Preliminary **Comments Appreciated**

The Skill Content of Recent Technological Change: An Empirical Exploration

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July 29, 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. In this paper, we apply an understanding of what computers do – the execution of procedural or rules-based logic – to develop a simple model of how the widespread adoption of computers in the workplace might alter workplace skill demands. An essential contention of our framework is that, to a first approximation, computer capital substitutes for a limited and well-defined set of human activities, those involving repetitive information processing (cognitive) and routine manual tasks. This observation leads to a set of hypotheses that we test using samples of workers from Census and CPS files for 1960 – 1998 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 (both interactive and analytical). We document that these demand shifts are evident both in changes in occupational distributions within detailed industries and changes in skill requirements within detailed occupations. The combination of task shifts within industries and within occupations translates into meaningful growth in implied demand for college relative to non-college labor over 1970 – 1998. Combining our results, we find a net decline in demand for routine cognitive and routine manual tasks and growth in demand for non-routine cognitive tasks over 1970 to 1998 that is concentrated in computer intensive sectors.

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We wish to 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, Lawrence Katz, Sendhil Mullainathan, and Kathryn Shaw 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 expert advice on the Dictionary of Occupational Titles and for providing access to key data sources. The usual disclaimer about responsibility for errors deserves special emphasis here.

1. 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 consistently appear not only in U.S. data but in data from Canada (Gera, Gu, and Lin, 1999), the OECD (Machin and Van Reenan, 1998), and other developed countries (Berman, Bound and Machin, 1998).

While the empirical relationship between industry- and firm-level computer investments and the increasing use of college educated workers is 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]

At first glance, the missing details 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 (likely 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

[2] Herbert Simon (1960) provides the first detailed treatment of this question that we are familiar with, and his essay encapsulates many of the ideas explored here. Other important exceptions to the generalization above are Bresnahan, 1999; Bresnahan, Bryjnolfson and Hitt, 1998; and Goldin and Katz, 1998. Influential studies in the ethnography of

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 objective of the present paper is to apply an understanding of what computers do – by which we mean the *tasks* that present computer technology is particularly suited to performing – towards developing a conceptual model of how an exogenous decline in the price of computing power may alter workplace skills demands. By defining skill demands in terms of tasks rather than the educational credentials of workers performing those tasks, we hope to document how technological change has altered the task content of work and to use this understanding to elucidate the mechanisms underlying the observed complementarity between computerization and educated labor.

Below, we discuss the tasks computers can perform and their relation to human tasks, distinguishing between cognitive and manual tasks that are readily proceduralized – 'routine' tasks in our terminology – and those that are poorly specified for purposes of automation ('non-routine' tasks). We formalize these observations in a stylized model of the use of 'routine' and 'non-routine' skills in production in Section 3, and use this model to derive empirical implications of how an exogenous decline in the price of computing would impact labor market quantities and prices.

In Sections 4 and 5, we give empirical content to our framework by combining data on industry computer investment and computer usage with employment data from the 1960 – 1990 decennial Censuses of populations and 1980 – 1998 Current Population Surveys in which an individual's occupation has been augmented with the skills required for that occupation from the Department of

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work literature (e.g. Zuboff, 1988; Orr, 1996) provide a detailed discussion of what computers and related technology do on a day-to-day basis but do not consider economic implications.

Labor's *Dictionary of Occupational Titles* (DOT). After identifying in the DOT a number of rough proxies for 'routine' and 'non-routine' skills in our framework, we use data on changes in occupational composition over four decades – both economy-wide and within detailed industries – to explore three questions: 1) has the composition of employment shifted towards 'non-routine' tasks as predicted by our framework; 2) is this compositional shift driven by computer-intensive sectors; 3) are these content shifts visible *within* computer-intensive occupations; and 4) have the implicit labor market prices of routine and non-routine skills diverged as our model predicts.

Consistent with the conceptual framework, there have been substantial economy-wide declines over the period 1960-98 in the percentage of the labor force engaged in routine cognitive tasks and routine manual tasks, and an increase in the percentage engaged in nonroutine cognitive tasks. These are driven by within-industry shifts in employment patterns starting in the 1970s and by changes in skill requirements within occupations. Models of the determinants of employment patterns within detailed industries – what we label the extensive margin – indicate that proxies of computer usage and investment are able to "explain" a substantial share of the observed shifts favoring routine over non-routine tasks starting in the 1970s. Moreover, changes in skill content within occupations – the intensive margin – are at least as important as changes along the extensive margin and are also strongly predicted by patterns of occupational computerization. Translating these content shifts back into educational units, our task framework explains a substantial share, approximately two-thirds, of the growth in college relative to non-college employment during 1980 – 1998, and a somewhat smaller fraction over 1970 – 1998. Analysis of the labor market prices of routine and non-routine tasks provides less clear-cut results, however. While skill prices move in the direction predicted by our model, limited statistical precision prevents us from drawing sharp inferences.

