The Skill Content of Recent Technological Change: An Empirical Exploration

David H. Autor
MIT Department of Economics and NBER

Frank Levy
MIT Department of Urban Studies and Planning and Russell Sage Foundation

Richard J. Murnane
Harvard University Graduate School of Education and NBER[1]

December 2000
Revised from January 2000

Abstract

Recent empirical and case study evidence documents a strong association between the adoption of computers and increased use of college educated or non-production workers. With few exceptions, the conceptual link explaining *how* computer technology complements skilled labor or substitutes for unskilled labor is less well developed. This paper applies an understanding of what computers do – the execution of procedural or rules-based logic – to develop and test a simple model of how the widespread adoption of computers in the workplace might alter workplace skill demands. Two essential contentions of our framework are that computer capital (1) substitutes for a limited and well-defined set of human activities, those involving routine (repetitive) cognitive and manual tasks; and (2) complements a second set of activities, those involving non-routine problem solving and interactive tasks. Under the assumption that routine and non-routine tasks are imperfect substitutes, the task framework implies measurable changes in the task content of employment. We examine these changes using representative samples of workers from 1960 to 1998 where individual characteristics are augmented with Dictionary of Occupational Title variables describing their occupations' requirements for routine and non-routine cognitive and manual skills. We find that computerization is associated with declining relative industry demand for routine manual and cognitive skills and increased relative demand for non-routine cognitive skills. These demand shifts are evident both in changes in occupational distributions within detailed industries, changes in occupational distributions within education groups within industries, and changes in task requirements within detailed occupations. Translating the task shifts induced by computerization into educational demands, we find that the sum of within-industry and within-occupation task shifts can explain approximately thirty percent of the observed relative demand shift favoring college versus non-college labor between 1970 – 1998, with the largest impact felt during 1980 – 1998. Changes in task content within nominally unchanging occupations explain more than half of the overall demand shift induced by computerization.

[1] We thank the Alfred P. Sloan Foundation, the Russell Sage Foundation and the MIT-Ford Research Collaboration for financial support and Kokkeong Puah, Detelina Vasileva, and especially Melissa Schettini for excellent research assistance. We are indebted to Daron Acemoglu, Lex Borghans, Lawrence Katz, Thomas Lemieux, Sendhil Mullainathan, Kathryn Shaw, and Bas Ter Weel for valuable suggestions. Thanks go to Randy Davis of MIT's Artificial Intelligence Laboratory and Pete Szolovits of MIT's Laboratory for Computer Science for clarifying issues in artificial intelligence. We are grateful to Michael Handel for providing access to key data sources and for expert advice on using the Dictionary of Occupational Titles. The usual disclaimer about responsibility for errors deserves special emphasis here.

Introduction

Much empirical and case-study evidence documents a strong association between the adoption of computers and computer-based technologies and the increased use of college-educated and non-production labor within detailed industries (Autor, Katz and Krueger, 1998; Berman, Bound and Griliches, 1994), within firms (Bresnahan, Brynjolfsson, and Hitt, 1999; Levy and Murnane, 1996) and across plants within industries (Doms, Dunne, and Troske, 1997). These patterns implicating computerization as a potential source of a demand shift favoring better-educated labor appear consistently in studies from the U.S., the OECD (Machin and Van Reenen, 1998), Canada (Gera, Gu, and Lin, 1999), and other developed and developing countries (Berman, Bound and Machin, 1998; Berman and Machin, 2000).

While the empirical relationship between industry- and firm-level computer investments and the increasing use of college educated workers is now firmly established, it is our view that the conceptual link explaining specifically *how* computer technology complements skilled labor or substitutes for unskilled labor is much less well developed. In particular, most studies in this literature do not ask, or are prevented by data limitations from exploring, 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.[2]

Although at first glance, these mechanisms may appear trivial – computers substitute for less educated workers in the performance of simple tasks or and/or complement the performance of more educated workers in complex tasks – reflection suggests 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 both cases. 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. In a similar vein, 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 are intended to suggest that neither all 'high' nor all 'low' skilled tasks are equally amenable to computerization. In fact, present computer technology has quite specific applications and limitations that make it an incomplete substitute for both well-educated and less educated human labor.

The goal of this paper is to develop and test a model of how an exogenous decline in the price of computing power alters job task content and thereby human skill demands.[3] We base the model on an understanding of what computers do – by which we mean the *tasks* that present computer technology is particularly suited to performing. By conceptualizing and measuring job skill demands in terms of job tasks *rather than the educational credentials of workers performing those tasks*, we believe our analysis makes a contribution along three dimensions.

First, we provide an explicit account of how computerization alters work content, exposing what we believe are the mechanisms undergirding the widely documented observation that computers and education are complements. Second, by analyzing representative observational metrics of job task content from the Dictionary of Occupational titles, we provide direct evidence on the degree to which technological change has altered the cognitive and manual content of jobs between 1960 and 1998. We examine changes *within* industries, *within* education groups, and *within* occupations – phenomena that, in all but the first case, are normally unobserved. Third, we use these results to

[2] Herbert Simon (1960) provides the first treatment of this question of which we are familiar. His essay introduces many of the ideas explored here. Influential studies in the ethnography of work literature provide insightful discussions of what computers and related technology do in the workplace but do not consider economic implications (Adler, 1986; Orr, 1996; and Zuboff, 1988). Important studies in the economic literature exploring why new technologies and educated labor appear to be complements in production are discussed below.

quantify the extent to which changes in the task structure of work induced by computerization may have contributed to recent observed increases in the relative demand for educated labor. We find that this contribution is sizable. Although shortcomings of the Dictionary of Occupational Titles discussed below place some limitations on the certainty and precision of our analysis, we believe that these limitations are worth tolerating here because the DOT data support a needed exploration of the mechanisms through which recent technological change may have altered the structure of work.

Our analysis builds upon two other branches of the literature on the demand for skill. The first, exemplified by Juhn (1999), Juhn, Murphy and Pierce (1993), Katz and Murphy (1992), Murphy and Welch (1992 and 1993), and Welch (2000), infers shifts in the demand for skills from secular trends in the occupational, educational, and gender composition of employment. The second branch posits, and in several cases tests empirically, individual and organizational level complementarities between technological change and workers' learning and problem solving capabilities. Prominent examples include Acemoglu (1999), Bartel and Lichtenberg (1989), Bresnahan (1999), Bresnahan, Brynjolfsson and Hitt (forthcoming), Casselli (1999), Goldin and Katz (1998), Lindbeck and Snower (2000), Nelson and Phelps (1966), Schultz (1975), and Welch (1970). Our analysis contributes to both of these avenues of research. We first offer a conceptual framework that makes specific predictions about complementarity and substitutability between new technology and labor in carrying out workplace tasks. We next explore the empirical implications of this framework using economy-wide data on the task distribution of employment over four decades.

1. Framework

a. Routine and non-routine manual tasks

For purposes of our framework, it is useful to conceptualize a job as a series of tasks: moving an object, executing a calculation, communicating a piece of information, resolving a discrepancy. In

---

[3] As an example of these price changes, the Bureau of Economic Analysis' price index for memory chips declined at a 37-percent average annual rate from 1975 to 1985 and at a 20-percent average annual rate from 1985 to 1996. Its

this context, we ask the question: which tasks can be performed by a computer?[4] A good first answer to this question is that computers can perform tasks that can be expressed using procedural or 'rules-based' logic – that is in terms of a fully specified sequence of logical programming commands ("If-Then-Do" statements) that designate precisely and unambiguously what actions the machine will perform and in what sequence at each contingency to achieve the desired result.[5] The simple observation that tasks cannot be computerized unless they can be proceduralized is the point of departure for our discussion. To structure the discussion, we focus first on the computerization of manual tasks and subsequently discuss information processing (cognitive) tasks.[6]

Many manual tasks that humans perform (or used to perform) at their jobs can be 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 that, as Michael Polanyi (1966) put it, "we do not know how to do many of the things we do." In other words, the means by which humans accomplish many physical tasks are at present not well understood. This makes it exceedingly difficult to develop

---

price index for microprocessors declined at a 35-percent average annual rate from 1985 to 1996 (Grimm, 1998).

[4] We take as given that the rapidly declining price of computer capital provides firms with ample economic incentive to answer this question. Borghans and Ter Weel (2000) provide a formal model of firms' decisions to computerize workplace tasks as a function of wages and the price of computer capital. This model underscores that computers are particularly likely to substitute for (in our terminology) routine tasks performed by high wage workers.

[5] The *Encyclopedia Brittanica* (2000) defines a computer program as a "detailed plan or procedure for solving a problem with a computer; more specifically, an unambiguous, ordered sequence of computational instructions necessary to achieve such a solution."

[6] A logical question is whether this requirement for proceduralization is intrinsic to computer technology or is in fact an outcome of the economic incentives that shaped its development. Our view is that proceduralization is inherent, although other specific aspects of computer technology may not be. As evidence for this point, we note that Charles Babbage articulated the notion of procedural programming in his description of the "Analytical Engine" in 1837, almost a century before the first computer was developed (cf. Babbage, 1888). Babbage's device was in turn inspired by what may be the first mechanical computer, the Jacquard Loom developed by Joseph Marie Jacquard in 1801 (Mokyr, 1990). What the Jacquard loom shares with essentially all computers is first, that it is a symbolic processor – acting upon symbolic representation of information such as binary numbers or, in this case, punched cards – and second, that its actions are deterministically specified by explicit procedures or programs. Despite the substantial time interval between initial vision and ultimate implementation, the modern computer is a close relative of Babbage's machine. Of course, the specific characteristics and applications of the technology may (and indeed likely are) endogenously shaped by market forces. See Acemoglu (1998 and 2000) for an intriguing perspective on these issues.

machines that perform 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.[7] The reason is that both optical recognition of objects in a visual field and bipedal locomotion across an uneven surface appear to require enormously sophisticated algorithms, the one in optics the other in mechanics, that are at present poorly understood by cognitive science (Pinker, 1997). These same problems explain the earlier mentioned inability of computers to perform the tasks of long haul truckers.[8]

In this paper 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 visual or manual skills that at present are poorly simulated by machines (as, for example, in the case of industrial robots on assembly lines). It is this 'routineness' or predictability that is lacking in the truck-driving example.[9]

That computers and computerized capital are used to carry out routine physical tasks such as manipulating objects in an assembly line environment and monitoring temperature or flow in a

---

[7] 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.

[8] It is of course a fallacy to assume that a computer must reproduce all of the functions of a human to perform a task historically done by people. Automatic Teller Machines, for example, have supplanted many bank teller functions although they cannot verify signatures or make polite conversation while tallying change. Similarly, domestic appliances make coffee in the morning and take phone messages and yet do not wear pressed black and white tuxedos or greet us at the door like robots in Woody Allen's *Sleeper*. This observation raises the important question of which if any attributes of a task are intrinsic and which are artifactual characteristics that these tasks may have obtained precisely because humans traditionally performed them. We do not attempt to address this question here. We surmise, however, that whether the characteristics of a task are intrinsic or merely artifactual, these historical characteristics generate real costs when automating a task. For example, if robotic technology had preceded the automobile, it is likely that vehicle navigation would have been designed to rely less heavily on sightedness. Given our present (sunk) infrastructure of sight-dependent vehicles and visually cued roads, a major cost of automating the task of driving appears to be developing computers that can perform visual processing approximately as well as humans.

production process is not, of course, novel. The substitution of machinery for repetitive human labor is a central component of the industrial revolution (cf., Hounshell, 1985; Mokyr, 1990; Goldin and Katz, 1998). What we emphasize here is that while the declining price of computer capital has unambiguously advanced the automation of routine physical activities, computers have made far fewer inroads into (and may be largely orthogonal to) non-routine physical activities that rely heavily on visual or manual processing in an imperfectly controlled environment.[10] To be concrete, there is little reason to expect that computerization will supplant the jobs of truck drivers or janitors in the near future.[11]

b. Routine and non-routine cognitive tasks

One should not conclude from these examples that computerization is simply a continuation of past trends in mechanization. What computer capital uniquely offers is the capability to perform symbolic processing, that is, to calculate, store, retrieve, sort, and act upon information. Although symbolic processing requires little more than basic mathematics, the incredible generality of this tool allows computers to supplant or augment human cognition in a vast range of information processing tasks that had historically been the mind's exclusive dominion. Examples include predicting weather, analyzing consumer tastes, correcting grammar in natural language documents, and hosting markets for products and services.[12]

While this characterization might caution against defining any limits to the present scope of

---

[9] Industrial robots may, for example, select distinct parts from bins, transport parts to work stations on demand, and perform other non-repetitive manual tasks that require responding appropriately to environmental stimuli. What makes these robotic feats of visual recognition and locomotion possible is the extreme predictability of the assembly line, a purposefully engineered attribute. As Simon (1960) notes, environmental control is a substitute for flexibility.

[10] We do not wish to imply that these tasks cannot be computerized or that they will not be ultimately be substantially automated. We simply observe that given the state of science and the current set of factor prices, automating these non-routine motor tasks is significantly less economically attractive than automating routine motor tasks.

[11] This simple distinction is of course not absolute. For example, by calculating more efficient long haul trucking routes, computers can 'substitute' for the labor input of long haul truck drivers without actually driving trucks. This observation suggests that there is a non-zero elasticity of substitution between routine and non-routine tasks in production, a point we encapsulate in our model.

[12] As Bryjolfsson and Hitt (2000) stress, "Computers are not fundamentally number crunchers. They are symbol processors."

computerization, we nevertheless hazard an attempt here. In particular, while the capability of computer capital to perform certain information-processing tasks is unprecedented, its applicability is nevertheless circumscribed by the need for an unambiguous, ordered sequence of computational instructions that specify how to achieve a desired end. At present, this requirement places distinct limits on the tasks to which computers are applied.

A central observation for this paper is that effectively all current commercial computer technology engages in what cognitive scientist call 'rules-based reasoning' (Rasmussen et al, 1994); that is, it follows procedures. There is little computer technology that can develop, test, and draw inferences from models, solve new problems, or form persuasive arguments – tasks that many jobs require.[13] 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."

In basic economic terms, advances in information technology have sharply lowered the price of accomplishing procedural cognitive tasks (i.e., rules-based reasoning). Accordingly, they have subsumed many of the routine information processing, communications, and coordinating functions once performed by clerks, cashiers, telephone operators, bank tellers, bookkeepers, and other handlers of repetitive information processing tasks, a point emphasized by Bresnahan (1999).[14]

The same argument does not, however, imply that computers will soon substitute for the non-routine task component of jobs performed by managers, attorneys, educators, scientists, health

[13] This generalization is not absolute. Programs that solve problems based upon inductive reasoning from well-specified models are in their infancy. Neural network software also appears to engage in a statistical form of learning although it's not clear at present how much promise this holds. See Davis (1984) and Winston (1999) for further discussion. Both areas, however, are largely experimental and substantially all software and hardware in current commercial use is built on "rules-based" procedures. For a discussion of rules-based and model-based reasoning in the context of auto repair, see Levy et al. (1999).

[14] Autor, Levy, and Murnane (2000) provide an example of this generalization in a study of the automation of the check-clearing department of a large bank.

professionals, architects, or salespeople. In fact, by taking over routine manual and cognitive tasks – such as filing medical forms, preparing boilerplate legal documents from expensive professionals – computers are likely to increase the share of human labor devoted to non-routine cognitive tasks.

We also see two mechanisms through which computerization of routine cognitive tasks increases the marginal productivity of workers in carrying non-routine cognitive tasks. The first is that greater availability of routine informational inputs increases the efficiency with which workers can pursue non-routine tasks. 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. A second mechanism, noted frequently in firm-level studies of technological change (Adler, 1986; Autor, Levy and Murnane, 2000; Bartel, Ichniowski and Shaw, 2000; Fernandez, 1999; Levy and Murnane, 1996; Zuboff, 1988), is that workplace computerization appears to increase the demand for problem-solving tasks, a non-routine cognitive task by our definition. Because 'solved' problems are intrinsically routine and hence readily computerized, the comparative 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.[15] In net, these arguments imply that price declines in computerization should augment the productivity of workers engaged in non-routine cognitive tasks.

Figure 1 provides examples of jobs in each cell of our two-by-two matrix of workplace tasks (routine versus non-routine, manual versus information processing). It also states our hypothesis about the impact of computerization on the jobs in each cell. Although we limit our focus here to task shifts within occupations, these same forces are likely to alter the task and organizational structure of firms along similar dimensions, an idea explored in more detail by Autor, Levy and Murnane (2000), Bartel, Ichniowski and Shaw (2000), Bresnahan (1999), Bresnahan, Brynjolfsson, and Hitt (1999), and Brynjolfsson and Hitt (2000), Caroli and Van Reenen (2000), Lindbeck and Snower (2000), and Thesmar and Thoenig (2000).[16]

Figure 1: Potential contribution of computerization to four categories of workplace tasks.

	Routine	**Non-Routine**
Visual/ Motor/Manual	Examples: • Picking and sorting engineered objects on an assembly line; • Reconfiguring production lines to enable short runs.	Examples: • Janitorial services; • Truck driving.
	Computer Impact: • Computer control makes capital substitution feasible.	Computer Impact: • Limited opportunities for substitution or complementarity.
Information Processing/ Cognitive	Examples: • Bookkeeping; • Filing/retrieving textual data; • Processing procedural interactions/ transactions (e.g., bank teller)	Examples: • Medical diagnosis; • Legal writing; • Persuading/selling.
	Computer Impact: • Substantial substitution.	Computer Impact: • Strong complementarities.

