may be overstated due to the changing age composition of college graduates (which results in larger reductions in net supply than are normally estimated). Adjusting for this factor is not likely to change our qualitative conclusions in this section.

technologies and the increased use of college-educated labor within plants, firms, and industries. Similar patterns are found in the United States, the OECD, Canada, and other developed and developing countries.[11] Two specific pieces of evidence also favor this indirect case.

One is timing. As shown in Table 3, business investment in computer equipment per capita rose by 1,800 percent (that is, a factor of 18) during the 1970s, and by another 1,500 percent in the 1980s. Not surprisingly, computer investment was highest in the 1990s, but its growth significantly decelerated after the 1980s. Hence, the surge in private sector computer investment roughly coincides with the estimated acceleration and deceleration of skill demand. Interestingly, the rate of overall capital accumulation slowed from the 1960s forward and did not rebound until the 1990s. Hence, it is unlikely that other noncomputer capital investment can account for the acceleration in skill demand.[12]

Table 3. Estimated Annual Computer and Noncomputer Capital Investment per Full-Time Equivalent Worker in Nonagricultural, Predominantly Private Sector Industries, 1960–98

	Annual computer investment/FTE (1992$)	Growth in capital stock/FTE
1960–70	0.06	3.72
1970–80	1.18	1.32
1980–90	17.00	0.59
1990–98	62.88	1.35

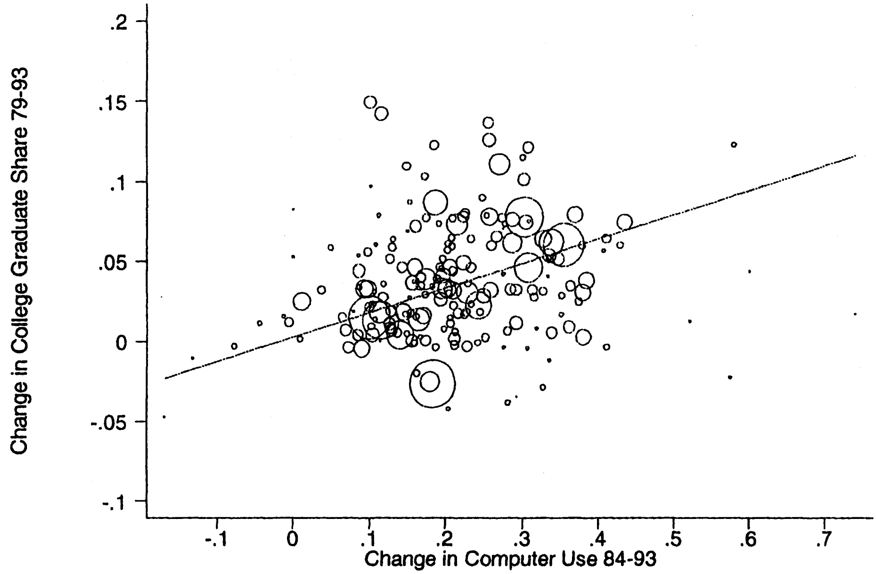
Note: Constant 1992 dollars.
Source: Autor, Levy and Murnane (2001) based on data from the National Income and Product Accounts. Left-hand column is average real annual computer investment per full-time equivalent worker over decade. Right hand column is 100 times the annual log growth rate of the real net capital stock per worker.

The second piece of indirect evidence favoring the link between computerization and increased skill demand is the remarkably strong correlation between computerization and changes in the employment shares of educated workers observed across sectors. Chart 4 plots the change in employment of college (panel A) and high school (panel B) graduates over 1979 to 1993 within 140 detailed industries representing the entire U.S.