Although in several respects our task-based analysis recapitulates findings in the economic literature documenting a positive correlation between technology investments and skill upgrading, we also present evidence that our task framework is able to explain changes in job tasks *within* education groups and *within occupations*, a fact that distinguishes it from the existing literature. While our reliance on the Dictionary of Occupational Titles places some limitations on the certainty and precision of our analysis, we believe it also provides a more detailed account of the mechanisms underlying the well-documented relationship between computerization and skill change, demonstrating what skills workers at different educational levels use at their jobs and how these skills appear to be shifting during the era of computerization.

2. Framework[3]

a. Routine and non-routine manual tasks

For purposes of our framework, it is useful to conceptualize performing a job as executing a series of tasks: moving an object, executing a calculation, communicating a piece of information, resolving a discrepancy. In 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 proceduralized in a fully specified series of logical programming commands ("If-Then-Do" statements) that designate precisely what actions the machine will perform and in what sequence at each contingency.[5] The simple observation that tasks cannot be computerized unless they can be proceduralized is the point of departure for our discussion. To clarify the discussion, we focus first on the computerization of manual/motor tasks and subsequently discuss information processing (cognitive) tasks in the next sub-sections.[6]

[3] We are grateful to Randy Davis of MIT's Laboratory for Artificial Intelligence and Pete Szolovits of MIT's Laboratory for Computer Science for valuable input on this section.

[4] We take as given that price declines in computing power provide ample motivation for asking this question.

[5] We note that a procedure can be completely specified without being of unbounded length. For example, a computer does not require tables of solutions to perform multiplication.

[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). Despite the substantial time interval between initial vision and ultimate implementation, the modern computer is a close relative of Babbage's machine. However, the specific characteristics and applications of the technology may be endogenously shaped by market forces. See Acemoglu (1998 and 2000) for an intriguing perspective on these issues.

Many manual tasks that humans perform (or used to perform) at their jobs can be specified in straightforward computer code and accomplished by machines, such as monitoring the temperature of a steel finishing line or moving a windshield into place on an assembly line. The problem arises, however, that in the words of Michael Polanyi (1966), "we do not know how to do many of the things we do." In other words, the means by which humans accomplish many routine physical tasks are at present not well understood. This fact in turn makes it exceedingly difficult for programmers and engineers to develop 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

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[7] It is a well-known paradox of early work in artificial intelligence that many of the tasks that programmers assumed would be negligible ultimately developed into formidable (and still unsolved) problems such as walking on two legs over uneven terrain, while many tasks that humans find next to impossible such as calculating Pi to the 10,000th decimal place are minor programming exercises.

[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 characteristics still generate real costs in automating a task. For example, if robotic technology had preceded the automobile, it is likely that vehicle navigation would have been designed to rely much less heavily on sightedness. Given our present (sunk) infrastructure of sight-dependent vehicles and visually cued roads, however, a major cost

example, in the case of industrial robots on assembly lines).[9] It is this 'routineness' or predictability that is lacking in the truck-driving example.

In our framework, we hypothesize that computers and computerized capital are used to substitute for routine physical tasks such as manipulating objects in an assembly line environment, monitoring temperature or flow in a production process, or continually 'retooling' a line so that varied items can be produced without intervening downtime (Fernandez, 1999). We stress that the notion that machinery may substitute for repetitive human labor is not unique to computer capital but is central to automation since the industrial revolution (cf., Goldin and Katz, 1998; Hounshell, 1985). Our economic insight is therefore a minor one: while price declines in computer capital have unambiguously advanced the automation of *routine* physical activities beyond what was feasible by non-computer capital, it has made far fewer inroads into (and may be largely orthogonal to) the automation of non-routine physical activities that rely heavily on visual or manual processing in an imperfectly controlled environment.[10] More concretely, there is little reason to expect that the jobs of truck drivers or janitors will be supplanted by computerization in the near future.[11]

b. Routine and non-routine information processing

While substitution of physical capital for repetitive labor is not novel, what appears distinctive to computer capital and its mechanical predecessors (such as the adding machine) is the capability to perform tasks that previously were almost uniquely cognitive: calculating, storing, retrieving, sorting,

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of automating the task of driving appears to be developing computers that can perform visual processing as do humans.

[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. This predictability is a purposefully engineered attribute without which current robotic technology would be nonviable in many production settings.

[10] We do not mean 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, doing so is not presently economically viable.

[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.

and acting upon information. Although computers were developed to perform mathematical calculations rapidly, the range of symbolic processing tasks to which computers are applied has become increasingly vast, for example analyzing consumer tastes, searching natural language documents, and enabling electronic markets for products and services..[12] As Bresnahan and Trajtenberg (1995) argue, computing as a General Purpose Technology is likely to enhance and alter economic activity in virtually all sectors.