2. A model of routine and non-routine skills in production

The manner in which an exogenous price decline in 'routine' tasks alters the task content of jobs and the wages attached to them depends on the elasticity of substitution between routine and non-routine tasks and the supplies of workers and capital to each. While these parameters are not known with any precision, we believe our discussion motivates several plausible assumptions.

First, we have argued above that computer capital is more substitutable for humans in carrying out routine tasks than non-routine tasks; it is easier to program a computer to balance a bank's ledgers than to manage its branches. Second, we believe it is non-controversial that routine and non-routine tasks are themselves imperfect substitutes.[17] Third, at least in the domain of cognitive tasks, we observe that greater intensivity of routine inputs increases the marginal productivity of non-

[15] The firm level studies cited earlier provide numerous illuminating examples of these generalizations.
[16] Note that because our focus is exclusively on how the computerization of specific tasks alters the job content of jobs performed by workers, our approach is essentially orthogonal to the widely cited debate between Krueger (1993) and DiNardo and Pischke (1997) on the returns to computer skills.

routine inputs.[18]

These assumptions structure the production side of our model. Consider the following production function in which there are two skills, routine R and non-routine N, used jointly to produce output, q, with a constant returns to scale Cobb-Douglas technology:

(1) $q = R^{1-b} N^{b}$, $b \in (0,1)$

To encapsulate the notion that computers are more substitutable for routine than non-routine tasks, we assume that computer capital, C, and humans are perfect substitutes in carrying out routine tasks, R.[19] While this assumption is obviously extreme, the only substantive requirement for our model is that computer capital is *more* substitutable for humans in carrying out routine than non-routine tasks.

We take as given that computer capital is supplied perfectly elastically at market price P per efficiency unit, where P is assumed to fall exogenously over time due to technical advances. The decline in P is the causal factor in our model.

To model labor supply, we assume as in Roy (1951) that workers choose among occupations (here, routine and non-routine) according to comparative advantage. We model each worker as possessing a productivity endowment, $E(R_i, NR_i)$, in routine and non-routine tasks specified in efficiency units where $R_i, NR_i > 0\ \forall i$. Define the relative efficiency of individual (i) at non-routine versus routine tasks as $a_i = NR_i / R_i$. We make no assumption on the distribution of endowments in the population or their correlation except to require that the joint distribution of R_i, NR_i is non-degenerate, i.e., a_i varies in the population.

Formally, write the probability density function of relative efficiency endowments as $f(a)$, with

[17] For example, although ATMs now process many of the routine bank transactions formerly handled by tellers, bank customers still primarily resolve banking problems ('non-routine' transactions) such as lost checks or mishandled transactions via person-to-person interactions.
[18] While in the model below we aggregate our four tasks groups into only two categories – routine and non-routine – we suspect that in actuality routine and non-routine manual tasks are substantially less complementary as productive inputs than are routine and non-routine cognitive tasks.
[19] Cobb-Douglas technology implies that the elasticity of substitution between routine and non-routine skills is one.

$f(0)=0$ and $f(a)>0$ for $a \in (0,\infty)$. We assume an infinite number of workers who choose to supply either R_i efficiency units of routine task input or NR_i efficiency units of non-routine task input. In keeping with our discussion, we think of the decision to supply labor to routine or non-routine tasks as the choice of an occupation.

Using these assumptions, it is straightforward to trace out the implications of a technical advance – a fall in the price of computer capital – for occupational choice, marginal task productivity, and wages (specified in efficiency units). Given the perfect substitutability of computer capital and routine skills, the wage per efficiency unit of routine labor is given by:

(2) $$W_R = P.$$

Since workers choose occupations – that is, to supply routine or non-routine labor – to maximize earnings, the marginal worker with relative efficiency units a^* in routine vs. non-routine tasks is indifferent between routine and non-routine occupations when:

(3) $$a^* = \frac{W_R}{W_{NR}}$$

Equation (3) implies that for $a_i < a^*$, individual i supplies routine labor, and for $a_i \geq a^*$, i supplies non-routine labor.

To quantify factor supplies to each occupation as a function of a^*, we denote the correspondences $g(a)$, $h(a)$ that give the population endowment in efficiency units of routine and non-routine tasks for each value of a. Hence, we have $g(a), h(a) > 0 \;\forall\; a > 0$. For every a, there is a non-zero set of workers with total routine efficiency endowment $g(a)$ and total non-routine efficiency endowment $h(a)$.

Productive efficiency requires that:

(4) $$W_R = \frac{\partial q}{\partial R} = (1-b)\left(\frac{C + \int_0^{a^*} g(x) f(x) dx}{\int_{a^*}^{\infty} h(x) f(x) dx} \right)^{-b} ,$$

and

(5) $$W_N = \frac{\partial q}{\partial N} = b\left(\frac{C + \int_0^{a^*} g(x) f(x) dx}{\int_{a^*}^{\infty} h(x) f(x) dx} \right)^{1-b} .$$

Rearranging (4) and differentiating to obtain the derivative of the demand for non-routine skills as a function of the price of computer capital, we obtain:

(6) $$\frac{\partial R}{\partial P} = -\frac{\left(\frac{P}{1-b}\right)^{-\frac{1}{b}} \int_{a^*}^{\infty} h(x) f(x) dx}{bP} < 0 .$$

A price decline in routine capital raises its intensity of use and, as above, lowers the wage per efficiency unit of routine labor. Since routine and non-routine tasks are complementary inputs (specifically, q-complements), it follows that:

(7) $$\frac{\partial W_N}{\partial P} = -\left(\frac{P}{1-b}\right)^{-\frac{1}{b}} < 0 .$$

A price decline in computer capital raises the wage per efficiency unit of non-routine skills.

In the discussion above, wages are specified in efficiency units. Since efficiency units vary over the population and since workers choose occupations to maximize earnings, a decline in the price of computer capital will alter occupational choice.

Consider the impact of a price decline in computer capital on a^*, the relative efficiency endowment of the marginal worker in the routine occupation. It is easy to show that:

(8) $$\frac{\partial a^*}{\partial P} > 0 ,$$

A fall in the price of computer capital decreases labor supply to the routine occupation and increases labor supply to the non-routine occupation. Accordingly, an exogenous decline in P causes the marginal productivity of routine tasks to fall and the marginal productivity of non-routine tasks to rise.

Note, however, that although wages per efficiency unit of non-routine labor rise in absolute terms, the implications for *observed* wages are ambiguous without further assumptions. Because an increase in non-routine relative wages will typically reduce the average productivity (in efficiency units) of workers entering the non-routine occupation, quality change could reduce observed wages even as the per-unit price of non-routine tasks rises.

To summarize our simple conceptual framework, we find that a price decline in computer capital lowers the wages of workers carrying out routine tasks and causes employment in these tasks to contract. Although the demand for routine task input increases as the price of computer capital falls, this demand is satisfied by substitution of computer capital for human labor. As the capital intensity of routine task input increases, the marginal productivity of non-routine tasks and hence the wage per efficiency unit of non-routine labor input rise. Responding to this price change, labor supply to non-routine occupations expands.

Many of the details of our model were chosen for simplicity and are not essential to the basic results. What is critical, however, is our assumption that computer capital is more substitutable for routine than non-routine skills, an assumption that we believe is justified by the present state of information technology.

One dimension of the model we have not explored here is how consumer tastes interact with price declines and accompanying income gains to shape final demand. If we consider the model above to characterize production in a single industry and assume that industries have heterogeneous production technologies, it is plausible, depending on elasticities, that changes in final demand could amplify or offset changes in industry level demand for skills.[20] For this reason, we focus our empirical exploration below on the composition of demand at the industry level.

3. Empirical Implementation

Since our approach in this paper is to conceptualize jobs in terms of their component tasks rather than the educational attainments of the job-holders, we require measures of tasks performed in particular occupations. We also need measures of changes in task content within occupations over time. For these purposes 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) (U.S. Department of Labor, 1977 and 1991). Many of the details of our data construction are provided in the Data Appendix. Here we discuss the features of the DOT most salient to our analysis.

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."[21] Although the DOT has been updated four times in the ensuing seventy years (1949, 1965, 1977 and 1991), its basic structure is little altered. Based upon first-hand observations of workplaces, DOT examiners using guidelines supplied by the *Handbook For Analyzing Jobs* rated occupations along 44 objective and subjective dimensions including training times, physical demands, and required worker aptitudes, temperaments, and interests. The multiple ratings across sites were averaged and those average characteristics published in the DOT. 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 detailed occupations into three-digit Census Occupation Codes (COC) of which there are approximately 450.[22]

Using these COC-DOT aggregations, we appended DOT occupation characteristics to the Census IPUMS one percent extracts for 1960 to 1990, to CPS Merged Outgoing Rotation Group (MORG)

---

[20] Mobius (2000) and Thesmar and Thoenig (2000) provide insightful formal treatments of this set of issues.
[21] U.S. Department of Labor (1939:xi) as quoted in Miller et al (1980).

files for 1980, 1990 and 1998. We used all observations on non-institutionalized, employed workers, aged 18-64. For our industry analysis, these individual worker observations were aggregated to the level of 140 consistent Census industries spanning all sectors of the economy to provide indicators of average task requirements by industry for 1960, 1970, 1980, 1990 and 1998. All individual and industry level analyses are performed using as weights full-time equivalent hours of labor supply, which is the product of the individual Census or CPS sampling weight times hours of work in the sample reference week and, for Census samples, weeks of work in the previous year.

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 both economy-wide and within industries, holding constant task content within occupations at the DOT 1977 level. We refer to this source of variation as the 'extensive' (i.e., across occupations) margin, which we are able to measure consistently over the period 1960 to 1998. Variation on the extensive margin does not, however, account for changes in task content within occupations, such as is described in Levy and Murnane (1996), and is accordingly likely to provide an increasingly inaccurate picture of changing job task requirements over time.

To overcome this constraint, we exploit changes between 1977 and 1991 in skill content measures *within* occupations – the 'intensive' margin – using matched occupations from the Revised Fourth Edition of the Dictionary of Occupational Titles. This approach has some limitations. In the Revised Fourth Edition of the DOT, only a subset of occupations was reevaluated by DOT examiners, and moreover the year of reevaluation varies among occupations. In our data, the weighted fraction of employment reevaluated between 1978 and 1990 is 73 percent, with 32 percent reevaluated between 1978 and 1984 and 41 percent reevaluated between 1985 and 1990.[23] Measured

[22] The actual number varies by Census year. Details are found in the Data Appendix.
[23] Occupations were chosen for reevaluation by DOT examiners partly on the expectation that their content had changed since the previous evaluation. Hence, the subset that was not reevaluated may have changed less than the subset that was reevaluated.

changes along the intensive margin are therefore likely to provide a conservative picture of the total change in occupational task content. Nevertheless, these data provide a unique source of direct quantitative evidence on the changing task content of work within occupations.

Although the DOT provides unique, observational measures of occupational task requirements, it has a number of well-known limitations documented by Miller et al (1980). These include limited sampling of occupations (particularly in the service sector), imprecise definitions of measured constructs, and omission of important job skills. One result of these problems is that DOT measures of the skills required in particular occupations are likely to be imprecisely estimated, particularly for occupations outside of manufacturing. Despite these limitations, the DOT contains to our knowledge the best time series information available on the skill requirements for detailed occupations economy-wide.[24] Researchers who have used the DOT for related analyses include Howell and Wolff (1991), Ingram and Neumann (2000), Spenner (1983 and 1990), and Wolff (1996). Our focus on routine versus non-routine tasks, choice of DOT variables, and analysis of change in job content within occupations across successive DOT editions are distinct from these studies.[25]

a. Selecting DOT measures of routine and non-routine tasks

Many of the 44 occupational characteristics measured by the DOT are not germane to the hypothesized effects of computers outlined in Section 1. Moreover, the constructs identified by our conceptual model are only imperfectly proxied by DOT measures. 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 tabulations of means by major occupation for the year 1970, we selected five

---

[24] The Department of Labor's successor to the DOT, the O*NET, offers potentially more up to date information on occupational characteristics. Unfortunately, because of its recency, O*NET does not provide the time series information on which our analysis of changes in content *within* occupations depends.

variables that appeared to best approximate our skill constructs. Definitions of these variables and example tasks from the *Handbook for Analyzing Jobs* are provided in Table 1. Means of each variable by major occupation are found in Appendix Table 2 and a full set of cross-industry correlations is provided in Appendix Table 3.

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 variable DCP codes the extent to which occupations involve Direction, Control, and Planning of activities. This variable takes on consistently high values in occupations involving substantial non-routine managerial and interpersonal tasks.

The variable GED-MATH, our second measure of non-routine cognitive tasks, codes the quantitative skills ranging from arithmetic to advanced mathematics that are required in occupations. We employ this variable as a measure of occupations' analytic and technical reasoning requirements.

We identified STS, the acronym for adaptability to work requiring Set limits, Tolerances, or Standards, as an indicator of routine cognitive tasks and selected the variable FINGDEX, an abbreviation of Finger Dexterity, as an indicator of routine manual activity. As is clear from the DOT example tasks given in Table 1, there is overlap between our measures of routine manual and routine cognitive tasks. Although STS is weighted toward routine clerical and numerical tasks such as transcribing and calculating, and FINGDEX is weighted toward routine manual tasks such as feeding machines and performing repetitive movements, the correlation between the measures is high (0.61 using 1980 Census weights) and examples of both routine manual and cognitive tasks appear for each measure in the *Handbook for Analyzing Jobs.*

Finally, we selected EYEHAND, short for Eye-Hand-Foot coordination, as a measure of non-routine motor tasks. This variable takes on high values in occupations requiring physical agility, such

[25] Spenner (1983) provides an analysis of changes in measured occupational content between the 3rd and 4th editions of the DOT.

as firemen.

b. Why these DOT measures?

While we believe the selected measures are the most appropriate available from the DOT, we are sensitive to the concern that our choice of variables could be viewed as arbitrary (or worse). Here we explore whether the chosen variables are logical candidates and test whether initial results are similar if we employ alternative, composite variables generated by principal components analysis. In a subsequent section, we perform a second test of our variable choices by re-estimating key results using the composite measures in place of our direct DOT variables.

Observe that our model makes three specific predictions about which industries should have adopted computer capital most vigorously as its price declined: 1) industries intensive in routine cognitive and manual tasks (for which computers directly substitute for humans); 2) industries intensive in non-routine cognitive tasks (with which computers complement humans); and 3) industries relatively *non*-intensive in non-routine manual tasks (since non-routine manual tasks are mostly not amenable to computerization). If it were possible to measure industry task content *prior* to the computer era, these industry task measures should substantially predict later patterns of computer adoption.

To implement a variant of this test empirically, we pair DOT occupational task measures with industry occupational distributions from the 1960 Census to fit the following model:

$$\Delta C_{k,1959-1997} = a + b_1 T_{k,1959} + e_k \tag{9}$$

where $\Delta C_{k,1959-1997}$ is the percentage point change between 1959 and 1997 in the share of industry k employees using a computer on the job, $T_{k,1959}$ is an indicator of industry task intensity in 1959 from the DOT, and e is an error term.[26] Although we do not have a direct measure of the level of industry computer use in 1959, computer penetration was close to zero in all industries at this time. Hence, the

1997 industry level is effectively the change since 1959. To test whether the DOT task measures provide explanatory power beyond standard education variables, we fit models that include a measure of industry college graduate employment in 1959 as an additional control.

Estimates of (9) are found in the top panel of Table 2. For purposes of comparison we display the coefficient on each industry task measure from a specification does not include 1959 industry college graduate employment (row 1) as well as the relevant coefficients from a model that does include this control variable (row 2). Most notable from the table is that four of five task measures have the predicted sign. Industries intensive in non-routine cognitive tasks and intensive in routine cognitive and routine motor tasks in 1959 computerized significantly more than other industries over the subsequent four decades. Conversely, industries intensive in non-routine manual tasks computerized substantially less than others. All of these results are present in models that include 1959 industry college graduate employment as well as in those that do not include this control variable. The one unexpected pattern in the top panel of Table 2 is that the DOT measure of non-routine cognitive/interactive tasks does not predict subsequent computerization well. Overall, we take these patterns as evidence that our task measures do, for the most part, capture the relevant task dimensions outlined by our model.

We next explored whether similar patterns are present when we characterize industry task content by reasonable alternatives to our five DOT variables. To implement this test, we performed principal components analyses (PCA) to pool variation from each selected DOT task measure with several other plausible variables from the DOT. The PCA extracts eigenvectors that maximize common variation among selected measures, each standardized with mean zero and variance one, subject to

[26] Specifically, we apply 1977 DOT measures by occupation to the 1960 Census and aggregate them to the industry level.

the constraint that the sum of squared weights in the eigenvector equals one.[27] We then estimated equation (9) using the vector-weighted composites from the PCA in place of the direct DOT measures. To facilitate comparisons between the analogous coefficients in the two panels of Table 2, all DOT and composite variables are standardized to have mean zero and variance one.

The patterns displayed in the lower panel of Table 2 are for the most part comparable to the patterns displayed in the upper panel of the table. For three of the five task types, non-routine cognitive, routine manual, and non-routine manual, the coefficient on the relevant composite and the coefficient on the individual DOT variable both have the hypothesized sign and are significantly different from zero. For one of the other task types, non-routine cognitive/interactive, the composite predicts somewhat better than the single DOT variable. For a second task type, routine cognitive, the opposite is the case.

