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.[1] Figure 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.[2] Between 1963 and 1979, this difference in earnings hovered steadily at approximately two-hundred and twenty percent among men and one-hundred and ninety percent among women. Over the next ten years, these gaps grew into fissures. The 90-10 differential weekly earnings differential expanded by 110 percentage points for both genders between 1979 and 1989, and then edged slowly further 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 (Figure 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 demand and supply, in particular Skill Biased Technical Change (SBTC).[3] 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' appeal. Because inequality's rapid

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[1] Juhn, Murphy and Pierce (1993).

[2] That is, the worker earning *more* than 89 percent of the employed population and the worker earning *less* than 89 percent of the employed population

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 *demand and supply*, 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 increases the demand for more educated workers relative to less educated workers.

Culling from research conducted by ourselves and others, this article explores these three missing links.[4] 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

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[3] See Bound and Johnson (1992), Katz and Murphy (1992), and Levy and Murnane (1992).

[4] Key sources for our discussion are Bound and Johnson (1992), Katz and Murphy (1992), Johnson (1997), Autor, Katz and Krueger (1998), Katz and Autor (1999), Autor, Levy and Murnane (2001), and Acemoglu (forthcoming 2002).

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 trade, we focus on a model of the supply and demand for skill.[5] Consider a model of wage setting for high and low skilled workers depicted by Figure 3. Call these groups college and high school graduates. The X-axis in the figure 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.

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 $(N_C / N_H)_{1980}$, depicting the relative supply of college graduates in 1980 and the point $(W_C / W_H)_{1980}$, 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.[6] Using these two data points, we infer that the relative supply curve S_{1980} intersected the

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

[6] 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.

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 $(W_C / W_H)_{1998}$ to $(W_C / W_H)_{1980}$. 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 s. The shallower is this slope, the more elastic is 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 $s = 2$, 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 ($0.5 = 2^{-1}$).[7]

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 percentage differential in college/high school hourly earnings.[8] 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 sizable demand shift. Using elasticity estimates ranging 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).[9] Hence, substantial demand shifts were under way 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

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[7] Katz and Murphy (1992), Hammermesh (1993), Heckman, Lochner and Tabor (1998). Note that if this elasticity were infinite (i.e. 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.

[8] 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.

[9] More precisely, these figures are 100 times annual log changes and are a weighted averages of the estimated demand shifts over the 10 years from 1980 to 1990 and the 8 years from 1990 to 1998.

held a college degree. By 1998, this share exceeded 40 percent.[10] Yet, despite the quadrupling of their supply, wages of college graduates 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, 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 rose since 1980. Instead, we must ask whether recent technological changes *accelerated* demand growth for college graduates beyond its prevailing its post-war rate, thereby commencing a new era of *demand driven* inequality.

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.[11] 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 – 1998) in comparison to the prior three (1940 – 1970). This result is 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

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[10] High school graduates also increased their share of employment in this period, yet only by half of much.

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.[12]

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 s (1.0 – 1.4), we estimate that demand accelerated sharply in the 1970s and potentially accelerated further in the 1980s. For larger values of s, 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 counter-intuitively – the 'technology shock' that began in the 1970s or 80s 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

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[11] This observation is first offered by Katz and Murphy (1992).

[12] 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 consideration is not likely to change our qualitative conclusions in this section.

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 technologies and the increased use of college-educated labor within plants, firms and industries. Similar patterns are found in the U.S., the OECD, Canada and other developed and developing countries.[13] Two specific pieces of evidence also favor this indirect case.

One is timing. As show in Table 3, business investment in computer equipment per capita rose by 1,800 percent (i.e., a factor of 18) between the 1970s and 1980s, 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 60s forward and did not rebound until the 1990s. Hence, it is unlikely that other non-computer capital investment can account for the acceleration in skill demand.[14]

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

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[13] See, among others, Berman, Bound and Griliches (1994), Berman, Bound and Machin (1998), Machin and Van Reenan (1998), Berman and Machin (2000), Gera, Gu and Lin (1999), Caroli and Van Reenan (2001), and Bresnahan, Brynjolfsson and Hitt (forthcoming 2002).

[14] 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 almost certainly correct, the magnitudes are less certain.

employment shares of educated workers observed across sectors. Figure 4 [AKK, Figures 1a, 1b] 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. 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.[15] The strength of the association between computerization and educational upgrading visible in these figures is indisputable. Hence, the timing and industrial sectors of computerization closely coincide with rapid growth in college graduate employment.