While this characterization might caution against defining any limits to the present scope of computerization, we nevertheless hazard an attempt here. In particular, while computing's applicability to information-processing tasks is substantial, it is nevertheless circumscribed by the need for proceduralization as discussed above. To illustrate this point, it is useful to draw on a distinction made in cognitive science between 'rules-based' and 'model-based' reasoning (cf., Rasmussen et al, 1994).

A human engaging in 'rules-based' reasoning is analogous to a computer following a program: adhering to a procedure that precisely specifies each action taken at each contingency. While such reasoning is sufficient for accomplishing well-specified tasks, it is incomplete. Alongside procedures for accomplishing given tasks, humans possess mental tools to engage and often solve problems that are not addressed by known procedures. For example, research in cognitive science suggests that a trained physician holds in mind mental models of the body's functional systems that allow her to make educated guesses about the sources of maladies based upon discrepancies between the model and the observed behavior of the patient (i.e., symptoms). Additionally, a physician will update her mental model and accompanying diagnostic procedure based upon experiential data gathered during treatments. This latter modality of reasoning is referred to as 'model-based' (Rasmussen et. al.,

[12] See Bryjolfsson and Hitt (forthcoming) for an insightful discussion of the impact of computerization on the organization of firms and markets. As their essay stresses, "Computers are not fundamentally number crunchers. They are symbol processors."
[13] Without this ability, it would be impossible for knowledge to advance.

1994).[14] Analogous to our discussion above, we refer to these non-procedural mental activities as 'non-routine cognitive,' that is, cognitive tasks that cannot presently be described procedurally.[15] We use the term cognitive here broadly to encompass activities both intra- and inter-personal, all of which involve manipulating and communicating symbols.

A central observation for this paper is that effectively all current commercial computer technology engages in rules-based reasoning, that is, is procedural. There is little computer technology that can develop, test, and draw inferences from models, solve new problems, or form persuasive arguments – things that many workers do routinely.[16] 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 simple economic terms, advances in information technology have sharply lowered the price of accomplishing procedural cognitive tasks ('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 also emphasized by Bresnahan (1999).[17]

[14] One of the early disappointments of the field of Artificial Intelligence was the poor performance of so-called 'expert systems' – computer programs that simulated the behavior of expert professionals such as medical diagnosticians by following elaborate if-then decision rules (augmented with conditional probabilities), often culled from painstaking observation of professionals in the field.

[15] We stress that 'non-procedural' is a characterization of the current state of technology. Eventually, procedures may be developed for all of these tasks.

[16] 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).

[17] A useful example of the above generalization is found in Murnane et al. (1999) who study the automation of the check-clearing department of a large bank. Historically a labor intensive and monotonous activity performed almost exclusively by high school graduates, the bank in the 1990s redesigned the check clearing process to exploit

The same argument does not imply that computers will soon substitute for the non-routine functions of managers, attorneys, educators, scientists, health professionals, architects, or salespeople. We suspect the opposite is true. By increasing the speed and efficacy of routine information processing tasks typically performed by expensive professionals – filing medical forms, preparing boilerplate legal documents – computers are likely to increase the productivity of 'non-routine' information workers. In part, this is simply a matter of division of labor; computers offload rote information tasks from expensive professionals (e.g., completing forms, performing calculations). As importantly, since information is itself a complementary input into non-routine information processing tasks, productivity gains in routine information processing tasks increase the effectiveness of non-routine information workers – by, for example, providing better bibliographic searches, more timely management information, richer customer demographics, etc.[18] These changes in the efficacy and scope of non-routine information processing tasks are likely to reshape not only the content of individual occupations but the occupational and task structure of firms, an idea explored in greater detail by Bresnahan (1999), Bresnahan, Brynjolfsson, and Hitt (1999), Brynjolfsson and Hitt (forthcoming), Levy and Murnane (1996), and Murnane, Levy and Autor (1999).

To summarize, Figure 1 provides examples of the four task areas specified – routine vs. non-routine, manual vs. information processing – and states our hypothesis about the direct impact of

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advances in electronic imaging and Optical Character Recognition (OCR). Despite substantial efficiency gains, human labor was still needed to physically prepare checks for machine reading, to parse the check amounts on the approximately 45 percent of checks not recognizable to the OCR software, and to resolve discrepancies between deposit tickets submitted by customers and check totals tabulated by machines. While the bulk of tasks in check clearing are largely trivial for humans, current computing technology is only able to perform the most routine of them – sorting and reading amounts from hand-written checks – and then in only half of the cases. Left for humans are both non-routine motors tasks (unfolding checks, removing staples, reading handwriting) and non-routine cognitive (fixing errors).