Selecting additional DOT variables for the composites required us to employ measures that, while relevant to our conceptual task categories, matched them less well than the five primary DOT measures. Accordingly, we had expected that the results using the composites would be somewhat weaker than those using our chosen DOT variables. We view the similarity of the results using the composites and the individual DOT variables as supporting the choice of conceptual categories and corresponding DOT variable selections.

While it would of course be possible to perform our entire analysis using the composites in place of the direct DOT measures, we find this approach unappealing. Unlike the direct DOT measures, the composites lack a precise definition. Moreover, the composites are problematic to interpret when analyzing within-occupation changes in the DOT between 1977 and 1991 since they do not correspond to any specific occupational changes observed by DOT examiners. Hence, we concentrate our analysis on the direct DOT measures but again test the robustness of this choice later

[27] It can be shown that if the measurement error in selected variables is iid, the PCA extracts maximal true variation. We employ the first eigenvector from each composite. In most cases, other eigenvectors were not significant (i.e.,

in the analysis.

4. Trends in job tasks: 1959 – 1998

a. Economy-wide trends

Figure 2 illustrates the extent to which changes in the occupational distribution over the period 1960 – 1998 resulted in changes in the skill content of the work done by the U.S. labor force. The proportion of the labor force employed in occupations that made intensive use of non-routine cognitive skills – both interactive and analytic – increased substantially. In contrast, the percentage of the labor force employed in occupations intensive in routine cognitive, routine manual and non-routine manual activities declined over the period.

Table 3 provides the means of the DOT job content measures for 1960 – 1998 corresponding to the figure. As is apparent from Figure 2, 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. Equally notably, routine cognitive and routine manual tasks both trended *upwards* during the 1960s, before commencing a decline in the 1970s that became more rapid in each subsequent decade. By contrast, the steady trend again non-routine manual tasks appears to pre-date the computer era. As is visible in the second and third columns of each panel of Table 3, these aggregate patterns are also apparent for each gender, although given the large increases in women's educational attainment and labor force participation in recent decades, the patterns are more pronounced for women.[28]

Appendix Table 4 tabulates the DOT tasks measures by major educational group. Three of five skill variables are monotonic in educational attainment, with both measures of non-routine cognitive tasks rising with education and the measure of non-routine manual tasks declining with education.

---

eigenvalues below one). Further details of our compositing exercise are available from the authors.

Interestingly, both measures of routine tasks – cognitive and manual – are non-monotonic in education, with high school graduates performing substantially more of each task than either high school dropouts or college graduates. These patterns suggest that despite the limitations of the DOT job content measures, they may provide information about job task requirements that is distinct from standard education measures.

b. Shift-share analysis

Changes in the skill content of the work done by the U.S. labor force could stem from substitution of computer capital for routine labor inputs within detailed industries, as our model suggests. Alternatively, shifts in product demand favoring sectors intensive in non-routine activities could give rise to economy-wide increases in the utilization of non-routine skills. Since the focus of our conceptual model and empirical analysis is on changes in skill demands within industries, we next explore the extent to which changes in measured job content stem from within-industry shifts in task input as opposed to employment shifts between industries.

A decomposition of changes in task input into between- and within-industry components provides a measure of the importance of these channels. A standard decomposition of the change in the use of task j in aggregate employment between years t and t $(\Delta T_{jt} = T_{jt} - T_{jt})$ into a term reflecting the reallocation of employment across sectors and a term reflecting changes in task j input within industries is given by:

$$(10) \qquad \Delta T_{jt} = \sum_k (\Delta E_{kt} g_{jk}) + \sum_k (\Delta g_{jkt} E_k) = \Delta T_{jt}^b + \Delta T_{jt}^w$$

where k indexes industries, E_{jkt} is the employment of workers in task j in industry k in year t as a share of aggregate employment in year t, E_{kt} is total employment (in FTES) in industry k in year t,

[28] In the 1960s, women were more concentrated in both routine manual and routine cognitive tasks than men and substantially less concentrated in non-routine cognitive analytic and interactive tasks. By 1998, women's task distribution looked substantially more similar to men's. In particular, although women start the period higher in routine cognitive tasks than males, they end the period far lower.

g_{jkt} is the mean of task j in industry k in year t, $g_{jk} = (g_{jkt} + g_{jkt})/2$, and $E_k = (E_{kt} + E_{kt})/2$. The first term ($\Delta T_{jt}^b$) reflects the change in aggregate employment of task j attributable to changes in employment shares *between* industries that utilize different intensities of task j. The second term (ΔT_{jt}^w) reflects *within-industry* task change.

Table 4 presents between- and within-industry decompositions of our five DOT task measures during each decade from 1960 – 1998. These decompositions show quite consistent patterns of task change. For the measure of non-routine cognitive/interactive tasks, the growth in economy-wide input of this task is almost entirely a within-industry phenomenon.[29] Moreover, the rate of within-industry growth accelerates sharply from decade to decade.

Decomposition of the decade by decade changes in the non-routine cognitive/analytic measure presents a more nuanced picture. Although the overall growth rate of this variable is roughly comparable over the 1960s – 80s prior to a modest acceleration in the 1990s, these net trends mask changes in the relative importance of between- and within- industry shifts. Within-industry changes account for only one quarter of the overall changes in the average level of non-routine cognitive/interactive tasks during the 1960s and 70s. In contrast, during both the 1980s and 1990s, the within-industry component of the trend growth in non-routine/analytic input roughly doubles, accounting for 70 percent of the net growth during these two decades. In net, these patterns indicate substantial acceleration in within-industry production shifts favoring non-routine/analytic tasks beginning in the 1980s.

The time patterns of routine cognitive and routine manual task input are quite similar. The observed growth in each during the 1960s is about equally accounted for by between- and within-industry shifts. In the three decades thereafter, however, the pattern of reduced input of these routine

[29] Observe that during the 1960s, there are offsetting between-industry shifts that reduce the net change in DCP to approximately zero. After the 1960s, between industry effects are negligible.

tasks is dominated by within-industry shifts. In the case of routine manual tasks, the within-industry component entirely accounts for the economy-wide change between 1970 and 1998. For routine cognitive tasks, the within-industry component accounts for 71 percent of the economy-wide change over this period. Although not tabulated here, we find that similar patterns obtain when we operationalize equation (10) for manufacturing and nonmanufacturing sectors separately.

Input of non-routine manual tasks presents a distinctly different pattern. Table 4 indicates a steady trend against non-routine manual task input since the 1960s. Both declining employment shares in industries intensive in non-routine manual tasks and declines in the share of non-routine manual intensive occupations within industries have contributed to this trend. The secular trend against non-routine manual tasks is a pervasive phenomenon pre-dating the computer era. Because non-routine manual tasks are largely orthogonal to computerization, we view this as neither supportive nor at odds with our framework.

Because within-industry shifts dominate the task trends that we seek to analyze – particularly from the 1970s forward – an analysis of the determinants of within-industry changes in task demand has the potential to illuminate the sources of the economy-wide task changes shown in Table 3.

5. Computerization and industry task input over four decades

a. Computerization and industry task shifts: Initial evidence

In this section we examine whether a number of proxies for industry computer investment and change in industry computer use predict the within-industry patterns of changing skill input found in Table 4. Initially, we estimates model of the form:

(11) $$\Delta T_{jkt} = a + b\Delta C_j + e_{jkt}$$

where $\Delta T_{jkt} = T_{jkt} - T_{jkt}$ is the change in industry input of task j between years t and t and ΔC_k is the change in the fraction of industry workers using a computer at their jobs over 1984 to 1997 as estimated from the October Current Population Survey supplements of these years. Although the

CPS-based measure is not temporally aligned with our dependent variable, we use it to provide an initial test of whether computer-intensive industries shifted their task input more rapidly than other industries did.

In estimating (11), we choose the period 1960 – 1998 because it encompasses the recent computer era and, as importantly, *the prior decade*. Although the widespread diffusion of desktop computers and accompanying organizational changes in the workplace during the 1980s and 1990s represents a highly visible form of technology shock – with the share of the labor force using a computer at work increasing from 25 to 51 percent between 1984 and 1997 – it bears emphasis that the era of rapid computer investment began in the 1970s.[30] Hence, to the degree that industry computer proxies 'predict' occupational task change during the 1960s, this would suggest that observed trends in changing task content in computer intensive sectors *pre-date* the computer era and hence are unlikely to be caused by computerization. Conversely, if the relationship between industry computer intensity and task change is not detectable until the 1970s or later, this is more likely to be consistent with a causal relationship. Table 5 presents estimates of (11) for the decades 1960 – 70, 1970 – 80, 1980 – 90 and 1990 – 98. Each dependent variable measures ten times the annualized industry level change in the average value of one of the task indicators.

The time pattern of regression coefficients, summarized by Figure 3, is substantially consistent with the conceptual model. Industries that computerized relatively rapidly during 1984 – 1997 increased the percentage of jobs requiring high levels of non-routine cognitive/interactive tasks more than did other industries in both the 1980s and the 1990s. There is also evidence that computer intensive sectors were increasing their cognitive/interactive tasks relatively more rapidly than other sectors in the 1960s and 1970s. However, the magnitude and statistical significance of this relationship increases substantially during the 1980s and 1990s, consistent with the acceleration in within-industry trends shown in Table 4.

The patterns for the measure of non-routine cognitive/analytic task input also present a consistent picture. During the 1960s and 1970s, industries that subsequently increased computer use rapidly did not increase their input of non-routine cognitive/analytic tasks more rapidly than did other industries. During the 1980s and 1990s, however, they did, however. In fact, the positive relationship between computerization and the increase in non-routine cognitive/analytic tasks accounts for all of the observed within-industry growth in input of this task over both decades.[31]

The relationships between computerization and industry declines in routine cognitive and routine manual activities also fit our conceptual model. During the 1960s the industries that subsequently underwent rapid computerization did not change their routine cognitive or routine manual task intensities any faster than did other industries. However, beginning in the 1970s, these industries did reduce their routine cognitive and routine manual task intensities much more rapidly than did other industries..

There is no statistically significant evidence that industries that rapidly computerized during the period 1984-97 decreased their use of non-routine manual tasks any more rapidly than other industries did during the 1960s, 1970s, or 1980s. This is consistent with the view explained above that the declining role of non-routine manual activities in the U.S. economy is a long term trend largely unrelated to computer use. During the 1990s rapidly computerizing industries did decrease the non-routine manual task intensity of work *less rapidly* than did other industries. This result should be interpreted carefully, however. It is unlikely that computerization directly increases demand for non-routine manual tasks. Rather, a more plausible channel is that as routine tasks are displaced by information technology, the share of human labor devoted to non-routine manual tasks

---

[30] This point is emphasized by Autor, Katz and Krueger (1998) and Bresnahan (1999).
[31] That is to say, the intercept of the bivariate regression of the change in industry non-routine cognitive/analytic task input on computerization during the 1980s and 1990s is close to zero although the mean of the dependent variable is large and positive. In this sense, computerization ‘explains’ the entirety of the observed phenomenon.

mechanically increases.[32]

To probe the robustness of our variable choices, we estimated comparable models using the composite task measures in place of the pure DOT variables. These composite estimates, found in Appendix Table 5, provide a pattern of results largely comparable to that found in Table 5. In all cases, the relationship between the composite task measure and recent computerization is insignificant during the 1960s decade and becomes statistically and economically significant in subsequent decades.

b. Computer investment, capital intensity, and task shifts: 1960 – 1998

A concern with the estimates above is that the CPS measure of computer use may simply serve as a proxy for other variables related to industry-level skill demands such as the size of the capital stock per worker. Additionally, our CPS computer use variable does not measure contemporaneous computer investment during the earlier decades in our sample. To address these concerns, we follow Berndt, Morrison and Rosenblum (1995) and Autor, Katz, and Krueger (1998) in employing data from the National Income and Product Accounts (U.S. Department of Commerce, 1993 and 1999) to construct a measure of industry computer investment per worker and an explicit measure of the change in the value of the capital stock per worker. Each variable is calculated for 1960, 1970, 1980, 1990, and 1997. We matched data from the Census, CPS, and DOT to NIPA data in 42 aggregated industries covering all private industry sectors except private household services.

To measure computer investment in the NIPA, we sum data on investment in mainframe and personal computers, computer storage devices, and computer peripherals.[33] To isolate the relationship between computer investment and changes in task intensity, we include as a control variable the

[32] More concretely, a constant number of workers doing non-routine manual work such as cleaning and serving in company cafeterias would account for a growing share of the work forces in computer-intensive industries.
[33] We also experimented with disaggregating computer capital into its various sub-components. As it turns out, these sub-components are almost perfectly correlated.

change in the value of the capital stock per worker over each decade.[34] In fitting our models we pooled data by industry on changes over 1960-70, 1970-80, 1980-90, and 1980-98 to estimate models of the form:

$$(12) \qquad \Delta T_{jkt} = a + d_{70-80} + d_{80-90} + d_{90-98} + b_1 CI_{kt} + b_2 \Delta K_{kt} + e_{jkt}$$

where CI is log industry investment in computer capital per FTE over the contemporaneous decade, ΔK is the change in the log industry capital labor ratio (also measured in FTEs), the $d's$ are time dummies equal to one in each post-1960s decades corresponding to their subscripts, and a is a common intercept. Since the NIPA capital variables are measured at a higher level of aggregation than our dependent variables, we estimate Huber-White robust standard errors that account for clustering at the NIPA sectoral level.

Table 6 displays the results. The estimated relationships between the contemporaneous measure of computer investments per worker from the NIPA and changes in the industry-specific skill mix are quite consistent with the relationships found using the CPS computer measures. The NIPA measure of computer investment consistently predicts relative declines in industry employment of routine cognitive and manual tasks and relative growth in employment of non-routine tasks, both cognitive and manual. In all cases, this relationship is statistically significant. Moreover, the estimated coefficient on computer investment is of economically meaningful magnitude. By comparing the decadal intercepts in the first column of each panel to the actual decadal changes found at the bottom of the table, one may calculate the fraction of the observed change in the task measure explained by industry computer investment. Taking the 1960s as the baseline (pre-computer) decade, these comparisons indicate that computer investment is able to explain more than 100 percent of the trend increase in both measures of non-routine cognitive task input since the 1960s, and 87 and 82 percent

[34] Our computer measure is the log of real computer investment per full-time equivalent employee (FTE) over the course of the decade. Note that we do not use the *change* in this measure since the *level* is a measure of the flow of new computer capital into an industry over the decade.

respectively of the trend decline in routine cognitive and manual tasks.[35]

Because computer investment predicts relative increases in industry non-routine manual task input, the data also suggest that declines in non-routine manual task input would have been substantially larger in the absence of computerization. As noted above, we view this relationship as mechanical, albeit consistent with our task framework.

A second notable pattern in these results is that the estimated impact of capital deepening on changes in industry skill demands is only statistically significant in one of five models, non-routine manual tasks.[36] Yet the coefficient on computer investment is significant in all five models that contain the measure of capital deepening. Consistent with findings of Autor, Katz, and Krueger (1998) and Bresnahan, Brynjolfsson and Hitt (forthcoming), these results indicate that there is something distinctive about computer capital's relationship with industry tasks demands apart from the well-known pattern of capital-skill complementarity (Griliches, 1969).

In summary, the evidence displayed in Tables 5 and Table 6 reveals that in computer-intensive industries, the share of the labor force employed in occupations emphasizing routine, repetitive cognitive and manual work fell relatively more than in other industries beginning in the 1970s and 1980s. At the same time the proportion of the work force employed in occupations emphasizing non-routine manual and cognitive tasks – both interactive and analytic – increased more rapidly than in other industries.

6. Contemporaneous changes in computer use and task content within industries, occupations and education groups: 1980 – 1998

One could argue that the results presented above simply provide an explanation for the previously documented pattern that during recent decades computer intensive industries increased

[35] For example, the calculation for routine cognitive tasks is: [(-0.019 – 0.089 + 0.040 + (-0.122 – 0.089) + 0.002 + ((-0.216 – 0.089) + 0.012)*.8]/([(-0.019 – 0.089 + (-0.122 – 0.089) + (-0.216 – 0.089)*.8] = 0.87. Note that changes over 1990-98 are down-weighted by 20 percent due to the shorter time interval.

their college graduate employment and decreased their high school graduate employment more than did other industries.[37] The logic would be that since the work of college graduates is concentrated in performing non-routine cognitive tasks (cf. Appendix Table 4), an increase in the percentage of college graduates employed in computer intensive industries means a greater concentration of non-routine cognitive tasks in these industries. Similarly, since the work of high school graduates has been concentrated in routine cognitive and routine manual tasks, a decline in the percentage of high school graduates employed in computer intensive industries means a decline in the percentage of workers carrying out these tasks.

To explore whether our task framework provides explanatory power beyond these expected patterns, we turn to the heart of our analysis: an examination of changes in the task content of work *within* education groups and *within* occupations. These task changes within education and occupation groups are, by definition, unobservable to previous studies that have employed as outcome measures shifts in educational and occupational structure *across* industries. If, as suggested by our framework, changes in the demand for workplace tasks are a driving force underlying changes in the structure of labor demand, we should expect that these task shifts will be pervasive not only across but *within* education and occupation cells.