Yet, this evidence is circumstantial; it places computers at the scene of the crime but does not yield a conviction. What is missing is a motive. Specifically, what is it that computers do – or what is it 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 the performance of simple tasks or complement the performance 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,

[15] The data points in the figure are sized to reflect industry employment.

present computer technology has specific applications and limitations that make it an incomplete substitute for both well-educated and less educated human labor.

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 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 processors,' acting upon abstract representations of information such as binary numbers or, in the loom's case, punched cards.[16] 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,[17] 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?

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 these cases, we first explore the application of

[16] This point is emphasized by Brynjolfsson and Hitt (2000).

[17] Nordhaus, 2001.

computers to manual tasks and subsequently discuss information processing (i.e., 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, for example, 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." Accordingly, 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.[18] Both optical recognition of objects in a visual field and bipedal locomotion across an uneven surface appear to require poorly understood algorithms, the one in optics the other in mechanics. These same problems explain the inability of computers to perform the tasks of long haul truckers.[19]

We refer to tasks requiring visual and manual skills as 'non-routine manual activities.' We emphasize the phrase *non-routine* 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 non-routine visual or manual skills – as, for example, in the case of industrial robots working

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[18] 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.

[19] 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

on an assembly line. It is this ‘routineness’ or predictability – an engineered attribute of an assembly line – that the aforementioned truck-driving example lacks.[20]

Machinery has substituted for repetitive human labor since (at least) the industrial revolution.[21] What computer capital uniquely contributes to this process is the capability to perform *symbolic processing*, that is, to calculate, store, retrieve, sort, and act upon information. Although symbolic processing requires only Boolean algebra, 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.[22]

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

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Woody Allen’s *Sleeper*. We nevertheless take it as axiomatic that if a job is traditionally constituted of non-procedural tasks, it is more difficult to computerize.

[20] Note that the simple distinction between computer-substitutable and non-substitutable 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. In reality, there is a non-zero elasticity of substitution between routine and non-routine tasks, a point we encapsulate in the formal model in Autor, Levy and Murane (2001).

[21] See Hounshell (1985), Mokyr (1990), and Goldin and Katz (1998).

[22] See Bresnahan (1999) for further illustrations. Autor, Levy, and Murnane (forthcoming 2002) provide an example of this phenomenon in their case study of the automation of check clearing in a large bank.

models, solve new problems, or form persuasive arguments – tasks that many jobs require.[23] 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 non-routine tasks. By implication, computers are *relative complements* to workers engaged in non-routine tasks. This complementarity flows through three channels.

First, at a mechanical level, computers increase the share of human labor input devoted to non-routine cognitive tasks by offloading routine manual and cognitive tasks from expensive professionals. Second, an outward shift in the supply of routine informational inputs (both in quantity and quality) increases the marginal productivity of workers performing non-routine tasks that rely on these inputs. For example, comprehensive bibliographic searches increase the quality of legal research; timely market information improves the efficiency of managerial decision-making; richer customer demographics increase the productivity of salespersons, etc.

Third, and perhaps most significantly, workplace computerization appears to increase the demand for problem-solving tasks – a non-routine cognitive task by our definition.[24] Because 'solved' problems are intrinsically routine and hence readily computerized, the comparative

[23] 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.

[24] See for example Bartel, Ichniowski and Shaw (2000), Fernando (1999), and Levy, Beamish and Murnane (1999).

advantage of labor in a computerized environment is specifically in handling non-routine 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 non-routine cognitive tasks.

Table 4 provides examples of jobs in each cell of our two-by-two matrix of workplace tasks (routine versus non-routine, 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.[25]

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 approach), 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*. 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."[26] Although the DOT was updated four times in the ensuing seventy years (1949, 1965, 1977 and 1991), its structure has been little altered. Based upon first-

[25] See Mobius (2000), Lindbeck and Snower (2000), Thesmar and Thoenig (2000), and Bresnahan, Brynjolfsson and Hitt (forthcoming 2002).