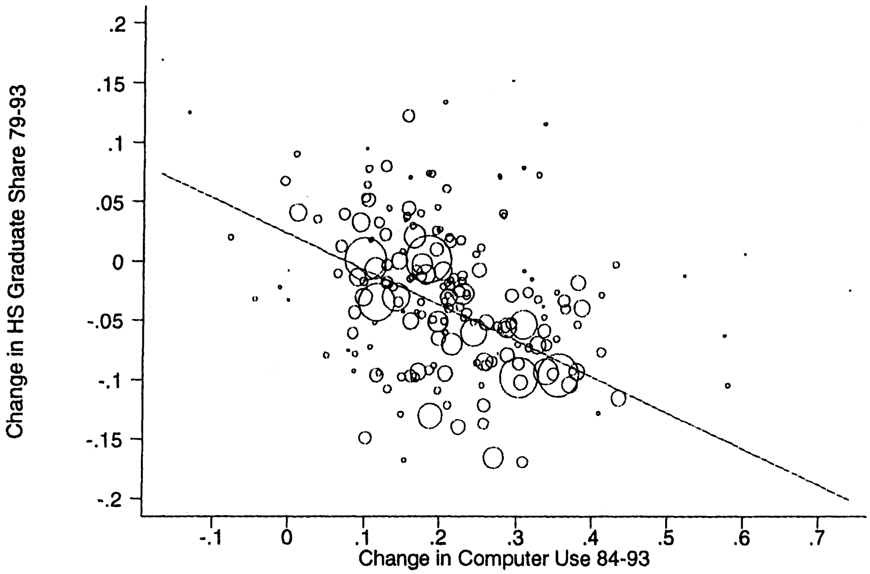
11. See, among others, Berman, Bound, and Griliches (1994), Berman, Bound, and Machin (1998), Machin and Van Reenen (1998), Berman and Machin (2000), Gera, Gu, and Lin (1999), Caroli and Van Reenen (2001), and Bresnahan, Brynjolfsson, and Hitt (2002).

12. As emphasized by Gordon (2000), the National Income and Products Account data used for these calculations may contain systematic inaccuracies. The figures in Table 3 should therefore be viewed as illustrative. Although the general trends are likely correct, the magnitudes are less certain.

Chart 4. Industry Computer Use and Changes in Employment Shares of College and High School Graduates in Detailed U.S. Industries, 1979–93



coef = -.301, se = .034, t = -8.96



Source: Autor, Katz, and Krueger (1998, figure 1) economy against computerization within those industries, measured by the 1984 to 1993 change in the share of industry workers using a computer on the job.[13] The strength of the association between computerization and educational upgrading visible in these charts is indisputable. Hence, the timing and industrial sectors of computerization closely coincide with rapid growth in college graduate employment.

Yet this evidence is circumstantial. What is missing is a motive. Specifically, what is it that computers do—or that people do with computers—that causes educated workers to be relatively more in demand? These mechanisms may initially appear trivial: computers substitute for less educated workers in performing simple tasks or complement the work of more educated workers in complex tasks. Reflection suggests, however, that the relationship between human education and "computer skills" is more complex.

In the economy of the 1970s, long-haul truck driving and double-entry bookkeeping were both tasks routinely performed by workers with modest education, typically high school graduates. In the present economy, computers perform a vast share of the routine bookkeeping via database and accounting software but do very little of the truck driving. Similarly, playing a strong game of chess and writing a persuasive legal brief are both skilled tasks. Current computer technology can readily perform the first task but not the second. These examples suggest that neither all "high"- nor all "low"-skilled tasks are equally amenable to computerization. As we argue below, present computer technology has specific applications and limitations that make it an incomplete substitute for both well-educated and less-educated laborers.

3. HOW COMPUTERIZATION IMPACTS SKILL DEMANDS: A TASK FRAMEWORK

We begin by conceptualizing a job from a "machine's-eye" view as a series of tasks: moving an object, performing a calculation, communicating a piece of information, or resolving a discrepancy. In this context, we ask which tasks can be performed by a computer. A general answer is found by examining what is arguably the first digital computer, the Jacquard Loom of 1801. Jacquard's invention, pictured in Chart 5, was a machine for weaving fabrics with inlaid patterns specified by a program punched onto cards and fed into the loom. Some programs were quite sophisticated; one surviving example uses more than 10,000 cards to weave a black and white silk portrait of Jacquard himself. Two centuries later, the electronic descendents of Jacquard's loom share with it two intrinsic traits. First, they are "symbolic