To provide a baseline of comparison with the results described above, we first explore the correlations between computerization and changes in the task content of work within industries between 1980 and 1998. We then test whether computerization has induced changes in task structure within industries among workers with the same educational attainments. Finally, we test whether changes in within-occupation task content observed by DOT examiners over 1977 to 1991 are explained by patterns of occupational computer penetration. In the final section of the paper, we

[36] Notably, in models not tabulated here, we find that capital deepening does have significant explanatory power for the growth in college graduate employment share, although of much smaller economic magnitude than the computer investment measure.

collect each of these strands to quantify the contribution of changes in task content induced by computerization to recent demand shifts favoring educated labor.

a. Extensive changes within industries: 1980 – 1998

Table 7 presents a series of estimates in which the dependent variable is the within-industry change between 1980 and 1998 in each of our five DOT task measures. The explanatory variable is the change in industry computer use between 1984 and 1997, which in this case is a contemporaneous measure.

The results underscore the story told by Tables 5 and 6. Industries that experienced the greatest increase in computer intensity between 1984 and 1997 increased the percentage of jobs requiring high levels of non-routine cognitive/interactive and cognitive/analytic tasks between 1980 and 1998 more than did other industries. They also decreased the relative proportion of jobs requiring routine cognitive and manual tasks more rapidly than did other industries. In each case, the estimated impacts are economically large. For example, between 1980 and 1998, the within industry growth of non-routine cognitive/interactive tasks was 0.212 units annually. The intercept of the bivariate regression in the second row of Panel 1 of Table 7, however, is only 0.16, quite close to zero. This implies that computerization can explain most (92 percent) of the observed growth in cognitive/interactive tasks. Similar calculations indicate that computerization accounts for essentially all of the growth in non-routine cognitive/analytic task input, all of the reduction in routine manual task input, and more than all (125 percent) of the decline in routine cognitive task input.[38]

b. Changes in job content within education groups

We next estimate models that measure the relationships between changes in industry computer use and contemporaneous within-industry, *within-education group* changes in task content.

---

[37] Note that the growth of non-routine *manual* tasks in computer intensive sectors would *not* have been predicted by this simple comparison.

[38] Paralleling previous estimates, results for non-routine manual tasks are weaker. The estimates imply that input of non-routine manual tasks would have fallen by an additional 60 percent but for computerization. However, this estimate is not statistically significant and as above, should be interpreted carefully.

Specifically, we estimate a variant of equation (11) where the dependent variable is the change in the industry mean of each DOT measure among workers in each industry who have the same educational attainments.[39] Since we pair the 1977 DOT task content measures to education-group-specific industry observations for 1980 and 1998, observed changes in task input stem solely from shifts in occupational distributions within education groups within industries.

The weighted means of the dependent variable in Table 8 indicate that during 1980 – 1998, high school graduates were increasingly employed in occupations high in non-routine cognitive/interactive tasks, and were increasingly scarce in occupations high in routine cognitive and routine manual tasks. There was, however, little change in the non-routine manual task content and the non-routine cognitive/analytic task content of high school graduate employment.

Estimates of (11) reveal that employment shifts away from routine cognitive and routine manual tasks among high school graduates were substantially more pronounced in industries undergoing rapid computerization during 1984 – 1997 than in other industries. Similarly, the movement of high school graduates into occupations intensive in non-routine cognitive/interactive tasks was significantly larger in the rapidly computerizing industries. There is no significant relationship between computerization and employment of high school graduates in non-routine cognitive/analytic and non-routine motor tasks over this period.

Comparison of the estimated intercepts for these models relative to their weighted means indicates that observed high school graduate employment shifts against occupations intensive in routine cognitive and manual tasks and towards occupations intensive in non-routine cognitive tasks are *entirely driven* by changing employment patterns within computer-intensive sectors during 1980 – 98. Hence, even within observably identical education categories, we find that computer intensive industries have been differentially shifted the task content of employment against routine, repetitive

[39] In particular, we replace ΔT_{jkt} in (11) with ΔT_{jklt} where l denotes education groups within industries.

tasks and towards tasks demanding cognitive flexibility.

Appendix Table 6 presents estimates of (11) for other education groups. The patterns for workers with some college are virtually identical to those for high school graduates. In contrast, there are no statistically significant relationships between within-industry computerization and changes in the task content of work for either college graduates or high school dropouts, although almost all coefficients have the predicted sign.[40]

c. Computerization and changes in within occupation task content: 1977 – 1991

Our model predicts that technological change will affect the task content of the work not only by altering the distribution of occupations (the extensive margin), but by shifting the task content of work within occupations (the intensive margin). To test this prediction and quantify its importance, we explore whether, paralleling the extensive margin shifts above, patterns of *occupational* computerization predict changes in task content within occupations. To operationalize this test, we employ direct measures of changes in job task content observed by DOT examiners between 1977 and 1991.

Specifically, we estimate the equation:

$$\Delta T_{mkt} = a + b\Delta C_m + e_{mkt} \tag{13}$$

where ΔT_{mkt} is the change in observed occupational task content between 1977 and 1991 in 3-digit COC occupation m and ΔC_m is the change in occupational computer penetration measured by the CPS between 1984 and 1997.

To make this test as clean as possible, our DOT 1977 – 1991 comparison data set is constructed using only the subset of occupations appearing in the 1977 DOT and represented by the 1973 CPS

[40] A likely explanation for the college graduate results is 'topping out': because in 1980 college graduates were already concentrated in occupations with high values of non-routine cognitive tasks and low levels of routine cognitive and routine manual tasks, there was little room for these task measures to attain further extremes. Although we are less certain of the explanation for high school dropouts, a possibility is that in a labor force with rising educational attainments, high school dropouts have access to primarily menial jobs even in rapidly computerizing industries. These jobs tend to be non-routine manual jobs largely unaffected by computerization.

file (National Academy of Sciences, 1981) that provides our DOT-COC crosswalk. In addition, although the distribution of employment in DOT occupations (of which there are approximately 12,000) has doubtless shifted within COC occupations in recent decades, we hold this distribution fixed at the 1973 level to again exclude extraneous variation. Accordingly, the variation exploited in estimates of equation (13) stems entirely from DOT examiners' reevaluations of the task content of individual occupations between 1977 and 1991.

Table 9 presents the estimates of the relationships between changes in occupational computerization penetration between 1984 and 1997 and changes in occupational task content between 1977 and 1991. For each task measure, we present the results from two specifications. The first includes only one explanatory variable, the change in computer use. The second also includes the change between 1984 and 1997 in the percentage of workers in the occupation who are college graduates.[41]

As shown in the next to last row of Table 9, the largest change in the task content of work within occupations between 1977 and 1991 was a very large decrease in routine cognitive tasks. The regression estimates show that routine cognitive tasks declined much more intensively in occupations that were rapidly computerizing than in occupations that were not. In fact, the positive value of the intercept in the bivariate equation predicting the change in routine cognitive tasks implies that the intensity of this task is predicted to increase in occupations in which there had been no increase in computer use. Hence, the implied change in the occupational mean due to computerization (cf., bottom row of table) is more than sufficient to explain the observed mean shift against routine cognitive tasks over this period.

[41] A third set of estimates available from the authors also includes the fraction of workers in the COC occupation employed in jobs that were re-evaluated in the Revised Fourth edition of the DOT (the weighted mean of which is 73 percent) and the interaction of this variable with occupational computerization. This specification explores whether estimated computer impacts on job task content are potentially biased downwards due to the incomplete re-evaluation of occupations. Results from these specifications reinforce our Table 9 findings.

The other relatively large change in within-occupation task content was an increase in cognitive/interactive tasks. This change was also concentrated in rapidly computerizing occupations. Again, the implied change in the occupational mean due to computerization more than fully accounts for the observed mean increase in non-routine cognitive/interactive tasks within occupations.

A third noteworthy pattern is the positive relationship between computerization and the importance of non-routine cognitive/analytic tasks. Even though the average level of this type of task declined slightly within occupations, the level increased in rapidly computerizing occupations.

We find little relationship between computerization and changes in the routine manual task content of occupations. Interestingly, computerization predicts significant increases in the non-routine manual task content of occupations, a pattern also noted at the industry level.

Comparison of the two columns of each panel demonstrates that the relationships between computerization and within-occupation task change are quite insensitive to inclusion of the college graduate employment share measure. Apparently, observed educational upgrading within occupations does not provide an adequate summary measure of shifts in occupational content.

7. Computers, task structure, and the demand for college labor

The estimates above show that computerization explains a significant proportion of observed industry and occupation task shifts over the past three decades. To examine whether these shifts are economically important, we now draw together the estimated impacts of computerization on task change to evaluate their contribution to shifts in the demand for skill as conventionally measured by educational attainments.

Since units of task input do not have a natural scale, we translate task inputs into educational requirements using a fixed coefficients model of occupational education requirements in 1970 as a function of occupational task inputs measured by the 1970 DOT. Specifically, we estimate:

(14) $$CLG_m = a + T_m l + e_m$$

where CLG_m is the employment share (in FTEs) of college graduates in occupation m, T_m is a column vector containing the DOT means of our routine and non-routine skill measures, and l is a conformable row vector of coefficients. $\hat{l}$ is therefore an estimate of college versus non-college demand as a function of occupational tasks.[42]

We then translate our estimates of changes in job tasks induced by computerization (Tables 6 and 7) into estimates of implied changes in college versus non-college employment along the extensive margin by calculating:

$$(15) \qquad \hat{\Delta}CLG_t = \sum_k h_{kt} \hat{\Delta}T_{kt} \, \hat{l}$$

where $\hat{\Delta}T_{kt}$ is a vector of predicted change in industry $k's$ input of each of our five task measures due to computerization between times t and t from estimates of equation (11) and (12), and h_{kt} is industry $k's$ average share of employment between t and t. Similarly, we incorporate predicted changes on the *intensive* margin of task input over 1980 to 1998 by adding to $\hat{\Delta}T_{kt}$ the vector $\hat{\Delta}T_{mt}$, which is the predicted change from equation (13) in *within* occupation tasks attributable to computerization (Table 9).

Two caveats apply to these estimates. First, given the limitations of the DOT discussed earlier, estimates of l are likely to be biased towards zero by measurement error. This will reduce our estimates of ΔCLG_t. Second, because equation (15) is a fixed coefficients model of education demand as a function of job tasks, it neglects task prices. To the degree that the implicit prices of non-routine tasks have risen (fallen) since 1970, our calculations will under- (over-) state accompanying demand shifts favoring these non-routine tasks, and vice versa for measured demand shifts against routine tasks.

Detailed calculations of (15) are found in Table 10. Panel 1 lists the results of calculations using

[42] We estimate this model using the 1970 Census sample because it is closest to the actual date of the workplace

the CPS computerization estimates from Table 7 over 1980 – 1998 to estimate $\hat{\Delta}T_{kt}$. Panel 1A tabulates estimates of $\hat{\Delta}T_{kt}$ for 1980 – 1998 both excluding and including task changes on the intensive margin. Panel 1B translates these task shifts into demand shifts for college graduate employment. Panel 2 performs analogous calculations for 1970 – 1998 using NIPA estimates in Table 6 to form $\hat{\Delta}T_{kt}$.

As is documented in Panel 1B of Table 10, task changes on the extensive margin attributable to computerization explain 1.8 percentage points of the growth in college vs. non-college employment over 1980 – 1998. Of this number, 43 percent is accounted for by shifts against routine cognitive and manual tasks and 57 percent by shifts favoring non-routine cognitive tasks.[43] Adding the effect of changes along the intensive margin, $\hat{\Delta}T_{mt}$, more than doubles the magnitude of this impact. Computerization is estimated to have shifted the share of college employment outward by 3.6 percentage points over 1980 – 1998. Moreover, because the intensive margin change is only measured over the short 1977 – 1991 interval, it is likely that a longer time series would show that these shifts have even greater explanatory power.

For reference, this estimate of 3.6 percentage points can be compared to the actual change in college graduate employment between 1980 and 1998, which is 6.83 percentage points.[44] However, this is not the most appropriate comparison since increases in college employment are likely to be driven in part by secular trends in the supply of college graduates rather than shifts in demand per se.

To make a formal comparison, we tabulate changes in log relative demand for college versus non-college labor using estimates from Autor, Katz, and Krueger (1998, Table 2) and updated to 1998 for this exercise. These estimates use a constant elasticity of substitution framework to calculate log relative demand shifts favoring college over non-college workers implied by changes in relative

---

observations reported in the 4th edition DOT measures (published in 1977).

supplies and wages over 1980 – 1998. The college/non-college elasticity of substitution used for these estimates is 1.4, a figure that receives broad empirical support from the literature.[45]

To form analogous demand shift estimates from our task shift measures, we calculate:

(16) $$\hat{\Delta} D_t = \ln[((CLG_t + \hat{\Delta} CLG_t)/(1-(CLG_t + \hat{\Delta} CLG_t))/(CLG_t/(1-(CLG_t))]$$

where $\hat{\Delta} D_t$ is the estimated induced change in log relative demand for college/non-college employment between years t and t, CLG_t is the (start of period) college graduate share of total employment (in FTEs) in year t and $\hat{\Delta} CLG_t$ is the estimated task-induced change in college graduate employment from equation (15).

Estimates of (16) are found in panels 1C and 2C of Table 10. For the period 1980 – 1998, task shifts induced by computerization increased relative college demand by 2.05 log points. Comparing this number to the estimated economy-wide shift of 6.69 log points over this period, we find that changes in task content explain approximately 30 percent of the observed shift. Equally notable, more than half of this impact is accounted for by shifts along the intensive margin – shifts that are typically unobservable.

Panel 2 of Table 10 performs the analogous exercise for the period 1970 – 1998. As with our NIPA estimates in Table 6, we perform all calculations here *relative* to the 1960s. That is, we take the 1960 trend change in occupational task content as the baseline against which estimated technology-induced shifts over the subsequent three decades are to be compared.[46] Using the earlier estimate of l, we find that task shifts accounted for by computerization explain approximately 0.3, 0.9, and 0.9 percentage points of the *increase* in college/non-college employment relative to the

---

[43] The increased demand for non-routine manual tasks makes a small offsetting contribution to increased demand for college graduates.
[44] We use the CPS MORG 1980 and 1998 files to form this estimate.
[45] Cf., Hamermesh (1993), Heckman, Lochner and Taber (1998), Katz and Autor (1999), and Katz and Murphy (1992).

1960s level in the 1970s, 1980s, and 1990s respectively (Panel 2B).

The final column of Panel 2B adds changes in the intensive margin over 1980 – 1998 to these calculations. The change along the intensive margin contributes substantially to the total change in college employment, raising the estimated contribution of task shifts by 75 percent. Translating these employment changes into relative demand shifts (Panel 2C), the DOT task shift measures again explain 30 percent – a substantial share – of the shift in log relative demand favoring college educated labor between 1970 – 1998.[47]

In interpreting these estimates, bear in mind, as Acemoglu (2000), Autor, Katz and Krueger (1998), Johnson (1997), and Mishel, Bernstein and Schmitt (1997) have emphasized, that relative demand for college-educated labor in the U.S. increased substantially from the 1940s through the 1960s, decades prior to computerization. Hence, a claim that computerization has increased the relative demand for educated labor requires evidence that computerization has *accelerated* demand growth beyond trends prevailing during the 1960s and earlier. It is therefore noteworthy that our estimates in Panel 2C indicate that computerization contributed to more rapid growth in college employment in the 1970s relative to the 1960s, and that this impact was greater still during the 1980s and 1990s. Hence, our evidence suggests that recent technological change has had an accelerating impact on the task structure of employment since the 1970s. Cumulatively, this impact has contributed substantially to demand shifts favoring college-educated labor.

8. Conclusion

There were substantial economy-wide declines during 1960 – 1998 in the share of labor input in

---

[46] To be precise, we subtract off the 1960s trend task change from the task estimates for the 1970s, 1980s, and 1990s on the assumption that these trends were not due to computerization and hence should be counted against any potential computer impacts.

[47] One point of uncertainty is over what time interval it is most appropriate to allocate the sizable intensive shift in job task demand. Since the shift is in fact observed in the DOT over 1977 – 1991, allocating the intensive shift primarily to the 1980s would be consistent with most of the acceleration in college demand occurring during the 1980s rather than the 1990s. Since the estimates of log relative demand in Table 9 indicate *deceleration* in college/non-college demand shifts during the 1990s, this temporal allocation of the intensive margin would also be most consistent with the demand data.

the U.S. economy devoted to repetitive cognitive and manual tasks, and an increase in the share devoted to non-routine cognitive tasks, both analytic and interactive. Beginning in the 1970s, these changes have primarily been driven by within-industry shifts in the task content of employment. Models of the determinants of task demands within detailed industries indicate that proxies for computer investment and changes in industry computer use account for a substantial share of the observed shifts favoring non-routine over routine tasks over the three decades from 1970 to 1998. These shifts are evident in changes in occupational distributions within detailed industries, changes in occupational distributions within education groups within industries, and changes in task requirements within detailed occupations. Translating the task shifts induced by computerization into measures of education demand, the sum of within-industry and within-occupation task shifts explain approximately thirty percent of the observed relative demand shift favoring college versus non-college labor between 1970 and 1998, with the largest impact felt during 1980 – 1998. Changes in task content within occupations explain more than half of the overall demand shift induced by computerization.

Many prominent studies in the economic literature document a positive correlation between technology investments and educational upgrading. Our study both complements and advances this line of research. By conceptualizing job skill demands in terms of job tasks rather than the educational credentials of workers performing those tasks, our framework provides an account of how computerization and associated organizational changes alter the composition of job tasks. This framework rationalizes the observed correlation between computerization and increased use of educated labor, and makes novel predictions about changes in task structure *within* education and occupations groups. By exploiting consistent, representative, time series data on direct observations of the task structure of occupations, we confirm that these predictions are present and of economically meaningful magnitude. While the limitations of the DOT also place constraints on the precision of our analysis, we believe our approach advances understanding of how recent technological change is reshaping the skill content of employment.