[26] U.S. Department of Labor (1939:xi) as quoted in Miller et al (1980).

hand observations of workplaces, DOT examiners using guidelines supplied by the *Handbook For Analyzing Jobs* rate occupations along 44 objective and subjective dimensions including training times, physical demands, and required worker aptitudes, temperaments, and interests.[27]

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' (i.e., across occupations) margin. Variation along this margin does not, however, account for changes in task content within occupations.[28] 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.[29]

To identify plausible indicators of the skills discussed above, we reduced the DOT measures to a relevant subset using their textual definitions and detailed examples provided by the *Handbook for Analyzing Jobs* (U.S. Department of Labor, 1972), the guidebook used by the DOT examiners. 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 non-routine 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

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[27] While the Dictionary of Occupational Titles categorizes more than 12 thousand 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.

[28] See for example Levy and Murnane (1996).

codes the extent to which occupations involve direction, control, and planning of activities, takes on consistently high values in occupations involving substantial non-routine managerial and interpersonal tasks. To quantify occupations' analytic and technical reasoning requirements, we draw on a DOT measure of the quantitative skills demanded, 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 use the variable measuring requirements for eye-hand-foot coordination as our index of non-routine motor tasks.[30]

Using these task measures paired to representative samples of workers for 1959 to 1998, Figure 5 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.[31] This figure reveals three striking patterns. First, the proportion of the labor force employed in occupations that make intensive use of non-routine cognitive tasks – both interactive and analytic – increased substantially. While both measures of non-routine 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

[29] 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.

[30] Definitions of these variables and example tasks from the *Handbook for Analyzing Jobs* are provided in Autor, Levy and Murnane (2001).

[31] In the figure, each DOT measures 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.

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 non-routine manual tasks that pre-dates the computer era.

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 non-routine activities, particularly non-routine cognitive activities. We further expect computerization to have had little impact on trends in non-routine manual task input (such as janitorial services) since computers neither substitute nor complement these activities. This appears consistent with the data.

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 non-monotonic patterns suggest that the DOT measures are likely to provide information about job task requirements that is distinct from standard educational categories.

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 non-routine 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 forty percent of the observed relative demand shift favoring college versus non-college 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 seventies followed by the 'bust' in the 1980s.[32] In conjunction with these factors, our best evidence indicates 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 non-routine 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

[32] Along with other changing institutional factors to which we have given short shrift. See footnote 5.

the remaining tasks are organized into jobs, with significant implications for skill demands.[33] Hence, our analysis 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 routine skills domestically.[34] 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.

[33] See Autor, Levy and Murnane (forthcoming 2002).

[34] See Feenstra and Hanson (1999) and Autor (2001). Mobius (2000), 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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Figure 1. (o) Males (+) Females
Source: Katz & Autor, 1999