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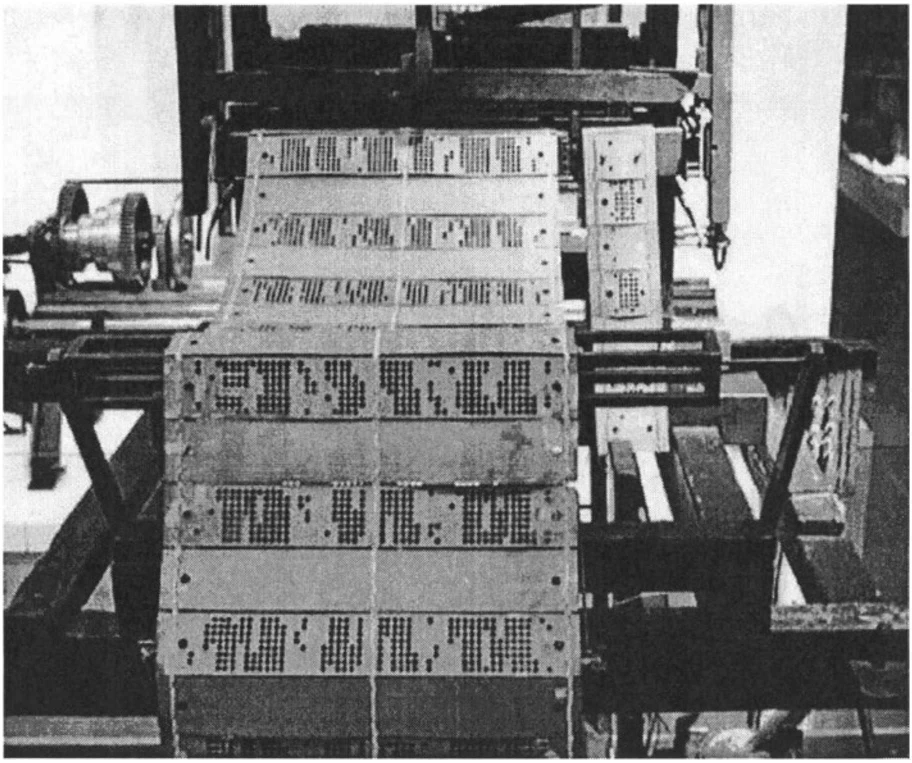
13. The data points in the chart are sized to reflect industry employment.

processors," acting upon abstract representations of information such as binary numbers or, in the loom's case, punched cards.[14] Second, they perform actions that are deterministically specified by explicit procedures or programs. Spurred by a trillion-fold decline in the real price of computing power since the 1800s (Nordhaus 2001), engineers have become vastly more proficient at applying the loom's basic capability—fast, accurate, repetitive execution of stored instructions—to a panoply of tasks. To which workplace tasks does this capability apply?

Chart 5. The Jacquard Loom



Source: <www.victorianweb.org>. Photograph by George P. Landow; used by permission.

The simple insight above is that tasks cannot be computerized unless they can be proceduralized. For a large swath of tasks, this requirement is no hindrance; for another critical set, it appears a binding constraint. To illustrate

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14. This point is emphasized by Brynjolfsson and Hitt (2000).

these cases, we first explore the application of computers to manual tasks and subsequently discuss information processing (that is, cognitive) tasks.

Many manual tasks that humans perform (or used to perform) at their jobs are readily specified in straightforward computer code and accomplished by machines, such as monitoring the temperature of a steel finishing line or moving a windshield into place on an assembly line. However, a problem that arises with many tasks is, as Michael Polanyi (1966) put it, "we do not know how to do many of the things we do." Consequently, it is difficult to develop machines that carry out these tasks. For example, it is a trivial undertaking for a human child to walk on two legs across a room to pick an apple from a bowl of fruit. This same task is presently a daunting challenge for computer science and robotics.[15] Both optical recognition of objects in a visual field and bipedal locomotion across an uneven surface appear to require poorly understood algorithms, one in optics and the other in mechanics. These same problems explain the inability of computers to perform the tasks of long-haul truckers.[16]

We refer to tasks requiring adaptive visual and manual skills as nonroutine manual activities. We emphasize the word nonroutine because if a manual task is sufficiently well specified or performed in a well-controlled environment, it often can be automated despite the seeming need for nonroutine visual or manual skills—as, for example, in the case of industrial robots working on an assembly line. It is this "routineness" or predictability—an engineered attribute of an assembly line—that the aforementioned truck-driving example lacks.[17]

Machinery has substituted for repetitive human labor since (at least) the industrial revolution (see Hounshell 1985; Mokyr 1990; and Goldin and Katz 1998). What computer capital uniquely contributes to this process is

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15. See Pinker (1997). It is a well-known paradox of artificial intelligence that many tasks that programmers assumed would be negligible to program developed into formidable (and still unsolved) engineering problems, such as walking on two legs over uneven terrain. Conversely, many tasks that humans find formidable turn out to be minor programming exercises, such as calculating pi to the 10,000th decimal place.