References

Acemoglu, Daron. 1998. "Why Do New Technologies Complement Skills? Directed Technical Change and Wage Inequality." *Quarterly Journal of Economics*. Vol. 113 (4), November, 1055 – 89.

Acemoglu, Daron. 1999. "Changes in Unemployment and Wage Inequality: An Alternative Theory and Some Evidence." *American Economic Review,* 89(5), December, 1259 – 78.

Acemoglu, Daron. 2000. "Technical Change, Inequality, and the Labor Market." NBER Working Paper #7800, July.

Adler, Paul S. 1986. "New Technologies, New Skills." *California Management Review*, 29(1), 9 – 28.

Autor, David H., Lawrence F. Katz, and Alan B. Krueger. 1998. "Computing Inequality: Have Computers Changed the Labor Market?" *Quarterly Journal of Economics,* 113(4), November, 1169 – 1214.

Autor, David H., Frank Levy and Richard J. Murnane. 2000. "Upstairs, Downstairs: Computer-Skill Complementarity and Computer-Labor Substitution on Two Floors of a Large Bank" NBER Working Paper #7890, September.

Babbage, Henry P. 1883. "The Analytical Engine." *Proceedings of the British Association*.

Bartel, Anne P. Ichniowski, Casey and Kathryn Shaw. 2000. "New Technology, Human Resource Practices and Skill Requirements: Evidence from Plant Visits in Three Industries" mimeo, Carnegie Mellon University.

Bartel, Ann P. and Frank R. Lichtenberg, "The Comparative Advantage of Educated Workers in Implementing New Technology." *Review of Economics and Statistics,* 69(1), February, 1 – 11.

Berman, Eli, John Bound, and Zvi Griliches. 1994. "Changes in the Demand for Skilled Labor within U.S. Manufacturing Industries: Evidence from the Annual Survey of Manufactures," *Quarterly Journal of Economics*, 109, 367 – 397.

Berman, Eli, John Bound, and Stephen Machin. 1998. "Implications of Skill-Biased Technological Change: International Evidence," *Quarterly Journal of Economics*, 113, 1245 – 1279.

Berman, Eli and Stephen. 2000. "Skill-Biased Technology Transfer: Evidence of Factor Biased Technological Change in Developing countries." mimeograph, Boston University, January.

Berndt, Ernst R. and Catherine J. Morrison. (1995) "High-Tech Capital Formation and Economic Performance in U.S. Manufacturing Industries: An Exploratory Analysis," *Journal of Econometrics*, 65, 9 – 43.

Borghans, Lex and Bas Ter Weel. 2000. "What Happens When Agent T Gets a Computer?" mimeo, Maastricht University, October.

Bresnahan, Timothy F. 1999. “Computerization and Wage Dispersion: An Analytical Reinterpretation” *Economic Journal*, 109, June, 390 – 415.

Bresnahan, Timothy F., Erik Brynjolfsson, and Lorin M. Hitt. Forthcoming. “Information Technology, Workplace Organization and the Demand for Skilled Labor: Firm-Level Evidence,”*Quarterly Journal of Economics*.

Bryjolfsson, Erik and Lorin M. Hitt. 2000. “Beyond Computation: Information Technology, Organizational Transformation and Business Performance” *Journal of Economic Perspectives*, 23 – 48.

Caroli, Eve, and John Van Reenen. 2000. “Skill-Biased Organizational Change? Evidence from a Panel of British and French Establishments.” mimeo, University College London, August.

Caselli, Francesco. 1999. “Technological Revolutions.” *American Economic Review* 89, 78 – 102.

DiNardo, John and Jörn-Steffen Pischke. 1997. “The Returns to Computer Use Revisited: Have Pencils Changed the Wage Structure Too?” *Quarterly Journal of Economics*, 112, 291 – 303.

Doms, Mark, Timothy Dunne, and Kenneth R. Troske. 1997 “Workers, Wages, and Technology,” *Quarterly Journal of Economics*, 112, 253 – 90.

Fernandez, Roberto. 1999. “Skill-Biased Technological Change and Wage Inequality: Evidence from a Plant Retooling,” mimeograph, Stanford University Graduate School of Business, June.

Freeman, Richard B. 1976. *The Overeducated American*, New York: Academic Press, 1976.

Gera, Surendra, Wulong Gu and Zhengxi Lin. 1999. “Technology and the Demand for Skills in Canada: An Industry-Level Analysis” Industry Canada Working Paper # 28, 1999.

Goldin, Claudia; Katz, Lawrence F. 1998. “The Origins of Technology-Skill Complementarity.” *Quarterly Journal of Economics*. 113(3), August, 693 – 732.

Griliches, Zvi. “Capital-Skill Complementarity.” 1969. *Review of Economics & Statistics*, 51(4), November, 465 – 68.

Grimm, Bruce T. 1998. “Price Indexes for Selected Semiconductors, 1974 – 1996” *Survey of Current Business*, February.

Hamermesh, Daniel S. 1993. *Labor Demand*, New Jersey: Princeton University Press.

Heckman, James J., Lance Lochner, and Christoper Taber. 1998. “Explaining Rising Wage Inequality: Explorations with a Dynamic General Equilibrium Model of Labor Earnings with Heterogeneous Agents.” *Review of Economic Dynamics*, 1(1), January, 1 – 58.

Howell David R. and Edward N. Wolff. 1991. "Trends in the Growth and Distribution of Skills in the U.S. Workplace, 1960-1985," *Industrial and Labor Relations Review*, 44(3), April, 486 – 502.

Hounshell, David A. 1984. *From the American System to Mass Production, 1800-1932 : The Development of Manufacturing Technology in the United States*, Baltimore: Johns Hopkins University Press.

Ingram, Beth F. and George R. Neumann. 2000. "The Returns to Skill," mimeo, University of Iowa, May.

Jaeger, David A. 1997. "Reconciling the Old and New Census Bureau Education Questions: Recommendations for Researchers," *Journal of Business and Economics Statistics*, 15, 300 – 309.

Johnson, George 1997. "Changes in Earnings Inequality: The Role of Demand Shifts," *Journal of Economic Perspectives*, 11, 41 – 54.

Juhn, Chinhui. 1999. "Wage Inequality and Demand for Skill: Evidence from Five Decades." *Industrial and Labor Relations Review*, 52(3), April, 424 – 43.

Juhn, Chinhui; Murphy, Kevin M; Pierce, Brooks. 1993. "Wage Inequality and the Rise in Returns to Skill. *Journal of Political Economy*, 101 (3), June, 410 – 442.

Katz, Lawrence F. and David H. Autor. 1999. "Changes in the Wage Structure and Earnings Inequality," in *Handbook of Labor Economics*, vol. 3, O. Ashenfelter and D. Card, eds. (Amsterdam: North Holland).

Katz, Lawrence F. and Kevin M. Murphy. 1992. "Changes in Relative Wages, 1963-1987: Supply and Demand Factors," *Quarterly Journal of Economics*, 107, 35 – 78.

Krueger, Alan B. 1993. "How Computers Have Changed the Wage Structure: Evidence from Micro Data," *Quarterly Journal of Economics*, 108, 33 – 60.

Levy, Frank, Anne Beamish, and Richard J. Murnane. 1999. "Computerization and Skills: Examples from a Car Dealership", mimeo, MIT Department of Urban Studies and Planning, November.

Levy, Frank and Murnane, Richard J. 1992. "U.S. Earnings Levels and Earnings Inequality: A Review of Recent Trends and Proposed Explanations." *Journal of Economic Literature*, 30(3), September, 1333 – 1381.

Levy, Frank and Richard J. Murnane. 1996. "With What Skills are Computers a Complement?" *American Economic Review Papers and Proceedings*. 86 (2) May, 258 – 262.

Lindbeck, Assar, and Dennis J. Snower. 2000. "Multitask Learning and the Reorganization of Work: From Tayloristic to Holistic Organization." *Journal of Labor Economics* 18, 353 – 76.

Machin, Stephen; Van Reenen, John. 1998. "Technology and Changes in Skill Structure: Evidence from Seven OECD Countries" *Quarterly Journal of Economics*, 113 (4), November, 1215 – 44.

Miller, Anne R., Donald J. Treiman, Pamela S. Cain and Patricia A. Roose (editors). 1980. *Work, Jobs and Occupations: A Critical Review of the Dictionary of Occupational Titles*, Washington, DC: National Academy Press.

Mishel, Lawrence, Jared Bernstein, and John Schmitt. 1997. “Did Technology Have Any Effect on the Growth of Wage Inequality in the 1980s and 1990s?” mimeo, Economic Policy Institute, Washington, DC, December.

Mobius, Markus. 2000. “The Evolution of Work.” Mimeograph, HarvardUniversity, September.

Mokyr, Joel. 1990. *The Lever of Riches: Technological Creativity and Economic Progress.* New York: Oxford University Press.

Murnane, Richard J. and Frank Levy. 1996. *Teaching the New Basic Skills*, New York: Free Press.

Murphy, Kevin M and Finis Welch. 1992. “The Structure of Wages.” *Quarterly Journal of Economics*, 107(1), February, 285 – 326.

Murphy, Kevin M and Finis Welch. 1993. “Occupational Change and the Demand for Skill, 1940 – 1990.” *American Economic Review*, 83(2), May, 122 – 36.

National Academy of Science, Committee on Occupational Classification and Analysis. 1981. “Fourth Edition Dictionary of DOT Scores for 1970 Census Categories.” ICPSR Document #7845, Ann Arbor Michigan.

Nelson, Richard R., and Edmund S. Phelps. 1966. “Investment in Humans, Technological Diffusion, and Economic Growth.” *American Economic Review*, 56.

Orr, Julian E. 1996. *Talking about Machines: An Ethnography of a Modern Job*. Ithaca: Cornell University Press.

Park, Jin Heum. 1994. “Estimation of Sheepskin Effects and Returns to Schooling Using the Old and the New CPS Measures of Educational Attainment,” Princeton University, Industrial Relations Section Working Paper No. 338, December.

Pinker, Steven. 1997. *How the Mind Works*, New York: Norton.

Polanyi, Michael. 1966. *The Tacit Dimension*, New York: Doubleday.

Priebe, J.A., J. Heinkel, and S. Greene. 1972. “1970 Occupation and Industry Classifications in Terms of their 1960 Occupation and Industry Elements.” Census Bureau Technical Paper # 26.

Rasmussen Jens, Annelise Mark Pejtersen and L.P. Goodstein. 1994. *Cognitive Systems Engineering*, John Wiley & Sons.

Roy, A. D. 1951. “Some Thoughts on the Distribution of Earnings.” *Oxford Economic Papers*.

Ruggles Steven, Matthew Sobek et. al.. 1997. *Integrated Public Use Microdata Series: Version 2.0*, Minneapolis: Historical Census Projects, University of Minnesota

Schultz, Theodore W. 1975. “The Value of the Ability to Deal with Disequilibria.” *Journal of Economic Literature*, 13, 827 – 846.

Simon, Herbert A. 1960. "The Corporation: Will it be Managed by Machines?" in M. L. Anshen and G. L. Bach (eds). *Management and the Corporations, 1985*, New York: McGraw-Hill, 17 – 55.

Spenner, Kenneth I. 1983. "Deciphering Prometheus: Temporal Change in the Skill Level of Work." *American Sociological Review*, 48, 824 – 837.

Spenner, Kenneth I. 1990. "Skill: Meaning, Methods and Measures" *Work and Occupations*, 17(4), 399 – 421.

Thesmar, David, and Mathias Thoenig. 2000. "Creative Destruction and Firm Organization Choice: A New Look into the Growth-Inequality Relationship," *Quarterly Journal of Economics,*115(4), 1201 – 1238, November.

U.S. Department of Labor, Manpower Administration. 1972. *Handbook for Analyzing Jobs*, Washington DC.

U. S. Department of Commerce. 1993. *Fixed Reproducible Tangible Wealth of the United States, 1925–89* (Washington, DC: U. S. Department of Commerce, Economics and Statistics Administration, Bureau of Economic Analysis.

U.S. Department of Commerce. 1999. F*ixed Reproducible Tangible Wealth of the United States, 1925–1997*. NCN-0229 (Washington, DC: U.S. Department of Commerce, Economics and Statistics Administration, Bureau of Economic Analysis).

U.S. Department of Labor, Manpower Administration. 1972. *Handbook for Analyzing Jobs*, Washington DC.

U.S. Department of Labor. 1939. *Dictionary of Occupational Titles: First Edition*, Washington DC.

U.S. Department of Labor, Employment and Training Administration. 1977. *Dictionary of Occupational Titles: Fourth Edition*, Washington DC.

U.S. Department of Labor, Employment and Training Administration. 1991. *Dictionary of Occupational Titles: Revised Fourth Edition*, Washington DC.

Welch, Finis.1970. "Education in Production." *Journal of Political Economy*, 78, 35 – 59.

Welch, Finis.2000. "Growth in Women's Relative Wages and Inequality Among Men: One Phenomenon or Two?" *American Economic Review*, May, 444 – 450.

Winston, Patrick H. 1999. "Why I am Optimistic" available at http://www.ai.mit.edu/people/phw/optimism.html, July, accessed 6/18/2000.

Wolff, Edward N. 1996. "The Growth of Information Workers in the U.S. Economy, 1950-1990: The Role of Technological Change, Computerization, and Structural Change," C.V. Starr Center for Applied Economics, New York University RR#96-41.

Zuboff, Shoshana. 1988. *In the Age of the Smart Machine*, New York: Basic Books

Data Appendix

A.1. Samples used from Current Population Survey and Census of Populations

To calculate occupational and educational distributions economy-wide and within industries for 1960 to 1998, we used observations on all non-institutionalized, employed workers ages 18 – 64 from the Census PUMS one percent samples for 1960, 1970, 1980, and 1990 (Ruggles and Sobek, 1997) and the Merged Outgoing Rotation Groups of the Current Population Survey for the years 1980, 1990, and 1998. All individual and industry level analyses are performed using as weights full-time equivalent hours of labor supply, which is the product of the individual Census or CPS sampling weight times hours of work in the sample reference week divided by 35 and, for Census samples, weeks of work in the previous year. Our method provides equal weight to each hour of labor input in the economy rather than over-weighting part-time hours as is implicitly done when using raw Census sampling weights. Because hours were not reported for the self-employed in the CPS prior to 1994, we assigned self-employed workers in all CPS samples the average labor hours in their industry-education-year cell. In cases where industry hours supplied by education category were unavailable (due to an empty industry-education-year cell), we assigned weekly hours as the mean of workers' education-year cells.

To attain comparable educational categories (high school dropout, high school graduate, some college, college-plus graduate) across the redefinition of Census's Bureau's education variable introduced in 1990 in the Census and in 1992 in the CPS, we use the method proposed by Jaeger (1997). In data coded with the pre-1992 education question (Census PUMS 1960, 1970, and 1980, and CPS MORG files 1980 and 1990), we defined high school dropouts as those with fewer than 12 years of completed schooling; high school graduates as those having 12 years of completed schooling; some college attendees as those with any schooling beyond 12 years (completed or not) and less than 16 completed years; and college plus graduates as those with 16 or more years of completed schooling. In data coded with the revised education question (1990 Census PUMS and 1998 CPS MORG file), we define high school dropouts as those with fewer than 12 years of completed schooling; high school graduates as those with either 12 completed years of schooling and/or a high school diploma or G.E.D.; some college as those attending some college or holding an Associate's Degree (either occupational/vocational or academic); and college plus as those with a B.A. or higher.

A.2. Computing DOT Task Means for Census Occupation Categories (COCs)

To compute DOT Task Means for 1970 CIC Occupations, we used a special version of the April 1971 CPS Monthly File issued by the National Academy of Sciences (1981) in which a committee of experts assigned individual DOT occupation codes and associated DOT measures to each of 60,441 workers in the sample. Because Census occupation categories are significantly coarser than DOT occupation categories, the 411 1970 census occupation codes represented in the 1971 CPS were assigned a total of 3,886 unique 1977 DOT occupations.[1] To convert this micro data sample into DOT task measures by CIC occupation, we used the CPS sampling weights to calculate weighted means of each DOT measure by occupation. Because the distribution of DOT occupations differs substantially by gender within COC occupation cells, we calculated DOT-occupation means for each occupation separately by gender. In cases where a COC cell contained exclusively males or females, we assigned the cell mean to both genders. This provided a set of 822 DOT occupation means by 1970 COC and gender.

[1] Although the DOT contains over 12,000 occupational titles created originally during the 1930s, many of these occupations correspond to extraordinarily narrowly defined manufacturing jobs that are no longer represented in employment.

We next required a method to consistently assign these means to COC occupations for 1960, 1980, and 1990.

To generate DOT means by 1960 occupation, we developed a crosswalk from the 1970 to 1960 COC occupational classification schemes using information in Priebe and Greene (1972). Our crosswalk (available on request) provides a set of 211 consistent 1960 – 1970 occupations that represent the lowest common level of aggregation needed to obtain a consistent occupation series. We applied the 1970 COC means to our 1970 Census sample by occupation and gender and calculated weighted gender-occupation means across the 211 consistent 1960 – 1970 occupational categories. These means provide our DOT task measures for 1960 occupational categories.