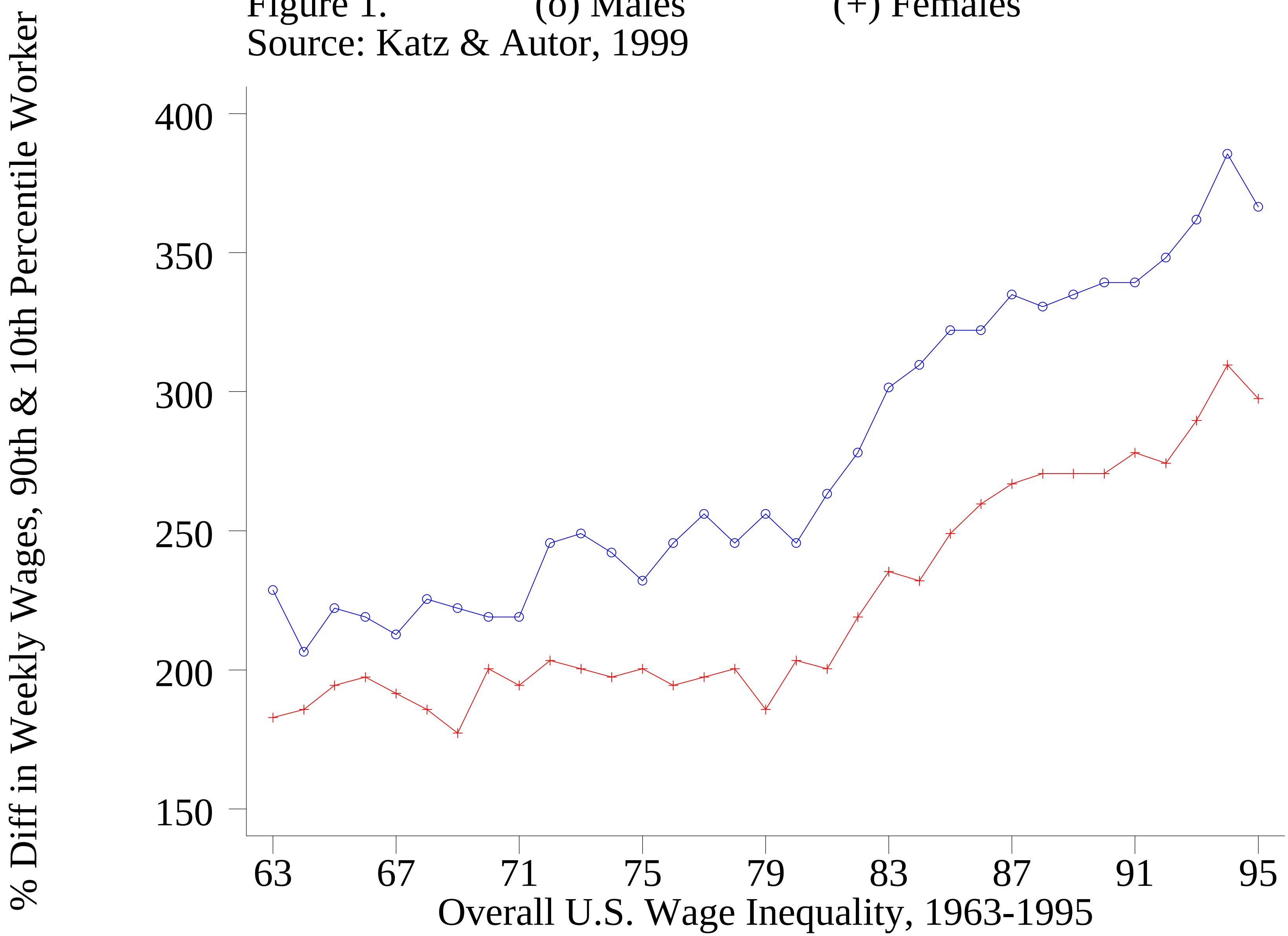


Figure 2. (o) All (+) 5 Years Experience
Source: Katz & Autor, 1999