16. It is a fallacy, however, to assume that a computer must reproduce all of the functions of a human to perform a human's job. Automatic teller machines have supplanted many bank teller functions, although they cannot verify signatures or make polite conversation while tallying change. Similarly, domestic appliances take phone messages and make morning coffee but do not wear pressed black and white tuxedos and greet us at the door like the robots in Woody Allen's Sleeper. We nevertheless take it as axiomatic that if a job is traditionally constituted of nonprocedural tasks, it is more difficult to computerize.

17. Note that the simple distinction between computer-substitutable and nonsubstitutable tasks is not absolute. For example, by calculating more efficient long-haul trucking routes, computers can "substitute" for the labor input of long-haul truck drivers. More formally, there is a nonzero elasticity of substitution between routine and nonroutine tasks, a point we encapsulate in the formal model in Autor, Levy, and Murnane (2001).

the capability to perform symbolic processing, that is, to calculate, store, retrieve, sort, and act upon information. The remarkable generality of this tool allows computers to supplant or augment human cognition in a vast set of information- processing tasks that had historically been the mind's exclusive dominion. In economic terms, advances in information technology have sharply lowered the price of accomplishing procedural cognitive tasks. Accordingly, computers increasingly substitute for the routine information processing, communications, and coordinating functions performed by clerks, cashiers, telephone operators, bank tellers, bookkeepers, and other handlers of repetitive information processing tasks.[18]

The applicability of computers to cognitive tasks is, however, circumscribed by the need for an unambiguous, ordered sequence of instructions specifying how to achieve a desired end. Consequently, there is little computer software that can develop, test, and draw inferences from models; solve new problems; or form persuasive arguments—tasks that many jobs require.[19] In the words of artificial intelligence pioneer Patrick Winston (1999): "The goal of understanding intelligence, from a computational point of view, remains elusive. Reasoning programs still exhibit little or no common sense. Today's language programs translate simple sentences into database queries, but those language programs are derailed by idioms, metaphors, convoluted syntax, or ungrammatical expressions. Today's vision programs recognize engineered objects, but those vision programs are easily derailed by faces, trees, and mountains."

The capabilities and limitations of present computer technology make it more suitable, in our terminology, for routine than for nonroutine tasks. By implication, computers are relative complements to workers engaged in nonroutine tasks. This complementarity flows through three channels.

First, at a mechanical level, computers increase the share of human labor input devoted to nonroutine cognitive tasks by offloading routine manual and cognitive tasks from expensive professionals (that is, computers remove the drudgery from economic analysis). Second, an outward shift in the supply of routine informational inputs (both in quantity and quality) increases the marginal productivity of workers performing nonroutine tasks that rely on these inputs. For example, comprehensive bibliographic searches increase the quality of legal research; timely market information improves the efficiency

18. See Bresnahan (1999) for further illustrations. Autor, Levy, and Murnane (2002) provide an example of this phenomenon in their case study of the automation of check clearing in a large bank.
19. Software that recognizes ill-structured patterns (neural networks) and solves problems based upon inductive reasoning from well-specified models (model-based reasoning) is under development and has been applied commercially in several cases. These technologies have had little role in the computer-induced technical change of the last three decades.

of managerial decision making; richer customer demographics increase the productivity of salespersons; and so on.

Third, and perhaps most significantly, workplace computerization appears to increase the demand for problem-solving tasks—nonroutine cognitive tasks by our definition (see, for example, Bartel, Ichniowski, and Shaw 2000; Fernandez 1999; and Levy, Beamish, and Murnane 1999). Because "solved" problems are intrinsically routine and hence readily computerized, the comparative advantage of human labor in a computerized environment is specifically in handling nonroutine problems such as resolving production deficiencies, handling discrepancies and exceptions, and detecting and resolving unanticipated bottlenecks. In net, these arguments imply that price declines in computerization should augment the productivity of workers engaged in nonroutine cognitive tasks.