To generate DOT means for 1980 and 1990 occupations required an additional step. Because there is not a close correspondence between the 1970 and 1980 COC coding schemes, it was not possible to develop a bridging crosswalk as we did for 1960 – 1970. Instead, we employed a special Census sample prepared for the Committee on Occupational Classification and Analysis chaired by Donald Treiman and kindly supplied to us by Michael Handel. This file contains 122,141 observations from the 1980 Census that have been individually dual coded with both 1970 and 1980 COC occupation codes based on occupational and other demographic information supplied by Census respondents.[2] To calculate DOT means by 1980 occupation, we merged the 1970 COC-DOT means describe above to the Treiman file by gender and 1970 COC occupation, achieving a 97 percent match rate. We next appended to the Treiman file a set of consistent occupation codes for the years 1980 to 1998 developed by Autor, Katz and Krueger. These codes resolve minor changes to the COC schemes employed in the 1980 and 1990 Censuses and corresponding CPS files. Finally, to form DOT means by 1980 COC, we calculated labor-supply weighted means of each DOT measure within consistent 1980 COC occupation gender categories. These steps provide a set of by-gender DOT means for each of 485 DOT occupations that are consistent for 1980 – 1998.

A.3. Computing DOT Task Means by Consistent 1960 - 1998 Industry

To compute DOT task means overall, by industry, and by industry-education cell for 1960 – 1998, we assigned the consistent DOT occupational task means for 1960 – 1998 by gender and occupation to each observation in our Census and CPS samples for 1960 – 1998. Using labor supply in FTEs as weights, we calculated means of each DOT measure for each occupation-industry-education-year cell. These means provide the primary outcome measures for our analysis.

To attain compatibility between changing Census Industry Codes for 1960 – 1998, we use a crosswalk developed by Autor, Katz, and Krueger (1998) providing140 consistent CIC industries spanning all sectors of the economy. This crosswalk includes all CIC industries and attains consistency by aggregating where necessary to the lowest common level of consistent industry definition among 1970, 1980 and 1990 CIC standards.

A.4. Calculating Within-Occupation Changes in DOT Task Measures: 1977 – 1991

To measure within-occupation changes in task content, we employed the 1991 Revised Fourth Edition of the Dictionary of Occupational Titles (available in electronic form as National Academy of Sciences, 1981). Based on a study of select industries to determine which jobs had undergone the most significant occupational changes since the 1977 publication of the DOT 4th edition, DOT analysts introduced, revised, and eliminated occupational definitions for occupations that were observed to have most

[2] Hence, 1980 COC codes vary within 1970 COC codes and vice versa in this hand-coded sample.

substantively changed between 1977 and 1991. In total, 2,452 occupations were reviewed, updated, and/or added. In addition, 646 nominal titles were revised, 136 titles combined, and 75 deleted.

We use the *Conversion Tables of Code and Title Changes: Fourth to Revised Fourth Edition Dictionary of Occupational Title,* kindly provided by the North Carolina Employment Security Commission, to construct a crosswalk between the 1991 DOT and 1977 DOT occupation codes. Using this crosswalk, we applied the DOT 1991 task variables to our 1971 CPS file, yielding a match rate of over 99.9 percent. Of these matched occupations, 73 percent had been updated between 1977 and 1991 by DOT examiners. We then calculated DOT means by 1970 and 1980 COC occupations and gender using a procedure identical to that described in A.3. Because we use identical procedures for processing both DOT files, the within-occupation variation in DOT task measures that we exploit stems exclusively from re-evaluation of occupational content by DOT examiners, rather than from changes in the relative size of DOT sub-occupations within CIC occupations.

A.5. Composite Task Indicators from the DOT

To verify that our results are robust to plausible alternative selections of DOT variables, we formed composite indicators of our intended constructs using Principal Components Analysis. As described in the text, we chose a short list of alternative DOT variables that appeared relevant to each of our conceptual categories. These choices are (including our preferred DOT measures):

Non-Routine Cognitive/Analytic Tasks: GED-MATH, GED-REASON, NUMER, INTELL

Non-Routine Cognitive/Interactive Tasks: DCP, GED-LANGUAGE, REPCON (-), AND DEPL

Routine Cognitive Tasks: STS, COLORDIS, MANDEX, AND MVC

Routine Manual Tasks: FINGDEX, MOTOR, FORM

Non-Routine Manual Tasks: EYEHAND, CLERICAL (-), SPATIAL

Note that a (-) sign next to variable means that it was considered to be *opposite* to the intended construct and hence a suitable candidate for the PCA.

Using these variables (standardized with mean zero and variance one), we performed a PCA for each set to identify the linear combinations that maximized common variation subject to the constraint that the sum of squared vector weights is equal to one. Consistent with our treatment of DOT measures above, we conducted PCAs separately for males and females using the occupation-by- gender data set described in section A.2 and weighting by the occupational distribution of employment in the 1970 Census. In every case, we used the first principal component as the gender- and occupation-specific composite indicator of the task measure. (In almost very case, only the first eigenvector was significant.) To aggregate these task composites to the industry by year level, we followed steps exactly analogous to those used for the non-composited DOT variables. Models that use these composites in place of the direct DOT task measures are found in Panel B of Table 2 and in Appendix Table 5.

A.6. Computer Usage Data from the Current Population Survey

Industry computer use frequencies were calculated from the October 1984 and 1997 School Enrollment Supplements to the Current Population Survey (CPS) as the weighted fraction of currently employed workers ages 18 - 65 who answered yes to the question, “Do you use a computer directly at work?”

within consistent CIC industries. A computer is defined as a desktop terminal or PC with keyboard and monitor and does not include an electronic cash register or a hand held data device. 61,712 and 56,247 observations were used to calculate these frequencies in 1984 and 1997 respectively.

A.7. Computer and Capital Investment Measures from the National Income and Products Accounts

We used data on capital stock (equipment and structures) and investment in computer equipment from the National Income and Product Accounts (NIPA) to measure capital stock and computer capital holdings at the industry level between 1950 – 1997. To reduce measurement error, all variables in the NIPA were constructed as 5-year centered averages of the respective data category. All NIPA stock and investment variables are measured in real dollars. Deflation of NIPA measures is performed by the Bureau of Economic Analysis using primarily Producer Price Indexes (PPI's). PPI's for computer investment are based on quality adjustment, price linking, and hedonic regression methods. As denominators for capital/FTE and computer investment/FTE variables, we used Census and CPS samples to calculate FTEs by industry by year.

We used two sources of NIPA data to form estimates of capital stock and computer investment. For the years 1950 – 1990, we relied on the 1993 revision of the NIPA (U.S. Department of Commerce, 1993). In this data set, we measure computer investment using the Office Computing and Accounting Machinery (OCAM) variable. Because this NIPA revision set only provides data to 1989, we utilized the as-of-yet incomplete 1999 revision to the NIPA (U.S. Department of Commerce, 1999) to form industry capital stock and computer investment measures for 1990 – 1997. In the 1999 NIPA release, computer investment is calculated as the sum of data on investment in mainframe and personal computers, computer storage devices, and computer peripherals. Because final capital stock measures by industry are not yet available in the 1999 NIPA data, we estimated each industry's capital stock as the sum of all individual asset items by industry by year.

In pairing these two NIPA series, we make every effort to maintain consistency. In particular, we rescale the revised NIPA variables for 1990 such that they are identical in weighted mean to the previous release of the NIPA. We then apply this scaling factor to all NIPA measures from 1990 – 1998. In addition, we examined the sensitivity of our results to this pairing by re-estimating the NIPA models in Table 6 excluding the years 1990 – 1998 (i.e., the years that use the revised NIPA data). Our results (available on request) are quite insensitive to this exclusion.

To match CPS and Census data to the NIPA, we relied on a crosswalk developed by Autor, Katz and Krueger (1998) and revised for this analysis to accommodate small changes in the NIPA sector scheme made during the recent NIPA revision. The resulting aggregation of NIPA and CIC data contains 47 consistent industries covering all industrial sectors excluding Government and Private Households, spanning the 1960 – 1998 CIC standards. Of these 47, we exclude from our analysis agriculture and government dominated services (5 NIPA industries).

Figure 2: Economy-Wide Measures of Routine and Non-Routine Task Input:
1959 - 1998 (1959 = 0)

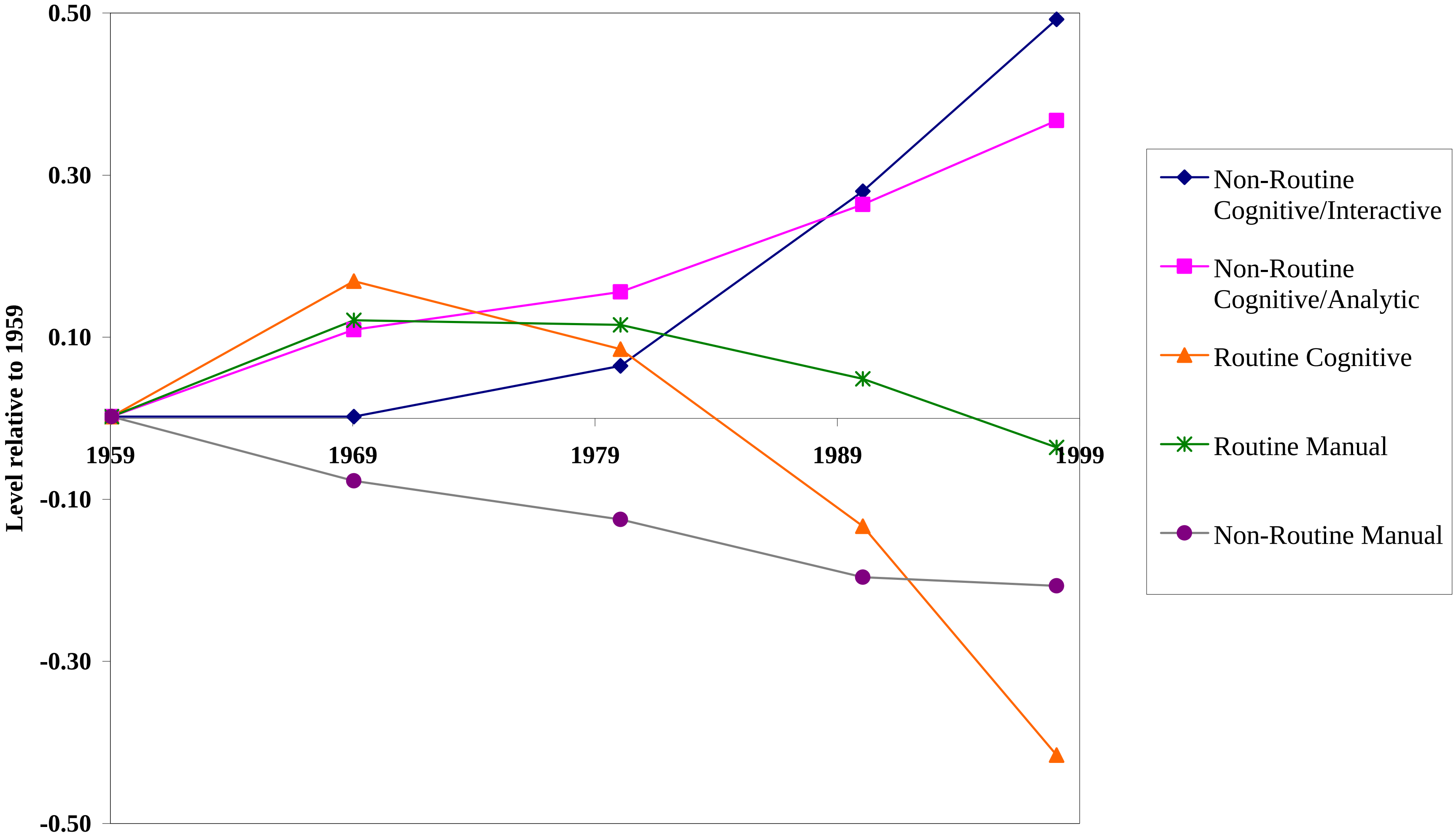

Figure 3: Bivariate Relationships Between Recent Industry Computerization 1984 - 1997 and Decadal Industry Task Change: 1959 - 1998

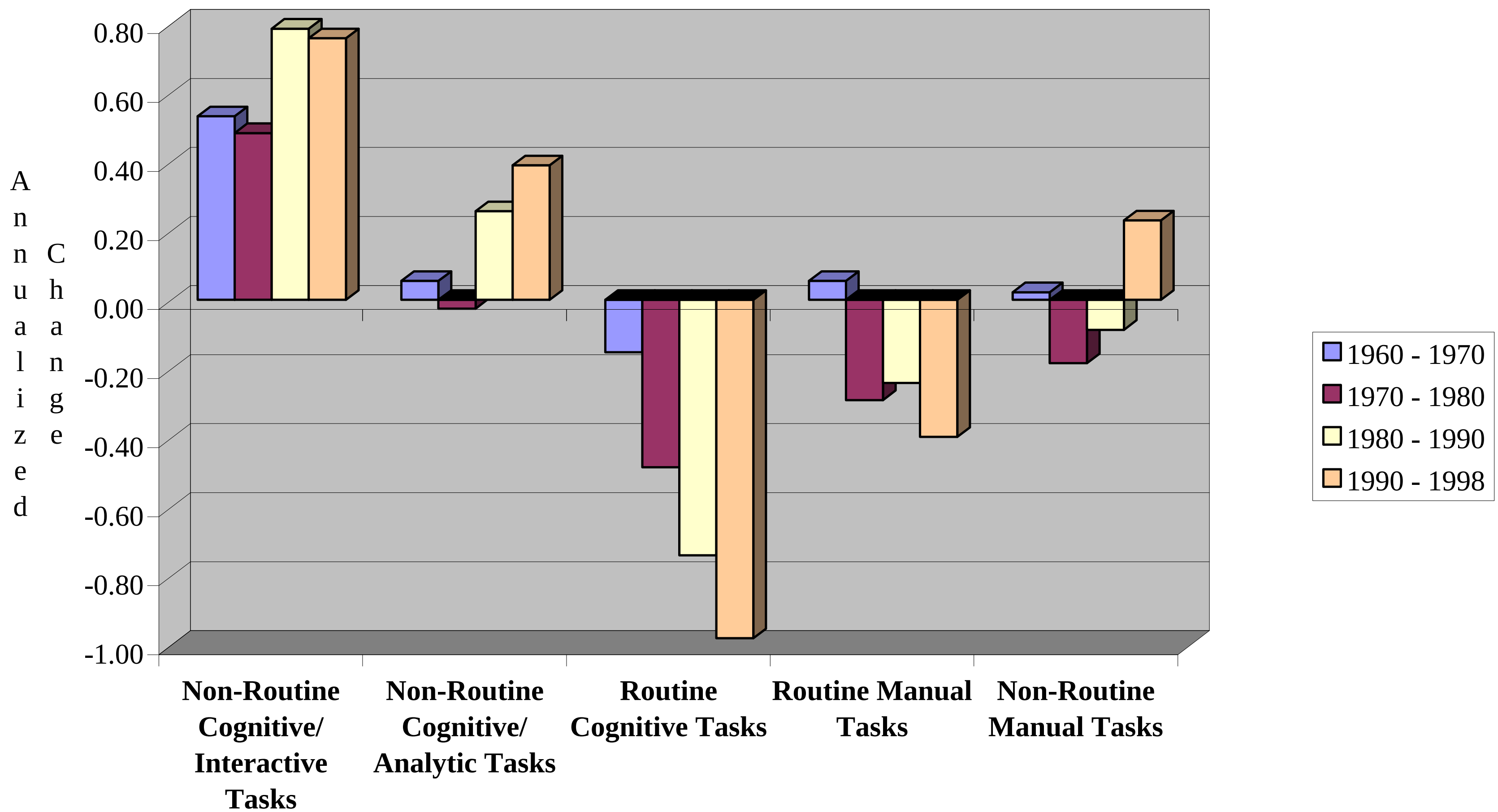

Table 1. Definitions of Task Measures Employed from the 1977 Dictionary of Occupational Titles.

Variable	DOT Definition	Task Interpretation	Example Tasks from *Handbook for Analyzing Jobs*
1. GED Math	General Educational Development, Mathematics.	*Measure of non-routine cognitive/ analytic tasks.*	Lowest level: Adds and subtracts 2-digit numbers; performs operations with units such as cup, pint, and quart. Mid-level: Computes discount, interest, profit, and loss; Inspects flat glass and compiles defect data based on samples to determine variances from acceptable quality limits. Highest level: Conducts and oversee analyses of aerodynamic and thermodynamic systems... to determine suitability of design for aircraft and missiles.
2. Direction, Control, Planning (DCP)	Adaptability to accepting Responsibility for the Direction, Control, or Planning of an activity.	*Measure of non-routine cognitive/ interactive tasks.*	Plans and designs private residences, office buildings, factories, and other structures; Applies principles of accounting to install and maintain operation of general accounting system; Conducts prosecution in court proceedings…Gathers and analyzes evidence, reviews pertinent decisions...Appears against accused in court of law; Commands fishing vessel crew engaged in catching fish and other marine life.
2. Set Limits, Tolerances, or Standards (STS)	Adaptability to situations requiring the precise attainment of Set limits, Tolerances, or Standards.	*Measure of routine cognitive tasks.*	Operates a billing machine to transcribe from office records data; Calculates degrees, minutes, and second of latitude and longitude, using standard navigation aids; Measures dimensions of bottle, using gages and micrometers to verify that setup of bottle-making conforms to manufacturing specifications; Prepares and verifies voter lists from official registration
4. Finger Dexterity (FINGDEX)	Ability to move fingers, and manipulate small objects with fingers, rapidly or accurately.	*Measure of routine manual tasks.*	Mixes and bakes ingredients according to recipes; Sews fasteners and decorative trimmings to articles; Feeds tungsten filament wire coils into machine that mounts them to stems in electric light bulbs; Operates tabulating machine that processes data from tabulating cards into printed records; Packs agricultural produce such as bulbs, fruits, nuts, eggs, and vegetables for storage or shipment; Attaches hands to faces of watches.
5. Eye Hand Foot Coordination (EYEHAND)	Ability to move the hand and foot coordinately with each other in accordance with visual stimuli	*Measure of non-routine manual tasks.*	Lowest level: Tends machine that crimps eyelets, grommets; Next level: Attends to beef cattle on stock ranch; Drives bus to transport passengers; Next level: Pilots airplane to transport passengers; Prunes and treats ornamental and shade trees; Higherst level: Performs gymnastic feats of skill

Source: U.S. Department of Labor, Manpower Administration, *Handbook for Analyzing Jobs* , Washington DC, 1972.