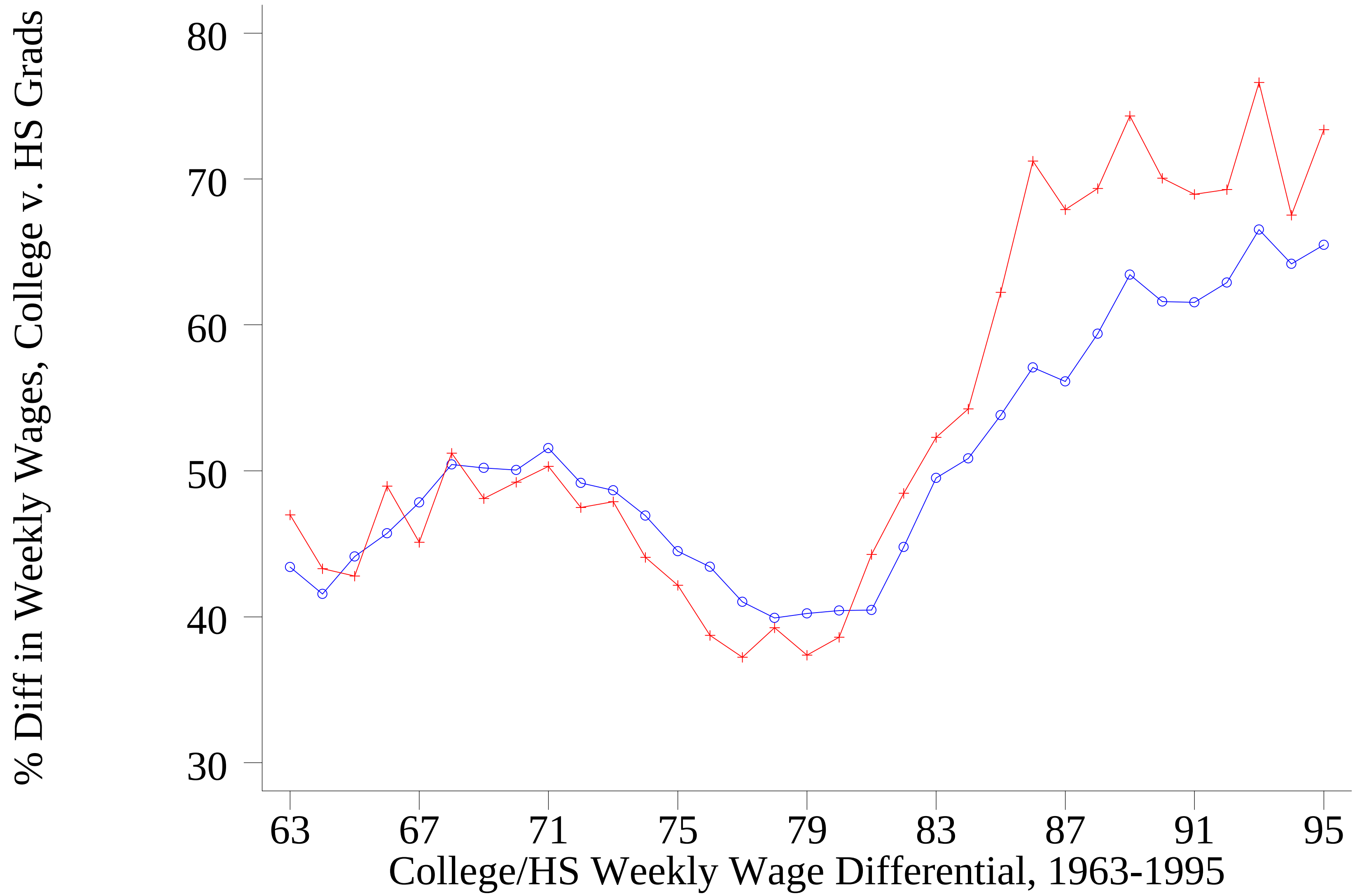


Figure 3. Impact of Demand and Supply Shifts on
the Relative Earnings of College vs. High School Graduates