Table 4 provides examples of jobs in each cell of our two-by-two matrix of workplace tasks (routine versus nonroutine, manual versus information processing) and states our hypothesis about the impact of computerization on the tasks in each cell. Although we limit our focus here to task shifts within occupations, these forces are also likely to alter the task and organizational structure of firms along analogous dimensions (see Mobius 2000; Lindbeck and Snower 2000; Thesmar and Thoenig 2000; and Bresnahan, Brynjolfsson, and Hitt 2002).

Table 4: Hypothesized Impact of Workplace Computerization on Four Categories of Job Tasks

	Routine tasks	Nonroutine tasks
	A. Visual/manual	
Examples	• Picking and sorting engineered objects on an assembly line • Reconfiguring production lines to enable short runs	• Janitorial services • Truck driving
Computer impact	• Computer control makes capital substitution feasible	• Limited opportunities for substitution or complementarity
	B. Information processing/cognitive	
Examples	• Bookkeeping • Filing/retrieving textual data • Processing procedural interactions/ transactions (e.g., bank teller)	• Medical diagnosis • Legal writing • Persuading/selling
Computer impact	• Substantial substitution	• Strong complementarities

Source: Autor, Levy and Murnane (2001, table 1)

4. THE CHANGING COMPOSITION OF WORKPLACE TASKS: A FIRST LOOK AT THE DATA

Because our approach conceptualizes jobs in terms of their component tasks rather than the educational attainments of the jobholders (the traditional alternative), we require measures of tasks performed in particular jobs and their changes over time. We draw on information from the Fourth (1977) Edition and Revised Fourth (1991) edition of the U.S. Department of Labor's *Dictionary of Occupational Titles* (*DOT*). The details of our data construction are provided in Autor, Levy, and Murnane (2001). Here we discuss the main features.

The U.S. Department of Labor released the first edition of the *DOT* in 1939 to "furnish public employment offices . . . with information and techniques [to] facilitate proper classification and placement of work seekers" (U.S. Department of Labor 1939, xi, as quoted in Miller et al. 1980). Although the *DOT* was updated four times in the ensuing seventy years (1949, 1965, 1977, and 1991), its structure was little altered. Based upon firsthand observations of workplaces, *DOT* examiners, using guidelines supplied by the *Handbook for Analyzing Jobs* (U.S. Department of Labor 1972), rate occupations along forty-four objective and subjective dimensions, including training times, physical demands, and required worker aptitudes, temperaments, and interests.[20]

We append *DOT* occupation characteristics to the Census and Current Population Survey employment files for 1960, 1970, 1980, 1990, and 1998. In measuring changes in task requirements, we exploit two sources of variation. The first consists of changes over time in the occupational distribution of employment economy-wide, within industries, and within education groups within industries, holding task content within occupations at its *DOT* 1977 level. We refer to this source of variation as the "extensive" (that is, across occupations) margin. Variation along this margin does not, however, account for changes in task content within occupations (see, for example, Levy and Murnane 1996). Accordingly, we exploit changes between successive *DOT* revision in 1977 and 1991 to measure changes in task content measures within occupations, what we label the "intensive" margin.[21]

To identify plausible indicators of the skills discussed above, we reduced the *DOT* measures to a relevant subset using their textual definitions

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20. While the *Dictionary of Occupational Titles* categorizes more than 12,000 highly detailed occupations, the *DOT* data we employ here are based on an aggregation of these occupations into detailed census occupations, of which there are approximately 450.

21. The *DOT* also has well-known limitations described in Miller et al. (1980). Accounting for these limitations, the *DOT* remains to our knowledge the best time series information available on the skill requirements within occupations economy-wide.

and detailed examples provided by the *Handbook for Analyzing Jobs*. Based on these definitions and examination of means by major occupation for the year 1970, we selected five variables that appeared to best approximate our skill constructs.