Table 2: Predicting Industry Computer Adoption 1959 - 1997 as a Function of Industry Task Content in 1959.
Dependent Variable: Percentage of Industry Employees Using a Computer on the Job in 1997

	1. Non-Routine Cognitive/ Analytic Tasks	2. Non-Routine Cognitive/ Interactive Tasks	3. Routine Cognitive Tasks	4. Routine Manual Tasks	5. Non-Routine Manual Tasks
	A. Specifications Using Individual DOT Task Measures				
(1) 1959 DOT Industy Task Measure	9.94	-2.09	5.52	8.16	-10.13
	(1.70)	(1.89)	(1.84)	(1.77)	(1.69)
R^2	0.20	0.01	0.06	0.13	0.21
(2) 1959 DOT Industy Task Measure	6.37	-3.89	6.43	6.60	-8.06
	(1.89)	(1.68)	(1.61)	(1.62)	(1.61)
1959 Industry College Grad.	7.00	10.89	10.78	9.12	8.22
	(1.89)	(1.68)	(1.61)	(1.62)	(1.61)
R^2	0.27	0.24	0.29	0.30	0.33
	B. Specifications Using Alternative Composite DOT Task Measures				
(3) 1959 Industry Task Composite	13.59	8.04	-0.66	5.86	-13.59
	(1.50)	(1.77)	(1.90)	(1.83)	(1.50)
R^2	0.37	0.13	0.00	0.07	0.37
(4) 1959 Industry Task Composite	12.75	3.18	1.70	4.96	-11.41
	(2.14)	(2.06)	(1.73)	(1.64)	(1.52)
1959 Industry College Grad.	1.19	8.40	10.62	9.79	6.28
	(2.14)	(2.06)	(1.73)	(1.64)	(1.52)
R^2	0.37	0.22	0.22	0.26	0.44

n is 140 consistent 3-digit CIC occupations. DOT industry means are calculated using 1960 Census IPUMS and DOT 1977 job content measures. To aid comparison between panels A and B, all DOT and composite variables are standardized to have mean zero and variance one. Mean of dependent variable is 45.4 percentage points. Industry computer use 1997 calculated from October 1997 CPS. Details of Construction of composite DOT measures provided in Data Appendix.

Table 3: Means of Dictionary of Occupational Titles Job Task Measures: Overall and by Gender, 1960 - 1998.

	1. Non-Routine Cognitive/ Analytic Tasks			2. Non-Routine Cognitive/ Interactive Tasks			3. Routine Cognitive Tasks		
	All	**Males**	**Females**	**All**	**Males**	**Females**	**All**	**Males**	**Females**
A. Census 1960	3.61	3.81	3.05	2.40	2.82	1.20	4.53	4.43	4.81
B. Census 1970	3.72	3.93	3.23	2.40	2.91	1.27	4.70	4.51	5.12
C. CPS 1980	3.76	3.95	3.46	2.46	2.94	1.71	4.61	4.47	4.84
D. CPS 1990	3.87	3.99	3.70	2.68	2.99	2.25	4.40	4.36	4.45
E. CPS 1998	3.97	4.07	3.84	2.89	3.10	2.62	4.11	4.24	3.95

	4. Routine Manual Tasks			5. Non-Routine Manual Tasks		
	All	**Males**	**Females**	**All**	**Males**	**Females**
A. Census 1960	3.78	3.60	4.29	1.37	1.56	0.82
B. Census 1970	3.90	3.64	4.48	1.29	1.50	0.80
C. CPS 1980	3.90	3.62	4.34	1.24	1.55	0.74
D. CPS 1990	3.83	3.60	4.14	1.17	1.49	0.72
E. CPS 1998	3.75	3.58	3.97	1.16	1.48	0.73

Sources: All employed workers ages 18 - 64, Census IPUMS 1960 and 1970, CPS MORG 1980, 1990, and 1998, and Dictionary of Occupational Titles 1977. See Data Appendix for details.

Table 4. Between- and Within- Industry Decomposition of the Change in Skill Use: 1960 - 1998: Dependent Variable is 10 x (Annualized Change in DOT Task Measure)

		1. Non-Routine Cognitive/ Analytic			2. Non-Routine Cognitive/ Interactive			3. Routine Cognitive Tasks		
		Btwn	**Wthin**	**Total**	**Btwn**	**Wthin**	**Total**	**Btwn**	**Wthin**	**Total**
A. **1960 - 70**	**Census-Census**	0.078	0.029	0.107	-0.056	0.061	0.005	0.088	0.077	0.166
B. **1970 - 80**	**Census-Census**	0.069	0.026	0.095	0.002	0.112	0.114	0.033	-0.033	0.000
C. **1980 - 90**	**CPS-CPS**	0.040	0.068	0.108	0.017	0.198	0.215	-0.100	-0.118	-0.219
D. **1990 - 98**	**CPS-CPS**	0.025	0.105	0.130	0.028	0.238	0.266	-0.100	-0.253	-0.353

		4. Routine Manual Tasks			5. Non-Routine Manual Tasks		
		Btwn	**Wthin**	**Total**	**Btwn**	**Wthin**	**Total**
A. **1960 - 70**	**Census-Census**	0.068	0.051	0.119	-0.062	-0.017	-0.079
B. **1970 - 80**	**Census-Census**	0.024	-0.010	0.014	-0.031	-0.045	-0.076
C. **1980 - 90**	**CPS-CPS**	-0.001	-0.066	-0.067	-0.034	-0.037	-0.071
D. **1990 - 98**	**CPS-CPS**	-0.009	-0.097	-0.105	-0.004	-0.010	-0.014

Notes. Shift-share analysis based on 140 CIC industries made consistent for 1960 - 1998. Samples are constructed for all employed workers from Census and CPS samples listed above. All calculations weighted by labor supply in FTEs (product of sample weight and annual hours worked). Observations use DOT 1977 occupational task content measures paired to Census and CPS samples. See Data Appendix for further details.

Table 5. OLS Estimates of the Relationship between Changes in Industry Task Input 1960 - 1998 and Industry Computerization 1984 - 1993. (Dependent Variables: 10 * Annual Changes)

Dep. Variable:	Decade	Intercept	D **Computer Use 1984 - 97**	R-squared	Wtd. Mean of Dep. Var.
1. D **Non-Routine Cognitive/ Analytic Tasks**	**A. 1960-70**	0.016	0.055	0.00	0.029
		(0.038)	(0.147)		
	B. 1970-80	0.032	-0.025	0.00	0.026
		(0.035)	(0.132)		
	C. 1980-90	0.003	0.257	0.02	0.068
		(0.039)	(0.143)		
	D. 1990-98	0.005	0.390	0.04	0.105
		(0.043)	(0.156)		
2. D **Non-Routine Cognitive/ Interactive Tasks**	**A. 1960-70**	-0.066	0.532	0.03	0.061
		(0.062)	(0.239)		
	B. 1970-80	-0.008	0.483	0.03	0.112
		(0.069)	(0.257)		
	C. 1980-90	0.000	0.786	0.06	0.198
		(0.075)	(0.276)		
	D. 1990-98	0.043	0.758	0.06	0.238
		(0.071)	(0.258)		
3. D **Routine Cognitive Tasks**	**A. 1960-70**	0.114	-0.152	0.00	0.077
		(0.062)	(0.238)		
	B. 1970-80	0.087	-0.485	0.02	-0.033
		(0.077)	(0.289)		
	C. 1980-90	0.068	-0.740	0.04	-0.118
		(0.083)	(0.309)		
	D. 1990-98	-0.002	-0.980	0.07	-0.253
		(0.080)	(0.294)		
4. D **Routine Manual Tasks**	**A. 1960-70**	0.038	0.055	0.00	0.051
		(0.021)	(0.081)		
	B. 1970-80	0.062	-0.290	0.06	-0.010
		(0.027)	(0.101)		
	C. 1980-90	-0.005	-0.241	0.03	-0.066
		(0.035)	(0.128)		
	D. 1990-98	0.005	-0.397	0.08	-0.097
		(0.031)	(0.114)		
5. D **Non-Routine Manual Tasks**	**A. 1960-70**	-0.022	0.022	0.00	-0.017
		(0.017)	(0.064)		
	B. 1970-80	0.001	-0.183	0.02	-0.045
		(0.030)	(0.114)		
	C. 1980-90	-0.015	-0.087	0.00	-0.037
		(0.028)	(0.105)		
	D. 1990-98	-0.069	0.230	0.06	-0.010
		(0.022)	(0.079)		

n is 140 consistent CIC industries. Standard errors are in parentheses. Weighted mean of Δ computer use 1984 - 1997 is 0.252. Estimates are weighted by mean industry share of total employment (in FTEs) over the endpoints of the years used to form the dependent variable. Computer use is the change in fraction of industry workers using a computer at their jobs estimated from October 1984 and 1997 CPS samples. Samples used are Census IPUMS for 1960, 70, and 80 and CPS MORG 1980, 90, and 98 samples.

Table 6. OLS Stacked First-Difference Estimates of the Relationship between Computer Investment, Capital Intensity, and Task Input in Three-Digit Industries 1960 - 1998. (10 * Annual Changes)

	1. D **Non-Routine Cognitive/ Interactive Tasks**		**2.** D **Non-Routine Cognitive/ Analytic Tasks**		**3.** D **Routine Cognitive Tasks**		**4.** D **Routine Manual Tasks**		**5.** D **Non-Routine Manual Tasks**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Log(CI/L)	0.854	0.822	0.228	0.202	-0.676	-0.623	-0.328	-0.275	0.254	0.201
	(0.244)	(0.245)	(0.091)	(0.106)	(0.204)	(0.187)	(0.086)	(0.070)	(0.043)	(0.049)
D **Log(K/L)**		0.041		0.033		-0.069		-0.068		0.068
		(0.133)		(0.056)		(0.109)		(0.040)		(0.028)
1970-80	0.002	0.011	-0.027	-0.020	-0.040	-0.055	-0.019	-0.034	-0.044	-0.028
	(0.067)	(0.066)	(0.035)	(0.035)	(0.094)	(0.091)	(0.022)	(0.022)	(0.016)	(0.018)
1980-90	-0.132	-0.114	-0.032	-0.018	-0.002	-0.032	-0.024	-0.054	-0.106	-0.076
	(0.117)	(0.103)	(0.048)	(0.050)	(0.116)	(0.122)	(0.031)	(0.036)	(0.021)	(0.022)
1990-98	-0.141	-0.123	-0.035	-0.020	-0.041	-0.072	-0.012	-0.042	-0.104	-0.074
	(0.108)	(0.105)	(0.047)	(0.053)	(0.111)	(0.111)	(0.039)	(0.039)	(0.023)	(0.027)
Intercept	0.473	0.443	0.152	0.127	-0.236	-0.185	-0.102	-0.052	0.106	0.056
	(0.119)	(0.127)	(0.050)	(0.062)	(0.116)	(0.111)	(0.044)	(0.037)	(0.023)	(0.031)
R-squared	0.172	0.173	0.061	0.067	0.145	0.147	0.285	0.296	0.095	0.111
Mean D **Dep. Variable**										
1960-70		0.064		0.042		0.089		0.055		-0.015
1970-80		0.151		0.038		-0.019		0.003		-0.033
1980-90		0.195		0.080		-0.122		-0.070		-0.043
1990-98		0.255		0.096		-0.216		-0.084		-0.021

Notes. n is 492: 123 consistent CIC industries times 4 decade changes. Standard errors in parentheses are heteroskedasticity consistent and allow for clustering of errors within NIPA-year sectors (42 clusters per decade). Private households, government, and government-dominated services are excluded due to NIPA data limitations. 1960-70, 70-80 use Census IPUMS samples, and 1980-90 and 1990-98 use CPS MORG samples. Log(CI/L) is 0.1 * log computer investment per FTE over decade in 1,000s of 1987$. Δ Log(K/L) is annualized change in the log capital/FTE ratio over deacde. Weighted mean of log(CI/L) is -0.480 in 1960-1970, -0.379 in 1970-1980, -0.172 in 1980-90, and -0.91 in 1990-97. Weighted mean of Δ(K/L) log capital per worker is 0.439 in 1960-1970, 0.099 1970-1980, 0.100 in 1980-90, and 0.222 in 1990-98. Estimates are weighted by mean industry share of total employment (in FTEs) over the endpoints of the years used to form the dependent variable.

Table 7. First-Difference Estimates of Changes in Industry Task Input 1980 - 98 and Change in Industry Computer Use 1984 - 97
Dependent variable is 10 x (Annualized Change in DOT Task Measure)

Dep. Variable:	**Intercept**	D **Computer Use '84-'97**	**R-Squared**	**Wtd. Mean of Dep. Var.**
1. D **Non-Routine Cognitive/ Analytic Tasks**	0.004	0.400	0.046	0.082
	(0.032)	(0.154)		
2. D **Non-Routine Cognitive/ Interactive Tasks**	0.016	1.008	0.093	0.212
	(0.056)	(0.268)		
3. D **Routine Cognitive Tasks**	0.043	-1.128	0.082	-0.177
	(0.067)	(0.321)		
4. D **Routine Manual Tasks**	0.000	-0.402	0.058	-0.079
	(0.029)	(0.137)		
5. D **Non-Routine Manual Tasks**	-0.041	0.080	0.006	-0.026
	(0.018)	(0.086)		

Notes. n is 140 consistent CIC industries. Standard errors are in parentheses. Dependent variables formed from CPS MORG 1980 and 1998 samples using uses DOT 1977 occupational task content measures Weighted mean of change in computer use 1984-97 is 0.198, estimated from October 1984 and 97 CPS samples. Models are weighted by mean industry share of total employment (in FTEs) over the endpoints of the years used to form the dependent variable.

Table 8. OLS First-Difference Estimates of the Relationship between High School Graduate Task Input 1980 - 1998 and Industry Computer Use 1984 - 1997 (Dependent Variables: 10 * Annual Changes)

Dependent Variable:	Intercept	D Computer Use '84-'97	R^2	Wtd. Mean of Dep. Var.
1. D **Non-Routine Cognitive/ Analytic Tasks**	-0.039	-0.011	0.000	-0.041
	(0.028)	(0.134)		
2. D **Non-Routine Cognitive/ Interactive Tasks**	-0.037	0.796	0.064	0.118
	(0.054)	(0.259)		
3. D **Routine Cognitive Tasks**	0.162	-2.297	0.197	-0.286
	(0.082)	(0.396)		
4. D **Routine Manual Tasks**	0.019	-0.833	0.176	-0.144
	(0.032)	(0.154)		
5. D **Non-Routine Manual Tasks**	0.001	0.056	0.002	0.012
	(0.023)	(0.108)		

Notes. n is 140 consistent CIC industries with high school graduate employment in 1980 and 1998. Standard errors are in parentheses. 1980-98 change uses CPS MORG 80 and 98 samples. All estimates use DOT 77 job task measures. Estimates are weighted by mean industry share of total employment (in FTEs) over the endpoints of the years used to form the dependent variable. Weighted mean of change in computer use 1984-97 is 0.198 using average of 1980 and 1998 MORG weights.

Table 9. OLS Estimates of Relationship Between Changes in Dictionary of Occupational Titles Task Content Measures 1977 - 1991 and Occupational Computerization 1984 -

	1. D **Non-Routine Cognitive/ Analytic Tasks**		**2.** D **Non-Routine Cognitive/ Interactive Tasks**		**3.** D **Routine Cognitive Tasks**		**4.** D **Routine Motor Tasks**		**5.** D **Non-Routine Motor Tasks**	
	(a)	**(b)**	**(a)**	**(b)**	**(a)**	**(b)**	**(a)**	**(b)**	**(a)**	**(b)**
D **Computer Use 84-97**	0.35 (0.13)	0.38 (0.13)	0.91 (0.41)	0.90 (0.41)	-2.64 (0.55)	-2.74 (0.55)	0.04 (0.13)	0.06 (0.13)	0.28 (0.13)	0.29 (0.13)
D **College Grad Emp. Share 84-97**		-0.74 (0.37)		0.14 (1.17)		2.19 (1.58)		-0.42 (0.38)		-0.11 (0.38)
Intercept	-0.14 (0.04)	-0.13 (0.04)	-0.06 (0.12)	-0.06 (0.12)	0.13 (0.16)	0.10 (0.16)	-0.03 (0.04)	-0.02 (0.04)	-0.16 (0.04)	-0.16 (0.04)
$\mathbf{R^2}$	0.02	0.02	0.01	0.01	0.05	0.05	0.00	0.00	0.01	0.01
Wtd. Mean Dep. Var.		-0.05		0.16		-0.50		-0.02		-0.09
Implied D **Due to Computerization**	0.08	0.09	0.22	0.21	-0.63	-0.65	0.01	0.01	0.07	0.07

Notes. n is 470 consistent 3-digit CIC occupations. Dependent variable is the change in the occupational DOT skill content measure between the DOT 1977 and DOT 1991 revisions. Within-occupation Δ Computer Use and Δ College Employment variables are estimated from the October 1984 and 1997 CPS files (means 0.237 and 0.022 respectively). Estimates are weighted by the mean occupational share of employment in 1984 and 1997.