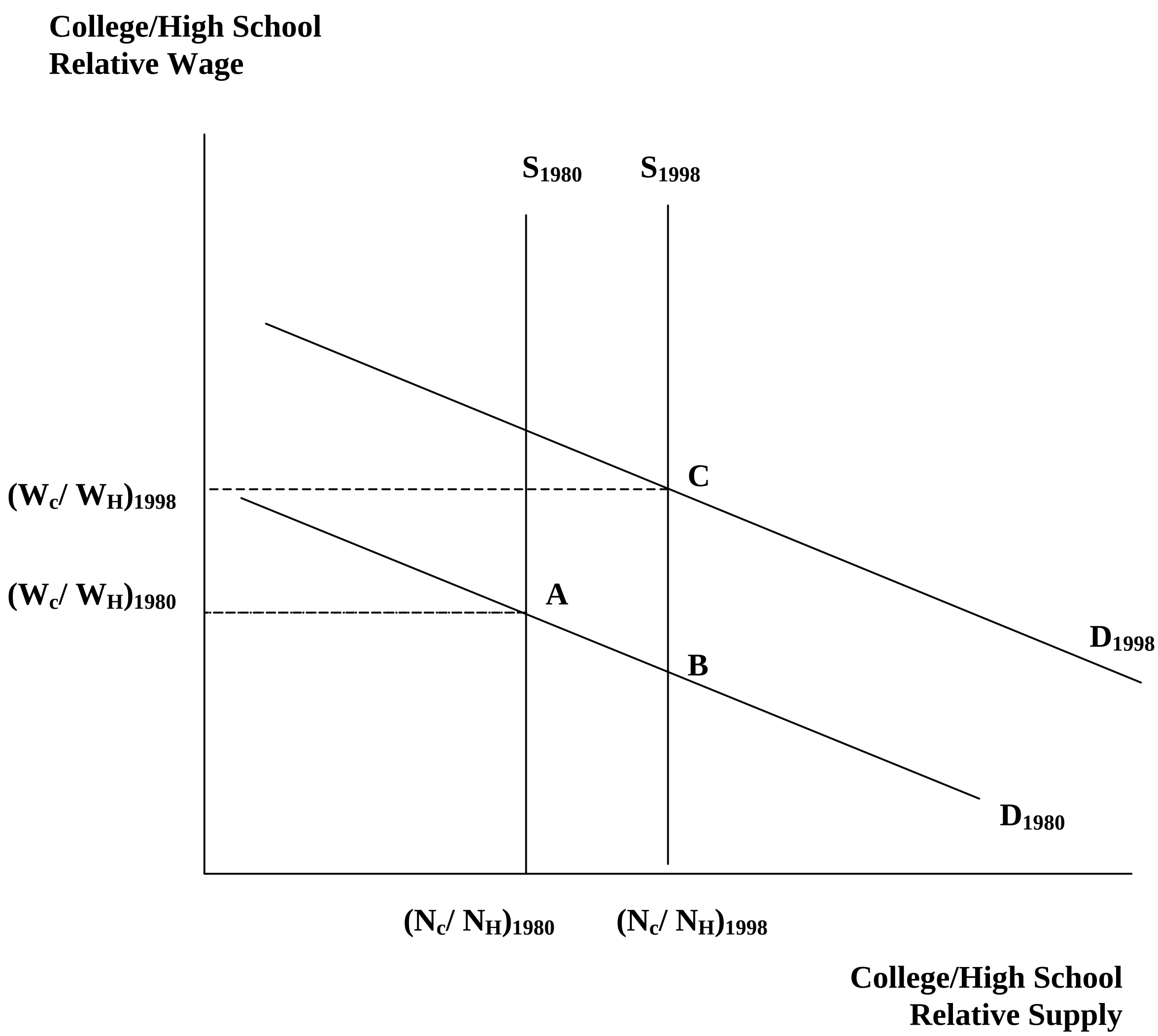
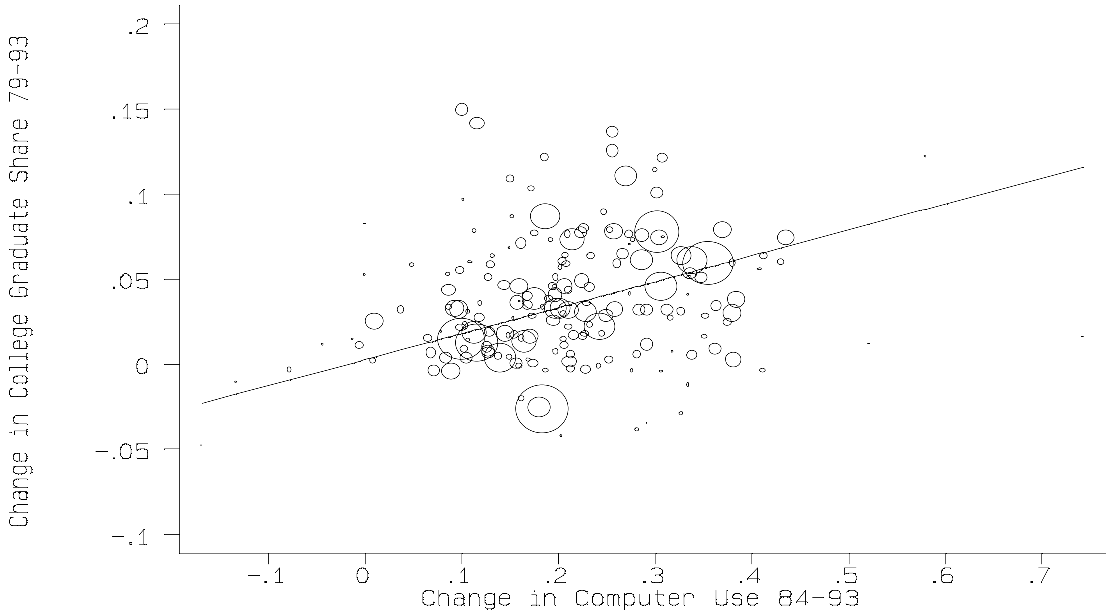