To measure nonroutine cognitive tasks, we employ two variables, one to capture interactive and managerial skills and the other to capture analytic reasoning skills. The first variable, which codes the extent to which occupations involve direction, control, and planning of activities, takes on high values in occupations involving substantial nonroutine managerial and interpersonal tasks. To quantify occupations' analytic and technical reasoning requirements, we draw on a *DOT* measure of the quantitative skills requirements, ranging from arithmetic to advanced mathematics. We identified a variable measuring adaptability to work with set limits, tolerances, or standards as an indicator of routine cognitive tasks, and we selected a measure of finger dexterity as an indicator of routine manual activity. Finally, we used the variable measuring requirements for eye-hand-foot coordination as our index of nonroutine motor tasks.[22]

Using these task measures paired with representative samples of workers for 1959 to 1998, Chart 6 illustrates the extent to which changes in occupational task content over four decades have altered the task content of work performed by the U.S. labor force.[23] This chart reveals three striking patterns. First, the proportion of the labor force employed in occupations that make intensive use of nonroutine cognitive tasks, both interactive and analytic, increased substantially. While both measures of nonroutine cognitive tasks trended upward during the 1960s, the upward trend in each accelerated substantially thereafter and was most rapid during the 1980s and 1990s.

In contrast, the percentage of the labor force employed in occupations intensive in routine cognitive and routine manual activities declined. Most notably, while routine cognitive and manual tasks were both increasing during the 1960s, both commenced a decline in the 1970s that became more rapid in each subsequent decade. Finally, we observe a steady downward trend against nonroutine manual tasks that predates the computer era.

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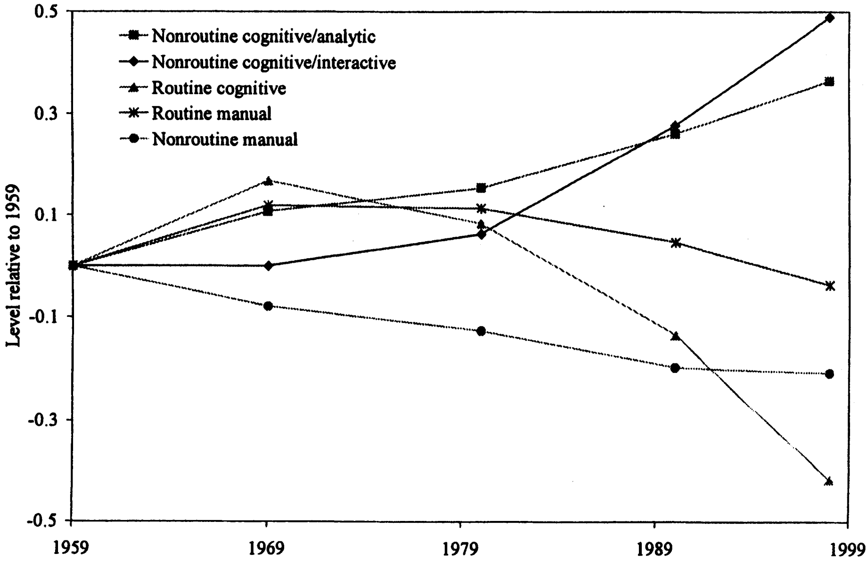
22. Definitions of these variables and example tasks from the Handbook for Analyzing Jobs are provided in Autor, Levy, and Murnane (2001).
23. In the chart, each *DOT* measure is scaled from zero to ten, with higher values indicating greater task input. Since these are not standardized metrics, it is potentially misleading to compare the magnitude of changes across dependent variables. In Autor, Levy, and Murnane (2001), we translate task demands into the more familiar metric of educational requirements.

While trends at this high level of aggregation are only suggestive, they are consistent with our conceptual model. In particular, our model posits a decline in the task share of human input devoted to routine manual and cognitive activities—the tasks most readily substituted by computers—and concomitant growth in human task input of nonroutine activities, particularly nonroutine cognitive activities. We further expect computerization to have had little impact on trends in nonroutine manual task input (such as janitorial services) since computers neither substitute nor complement these activities.