Table 10. Fixed Coefficient Demand Shift Calculations: Estimated Change in Log College vs. Non-College Relative Demand Due to Task Shifts Induced by Computerization: 1970 - 1998

1. 1980 - 1998: Using D Computer Use 1984 - 1997

1A. Change in DOT task input measures predicted by computerization (from Tables 7 & 9)

Task Variable	Extensive Margin 1980 - 98	Extensive + Intensive Margin 1980 - 98
N.R. Cognitive/Interactive	0.359	0.574
N.R. Cognitive/Analytic	0.143	0.234
Routine Cognitive	-0.402	-1.052
Routine Manual	-0.143	-0.129
Non-Routine Manual	0.029	0.097

1B. Predicted change in demand for College vs. Non-College employment (in percentage points)

Specifications	Extensive Margin 1980 - 98	Extensive + Intensive Margin 1980 - 98
1. Routine tasks	0.76	2.04
2. Non-routine tasks	0.99	1.60
3. All five tasks	1.75	3.64
Observed D College Emp	6.83	6.83

1C. 100 *Estimated shifts in log (College/Non-College)

	Extensive Margin 1980 - 98	Extensive + Intensive Margin 1980 - 98
Shift implied by task D's	1.01	2.05
C.E. S. estimated demand shift using s=1.4	6.69	6.69

2. 1970 - 1998: Using NIPA Computer Investment Measures

2A. Change in DOT task input measures predicted by computerization (from Tables 6 & 9)

	Extensive Margin			Extensive + Intensive Margin
Task Variable	1970 - 80	1980 - 90	1990 - 98	1980 - 98
N.R. Cognitive/Interactive	0.086	0.263	0.266	0.744
N.R. Cognitive/Analytic	0.023	0.070	0.071	0.232
Routine Cognitive	-0.068	-0.208	-0.211	-1.069
Routine Manual	-0.033	-0.101	-0.102	-0.188
Non-Routine Manual	0.019	0.070	0.074	0.212

2B. Predicted change in demand for College vs. Non-College employment (in percentage points)

	Extensive Margin			Extensive + Intensive Margin
Specifications	1970 - 80	1980 - 90	1990 - 98	1980 - 98
1. Routine tasks	0.13	0.39	0.39	2.06
2. Non-routine tasks	0.15	0.44	0.45	1.50
3. All five tasks	0.28	0.87	0.88	3.57
Observed D College Emp	5.74	4.27	2.56	6.83

2C. 100 *Estimated shifts in log (College/Non-College) demand

	1970 - 80	1980 - 90	1990 - 98	1980 - 98
Shift implied by task D's	0.22	0.51	0.45	2.01
C.E. S. estimated demand shift using s=1.4	3.26	4.60	2.09	6.69

Notes. Fixed coefficient estimates are based on a regression of occupational college employment shares on DOT means using the 1970 Census. Changes in DOT skill measures predicted by computerization are based on regression estimates in Tables 6 and 7. Predicted changes in intensive margin (within-occupation) of DOT job skills for 1980-98 are based on Table 9. Observed change in college employment (in FTEs) are estimated from Census 1970, Census 1980, Morg 1980, Morg 1990, Feb. 1990, and Morg 1998 samples for all employed workers. Source for Constant Elasticity of Substitution estimates of changes in log(college/non-college) relative demand is Autor, Katz, and Krueger (1998) Table 2, updated to 1998 using CPS Morg 1998 sample.

Appendix Table 1 DOT Occupational Characteristics, Fourth Edition (Reproduced from Miller et. al, 1980)

Variable Label	Description	Scoring
Worker functions		
DATA	complexity of function in relation to data	0-6
PEOPLE	complexity of function in relation to people	0-8
THINGS	complexity of function in relation to things	0-7
Training times		
GED	general educational development	1-6
GED – MATH	(GED sub-scale)	1-6
GED – REASON	(GED sub-scale)	1-6
GED – LANGUAGE	(GED sub-scale)	1-6
SVP	specific vocational preparation	1-9
Aptitudes		
INTELL	intelligence	1-4
VERBAL	verbal aptitude	1-5
NUMER	numerical aptitude	1-5
SPATIAL	spatial perception	1-5
FORM	form perception	1-5
CLERICAL	clerical perception	1-5
MOTOR	motor coordination	1-5
FINGDEX	finger dexterity	1-5
MANDEX	manual dexterity	1-5
EYEHAND	eye-hand-foot coordination	1-5
COLORDIS	color discrimination	1-5
Temperaments		
DCP	direction, control and planning	0/1
FIF	feelings, ideas, or facts	0/1
INFLU	influencing people	0/1
SJC	sensory or judgmental criteria	0/1
MVC	measurable or verifiable criteria	0/1
DEPL	dealing with people	0/1
REPCON	repetitive or continuous processes	0/1
PUS	performing under stress	0/1
STS	set limits, tolerances, or standards	0/1
VARCH	variety and change	0/1

Interests

DATACOM	communication of data versus activities with things	-1 to +1
SCIENCE	scientific and technical activities versus business contacts	-1 to +1
ABSTRACT	abstract and creative versus routine, concrete activities	-1 to +1
MACHINE	activities involving processes, machines or techniques versus social welfare	-1 to +1
TANGIBLE	activities resulting in tangible, productive satisfaction versus prestige, esteem	-1 to +1

Physical demands

STRENGTH	lifting, carrying, pulling, pushing	1-5
CLIMB	climbing, balancing	0/1
STOOP	stooping, kneeling, crouching, crawling	0/1
REACH	reaching, handling, fingering, feeling	0/1
TALK	talking, hearing	0/1
SEE	seeing	0/1

Working Conditions

LOCATION	outside working conditions	1-3
COLD	extreme cold	0/1
HEAT	extreme heat	0/1
WET	wet, humid	0/1
NOISE	noise, vibration	0/1
HAZARDS	hazardous conditions	0/1
ATMOSPHR	fumes, odors, dust, gasses, poor ventilation	0/1

Appendix Table 2. Means of DOT Skill Content Variables by Major Occupation, 1980

Task Intensity Measures (Scale: 0 - 10, Ascending)							
1. Non-Routine Cognitive/ Analytic	2. Non-Routine Cognitive/ Interactive	3. Routine Cognitive	4. Routine Motor	5. Non-Routine Motor	Mean Years of School	D Computer Use 1984 - 1997	Share of Employ-ment, 1980
1. Executive, administrative and managerial occupations							
5.61	7.97	1.94	2.76	0.36	14.12	0.35	12.4%
2. Professional specialty occupations							
5.98	4.45	3.23	4.02	1.32	15.93	0.36	12.5%
3. Technicians and related support occupations							
5.77	1.69	7.69	4.88	1.15	13.70	0.24	3.0%
4. Sales occupations							
4.19	2.31	1.74	3.54	0.31	13.00	0.32	9.5%
5. Administrative support occupations, including clerical							
3.51	0.86	7.51	5.01	0.15	12.62	0.30	16.3%
6. Private household occupations							
1.66	0.50	0.03	2.50	1.40	9.76	0.03	0.3%
7. Protective service occupations							
1.71	1.12	0.23	2.55	2.91	12.68	0.27	1.7%
8. Service occupations, except protective and household							
2.25	0.69	2.74	3.40	1.52	11.24	0.08	8.2%
9. Precision production, craft and repair occupations							
3.74	5.66	1.90	2.87	2.36	11.06	0.07	3.0%
10. Machine operators, assemblers, and inspectors							
3.95	2.13	8.47	4.57	1.92	11.62	0.15	14.2%
11. Transportation and material moving equipment occupations							
2.00	0.16	8.31	4.41	1.29	10.83	0.13	9.8%
12. Handlers, equipment cleaners, helpers and laborers							
1.54	0.48	2.80	2.77	4.38	11.03	0.13	5.0%
13. Farming, forestry and fishing occupations							
1.36	0.09	2.68	3.27	1.44	10.75	0.11	3.9%

Sample includes all employed workers ages 18 - 64 from 1980 Census IPUMS (n =912,978). All DOT variables are scaled from 0 to 10. Estimates are weighted by labor supply (in FTEs).

Appendix Table 3: Correlations among DOT skill measures, Education Measures, and Computer Use in Consistent 3-Digit Industries at mid-point of 1960 - 1998 sample.

GED-MATH - Non-routine cognitive/technical tasks
DCP - Non-routine cognitive/interpersonal tasks
EYEHAND - Non-routine motor tasks
STS - Routine cognitive tasks
FINGDEX - Routine manual tasks

	Industry Task Intensivity					*Industry Education Shares*				
	NR Cog/ Analytic	**NR Cog/ Interact-ive**	**Routine Cog.**	**Routine Manual**	**NR Manual**	**Mean Years**	**High School Drop.**	**High School Grad.**	**Some College**	**College Grad.**
NR Cog/ Analytic	1.00									
NR Cog/ Interactive	0.54	1.00								
Routine Cog.	-0.02	-0.34	1.00							
Routine Manual	0.23	-0.36	0.62	1.00						
NR Manual	-0.38	-0.14	0.09	-0.14	1.00					
Mean Yrs. Educ.	0.75	0.34	-0.31	0.00	-0.40	1.00				
High School Drop.	-0.78	-0.32	0.20	-0.10	0.50	-0.90	1.00			
High School Grad.	-0.47	-0.32	0.38	0.16	0.11	-0.77	0.46	1.00		
Some College	0.48	0.07	-0.03	0.20	-0.36	0.33	-0.64	0.04	1.00	
College Grad	0.63	0.38	-0.34	-0.10	-0.28	0.94	-0.72	-0.90	0.04	1.00

n is 140 consistent CIC industries drawn from 1980 Census file. Estimates are weighted by industry employment (in FTES) in 1980. Industry computer use frequencies are from October 1984 and 97 Current Population Survey files.

Appendix Table 4: Means of Dictionary of Occupational Titles Job Content Measures Overall and by Education Group at Mid-Point of 1960 - 1998 Sample.

	1. Non-Routine Cognitive/ Analytic Tasks			2. Non-Routine Cognitive/ Interactive Tasks			3. Routine Cognitive Tasks		
	All	**Males**	**Females**	**All**	**Males**	**Females**	**All**	**Males**	**Females**
Overall	3.76	3.95	3.46	2.46	2.94	1.71	4.61	4.47	4.84
HS Dropouts	2.55	2.76	2.11	1.32	1.55	0.84	4.93	5.25	4.26
HS Graduates	3.34	3.45	3.20	1.75	2.17	1.20	5.30	5.14	5.50
Some College	3.97	4.07	3.82	2.45	2.97	1.68	4.87	4.38	5.58
College Plus	5.36	5.67	4.75	4.76	5.30	3.69	2.86	2.86	2.87

	4. Routine Manual Tasks			5. Non-Routine Manual Tasks		
	All	**Males**	**Females**	**All**	**Males**	**Females**
Overall	3.90	3.62	4.34	1.24	1.55	0.74
HS Dropouts	3.72	3.59	4.00	1.80	2.12	1.12
HS Graduates	4.09	3.69	4.61	1.26	1.77	0.60
Some College	4.02	3.62	4.61	1.10	1.42	0.62
College Plus	3.57	3.52	3.67	0.87	0.85	0.92

Sources: CPS MORG 1980, all employed workers ages 18 - 64 and Dictionary of Occupational Titles, 1977.

Appendix Table 5. Estimates of the Relationship between Changes in Industry Task Input 1960 - 1998 and Industry Computerization 1984 - 1993 Using Principle Components Composites of Task Measures. (Dependent Variables: 10 * Annual Changes)

Dep. Variable:	Decade	Intercept	D Computer Use 1984 - 97	R-squared	Wtd. Mean of Dep. Var.
1. D **Non-Routine Cognitive/ Analytic Task Composite**	**A. 1960-70**	0.057	0.060	0.00	0.071
		(0.037)	(0.143)		
	B. 1970-80	0.070	-0.047	0.00	0.059
		(0.034)	(0.127)		
	C. 1980-90	0.030	0.157	0.01	0.070
		(0.035)	(0.130)		
	D. 1990-98	0.001	0.376	0.05	0.097
		(0.037)	(0.134)		
2. D **Non-Routine Cognitive/ Interactive Task Composite**	**A. 1960-70**	0.012	0.178	0.02	0.054
		(0.030)	(0.118)		
	B. 1970-80	0.051	0.017	0.00	0.056
		(0.024)	(0.092)		
	C. 1980-90	0.047	0.112	0.01	0.075
		(0.032)	(0.120)		
	D. 1990-98	0.006	0.318	0.06	
		(0.029)	(0.106)		0.087
3. D **Routine Cognitive Task Composite**	**A. 1960-70**	0.022	-0.031	0.00	0.015
		(0.019)	(0.075)		
	B. 1970-80	0.025	-0.239	0.04	-0.034
		(0.028)	(0.106)		
	C. 1980-90	-0.030	-0.106	0.01	-0.060
		(0.026)	(0.097)		
	D. 1990-98	-0.039	-0.181	0.02	-0.086
		(0.032)	(0.116)		
4. D **Routine Manual Task Composite**	**A. 1960-70**	0.016	0.101	0.01	0.040
		(0.026)	(0.102)		
	B. 1970-80	0.040	-0.390	0.07	-0.010
		(0.032)	(0.121)		
	C. 1980-90	-0.002	-0.321	0.04	-0.083
		(0.035)	(0.130)		
	D. 1990-98	-0.007	-0.341	0.06	-0.095
		(0.031)	(0.113)		
5. D **Non-Routine Manual Task Composite**	**A. 1960-70**	-0.008	-0.027	0.00	-0.014
		(0.015)	(0.057)		
	B. 1970-80	0.004	0.004	0.00	0.005
		(0.024)	(0.090)		
	C. 1980-90	-0.034	0.138	0.02	0.001
		(0.025)	(0.093)		
	D. 1990-98	-0.056	0.274	0.09	0.014
		(0.021)	(0.075)		

n is 140 consistent CIC industries. Standard errors are in parentheses. Weighted mean of Δ computer use 1984 - 1997 is 0.252. Estimates are weighted by mean industry share of total employment (in FTEs) over the endpoints of the years used to form the dependent variable. Computer use is the change in fraction of industry workers using a computer at their jobs estimated from October 1984 and 1997 CPS samples. Samples used are Census IPUMS for 1960, 70, and 80 and CPS MORG 1980, 90, and 98 samples.

Appendix Table 6. Industry Task Input by Education Group 1980 - 1998 and Industry Computerization 1984 - 1997 (Dependent Variables: 10 * Annual Changes)

Dependent Variable:	Intercept	D Computer Use '84-'97	R^2	Wtd. Mean of Dep. Var.
		A. High School Dropouts		
1. D **Non-Routine Cognitive/ Analytic Tasks**	-0.076	0.066	0.001	-0.063
	(0.045)	(0.215)		
2. D **Non-Routine Cognitive/ Interactive Tasks**	-0.201	0.682	0.015	-0.068
	(0.099)	(0.476)		
3. D **Routine Cognitive Tasks**	0.068	-0.522	0.006	-0.034
	(0.117)	(0.559)		
4. D **Routine Manual Tasks**	0.014	-0.185	0.010	-0.022
	(0.034)	(0.162)		
5. D **Non-Routine Manual Tasks**	0.015	-0.185	0.011	-0.021
	(0.031)	(0.150)		
		B. Some College		
1. D **Non-Routine Cognitive/ Analytic Tasks**	-0.052	0.210	0.012	-0.011
	(0.034)	(0.161)		
2. D **Non-Routine Cognitive/ Interactive Tasks**	-0.046	0.748	0.049	0.100
	(0.058)	(0.281)		
3. D **Routine Cognitive Tasks**	0.101	-1.433	0.099	-0.178
	(0.077)	(0.369)		
4. D **Routine Manual Tasks**	0.032	-0.649	0.117	-0.095
	(0.032)	(0.152)		
5. D **Non-Routine Manual Tasks**	0.008	-0.044	0.001	-0.001
	(0.022)	(0.107)		
		C. College Graduates		
1. D **Non-Routine Cognitive/ Analytic Tasks**	0.000	-0.035	0.000	-0.007
	(0.037)	(0.176)		
2. D **Non-Routine Cognitive/ Interactive Tasks**	-0.009	0.496	0.012	0.088
	(0.081)	(0.388)		
3. D **Routine Cognitive Tasks**	-0.160	0.395	0.007	-0.083
	(0.083)	(0.396)		
4. D **Routine Manual Tasks**	-0.007	-0.154	0.009	-0.037
	(0.028)	(0.135)		
5. D **Non-Routine Manual Tasks**	-0.059	0.254	0.029	-0.010
	(0.026)	(0.125)		

Standard errors are in parentheses. *n* in panels A, B and C is 139, 140, and 139 consistent industries respectively. Industries that did not have employment in the relevant educational category in both 1980 and 1998 were excluded. Data sources are CPS MORG 80 and 98 and DOT 77 job task measures. Estimates are weighted by mean industry share of total employment (in FTEs) in 1980 and 1988. Weighted mean of change in computer use 1984-97 is 0.198 using MORG 1980 and 1998 weights.