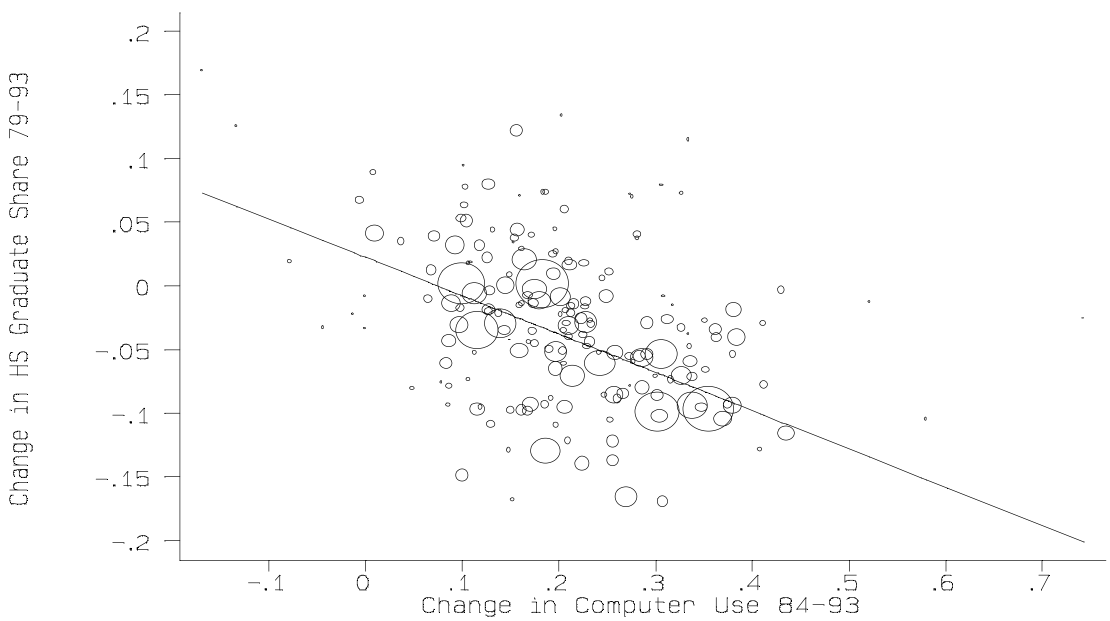