Chart 6. Economywide Measures of Routine and Nonroutine Task Input: 1959–98 (1959 = 0)



Source: Autor, Levy, and Murnane (2001)

As a further illustration, Table 5 enumerates the *DOT* task measures by major educational group. Notably, while three of five task measures are monotonically increasing in educational attainment, the two measures of routine tasks, cognitive and manual, show a U-shaped relationship to education. In particular, high school graduates perform substantially more of both types of routine task than either high school dropouts or college graduates. These nonmonotonic patterns suggest that the *DOT* measures are likely to provide information about job task requirements that is distinct from standard educational categories.

Table 5. Means of Dictionary of Occupational Titles Job Content Measures Overall and by Education Group at Mid-Point of 1960–98 Sample

	Task Measures (0 to 10 Scale)				
	1. Nonroutine cognitive/ analytic	2. Nonroutine cognitive/ interactive	3. Routine cognitive	4. Routine manual	5. Nonroutine manual
Overall	3.76	2.46	4.61	3.90	1.24
High school dropouts	2.55	1.32	4.93	3.72	1.80
High school grads.	3.34	1.75	5.30	4.09	1.26
Some college	3.97	2.45	4.87	4.02	1.10
College plus	5.36	4.76	2.86	3.57	0.87

Source: Autor, Levy and Murnane (2001, appendix table 2). Current Population Survey 1980, all employed workers ages 18–64, merged with *Dictionary of Occupational Titles* (1977)

These trends are only the beginning of an analysis. In a detailed investigation described in Autor, Levy, and Murnane (2001), we find that industries undergoing rapid computerization over the 1970s, 1980s, and 1990s exhibit declining relative demand for routine manual and routine cognitive tasks and increased relative demand for nonroutine cognitive tasks. These shifts are evident within detailed industries, within detailed occupations, and within education groups within industries. Translating these observed task shifts into educational demands, we estimate that computer-induced shifts in job task content can explain 40 percent of the observed relative demand shift favoring college versus noncollege labor during 1970 to 1998, with the largest impact felt after 1980. Most notably, changes in task content within nominally identical occupations explain more than half of the overall demand shift induced by computerization.

5. CONCLUSION

Did computerization cause U.S. earnings inequality to rise during the last two decades? Only in part. Substantial responsibility goes to secularly rising demand for college educated workers coupled with dramatic fluctuations in supply, particularly the college "boom" in the 1970s followed by the "bust" in the 1980s.[24] In conjunction with these factors, our best evidence indicates

24. Other changing institutional factors, to which we have given short shrift, also have affected earnings inequality. See footnote 5.

that computerization did augment inequality by accelerating the relative demand shift favoring educated workers during the 1970s and 1980s.

The framework and evidence we have presented point to (at least) three questions meriting close investigation. The first concerns the skills that computerization makes more important. Our framework posits that computerization has made skills in nonroutine cognitive activities increasingly valuable. But what specifically are these skills, and how can they be taught? A second question is what are the factors that influence job design and accompanying skill demands? A case study we have conducted of the back-office operations of a large bank indicates that, consistent with our conceptual model, improvements in computer technology create incentives for managers to substitute machinery for people in performing tasks that can be fully described by procedural logic. But this process typically leaves many tasks unaltered, and management discretion appears to play a key role—at least in the short run—in determining how the remaining tasks are organized into jobs, with significant implications for skill demands (see Autor, Levy, and Murnane 2002). Our analysis therefore cautions against an entirely deterministic view of the impact of computerization on skill demand. Social norms and institutions are likely to shape managerial decisions, thereby mediating computerization's impact on the labor market.

Finally, our work motivates study of alternative channels by which advances in information technology affect the labor market. In this paper, we have stressed computers' ability to substitute for human labor in routine information processing. Potentially as important—and also consistent with our results—is that advances in electronic communications have enabled firms to profitably outsource and monitor routine production processes offshore, thereby reducing the demand for these tasks domestically.[25] Thus, while economists have hotly debated whether trade or technology is primarily responsible for rising inequality, this example suggests that the distinction is far from clear cut. Here, too, careful case studies of the changing organization of work will prove important for developing and enriching hypotheses.

25. See Feenstra and Hanson (1999) and Autor (2001). Mobius (2000) and Thesmar and Thoenig (2000) make the further observation that technology (and other forces) may make product demand more fickle, causing firms to shift to flexible production processes that are more skill demanding.

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