Figure 4. Changes in Computer Use and Industry Work-Force Educational Shares

(a) College Graduates

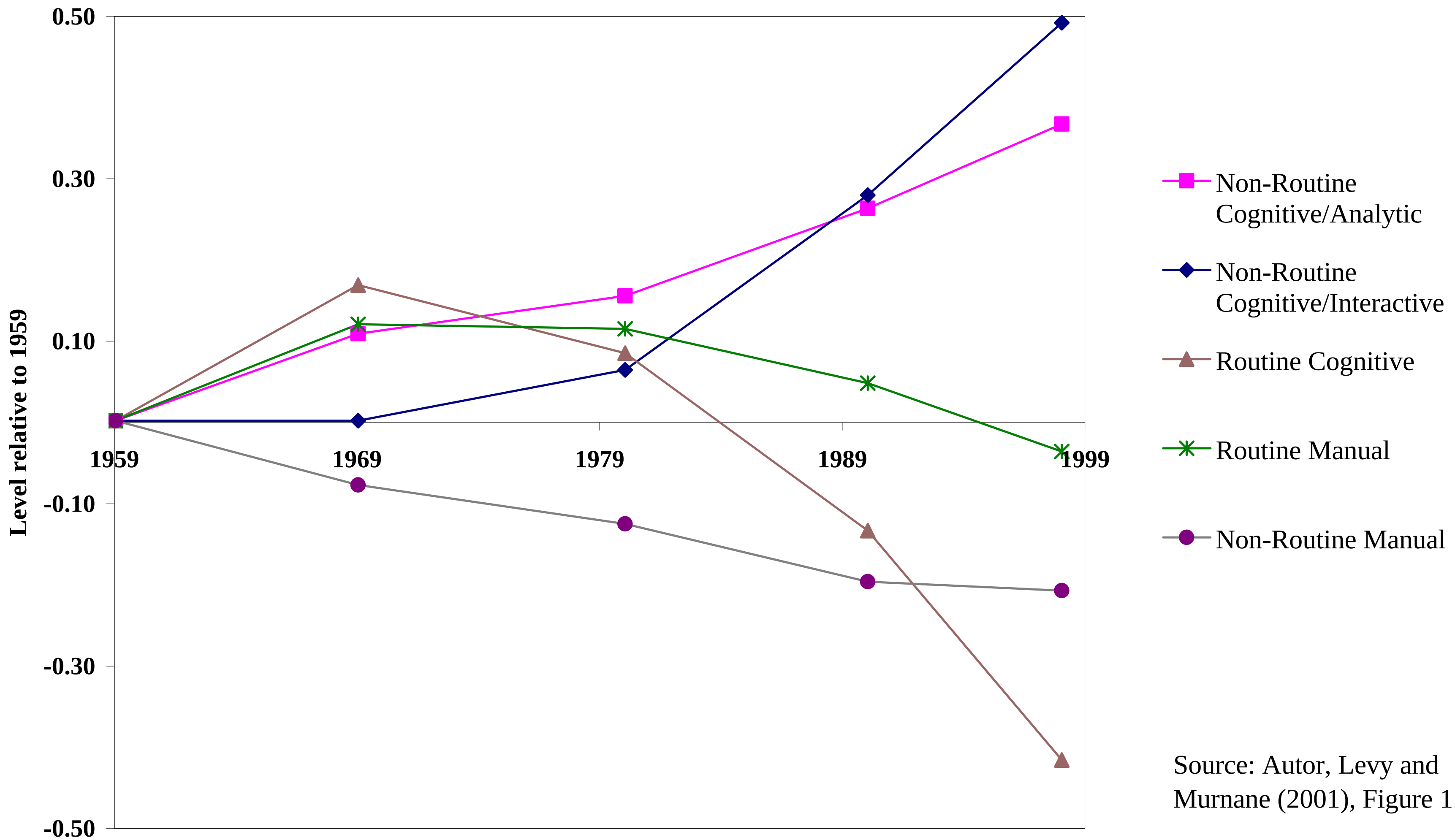


(b) High School Graduates



Source: Autor, Katz and Krueger (1998), Figure 1.

Figure 5. Economy-Wide Measures of Routine and Non-Routine Task Input:
1959 - 1998 (1959 = 0)



Source: Autor, Levy and Murnane (2001), Figure 1.

Table 1. Full Time Equivalent Employment Shares and Relative Wages of College and High School Graduates 1940 - 1998

	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 - 1980 is Census Public Use Micro Samples. Data source for 1990 - 1998 is Current Population Survey.

Table 2. Changes in College Equivalent/Non-College Log Relative Wages, Supply, and Estimated Demand 1940 - 1980.

	Relative Wage Change	Relative Supply Change	Implied Relative Demand Shift: College vs. HS Grads		
			s = 1.0	**s = 1.4**	**s = 2.0**
	A. 100 x Annual Log Changes by Decade				
1940 - 1950	-1.86	2.35	0.50	-0.25	-1.35
1950 - 1960	0.83	2.91	3.75	4.08	4.58
1960 - 1970	0.69	2.55	3.25	3.52	3.94
1970 - 1980	-0.74	4.99	4.25	3.95	3.50
1980 - 1990	1.51	2.53	4.05	4.65	5.56
1990 - 1998	0.36	2.25	2.61	2.76	2.98
	B. 100 x Annual Log Changes for Aggregated Time Periods				
1940 - 1970	-0.11	2.61	2.50	2.45	2.39
1970 - 1998	0.38	3.33	3.71	3.86	4.08

Source: Autor, Katz and Krueger, 1998 (updated to 1998 data). Data source for 1940 - 1980 is Census Public Use Micro Samples. Data source for 1990 - 1998 is Current Population Survey. σ is the assumed elasticity of substitution between college and high school equivalents.

Table 3. Estimated Annual Computer and Non-Computer Capital Investment per Full-Time Equivalent Worker in

	Annual Computer Investment/ FTE (1992$)	Growth in Capital Stock/ FTE
1960 - 1970	0.06	3.72
1970 - 1980	1.18	1.32
1980 - 1990	17.00	0.59
1990 - 1998	62.88	1.35

Constant 1992 dollars. Source: Autor, Levy and Murnane (2001) based on data from the National Income and Product Accounts. Left-most 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.

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

	Routine Tasks	Non-Routine 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.

Table 5: Means of Dictionary of Occupational Titles Job Content Measures Overall and by Education Group at Mid-Point of 1960 - 1998 Sample.

	Task Measure (0 to 10 scale)				
	1. Non-Routine Cognitive/ Analytic	**2. Non-Routine Cognitive/ Interactive**	**3. Routine Cognitive**	**4. Routine Manual**	**5. Non-Routine Manual**
Overall	3.76	2.46	4.61	3.90	1.24
HS Dropouts	2.55	1.32	4.93	3.72	1.80
HS Graduates	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.