[18] As above, computing power augments the marginal productivity of bank managers, analysts, and sales persons both by offloading their 'routine' activities and by providing richer complementary informational inputs into their 'non-routine' activities. While in the model below we aggregate our four tasks 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.

computerization on each. We stress that these computer impacts are independent of whether individual workers use computers at their jobs and are unrelated to the demand for computer skills *per se*. Rather, we are concerned with how computerization alters the types of work tasks performed and their allocation between labor and capital.

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 automation 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.

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

These simple observations are not by themselves sufficient to provide much predictive power. 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 routine than non-routine tasks; it is easier to program a computer to balance a bank's ledgers than to manage its branches. Second, routine and non-routine tasks are themselves imperfect substitutes. 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. Third, at least in the domain of information processing, greater intensivity of routine inputs is likely to increases the marginal productivity of non-routine inputs.[19]

These assumptions structure the production side of our model. To formalize, 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:

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

To encapsulate the notion that computers are more substitutable for routine than non-routine skills, we assume that computer capital, C, and routine skills, R, are perfect substitutes.[20]

On the input side, 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.

We make three additional assumptions on the supply of routine and non-routine skills. First, as in Roy (1951), we assume that workers choose among 'routine' and 'non-routine' occupations according to comparative advantage. Perhaps more speculatively, we further assume that workers' skills in routine and non-routine tasks are positively correlated. Finally, we assume that the underlying distribution of productivity (or skill measured in efficiency units) is more dispersed in non-routine than routine tasks. This latter assumption appears plausible since machinery rather than individual capability plays a greater role in setting the pace of routine tasks.

Formally, we allow an infinite number of income-maximizing workers, each of whom chooses to

[19] 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. The reason is that while the output of routine information processing is itself a productive input into non-routine information processing, this is not obviously true for manual tasks. Although we can cite instances where for example information technology increased the productivity of truck drivers through improved routing, we suspect that such cases are much less pervasive than for the non-routine information processing tasks. As noted earlier, it is not obvious that the computerization of routine manual tasks will improve the marginal productivity of janitors.

supply either $\alpha \geq 1$ efficiency units of routine skill or $h(\alpha)$ efficiency units of non-routine skill. In keeping with our discussion, we think of the decision to supply routine or non-routine skills as the choice of an occupation.

The density of α will be given by $f(\alpha)$, with $f(\alpha) > 0$ for $\alpha \in [1, \infty)$. We further assume that $0 \leq h(0) < 1$ and $h'(\alpha) > 1 \;\; \forall \alpha$. Hence, individual endowments of routine and non-routine skills are positively correlated and there is a single crossing (in efficiency units) between the two distributions in the population.[21] These assumptions imply that the distribution of ability is intrinsically more dispersed in non-routine activities. Hence, non-routine occupations will attract workers who have an absolute advantage in both routine and non-routine activities.

Under these assumptions, it is straightforward to trace out the implications of a technical advance – a fall in the price of computer capital – for the labor market. Given the perfect substitutability of computer capital and routine skills, it is immediate that the wage per efficiency unit of routine labor is given by:

$$W_R = P. \tag{2}$$

Since workers choose their occupation – that is, to supply routine or non-routine labor – to maximize earnings, the marginal worker with efficiency units of routine skill α^* will be indifferent between routine and non-routine occupations when:

$$\frac{\alpha^*}{h(\alpha^*)} = \frac{W_N}{W_R} \tag{3}$$

Given the assumptions on $h(\cdot)$, (3) implies that for $\alpha_i < \alpha^*$, individual i supplies routine skills, and for $\alpha_i \geq \alpha^*$, i supplies non-routine skills.

Productive efficiency further requires that:

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[20] Cobb-Douglas technology implies that the elasticity of substitution between routine and non-routine skills is one.
[21] If *h(•)* is a linear function of α, this correlation will be one.

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

and

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

Using these equilibrium conditions, we can explore how a price decline in computer capital influences wage levels, occupational choice, self-selection and earnings dispersion. Rearranging (4) and differentiating to obtain the derivative of demand for non-routine skills as a function of the price of computer capital, we obtain:

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

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 skills are complementary inputs, it follows that:

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

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 alters observed wages and wage dispersion both through price effects and through self-selection.

To measure self-selection, consider the impact of a price decline in computer capital on α^*, the routine skill endowment of the marginal worker in the routine occupation. Using (3) - (5), we obtain:

$$(8) \qquad \frac{\partial(\alpha^* / h(\alpha^*))}{\partial P} = (1-\beta)\frac{\left(\frac{P}{1-\beta}\right)^{\frac{1}{\beta}}}{\beta^2 P} > 0,$$

which implies that $\partial\alpha^*/\partial P < 0$.[22] A fall in the price of computer capital decreases labor supply to the routine occupation and increases labor supply to the non-routine occupation. Interestingly, since marginal workers – those switching occupations in response to a price decline – possess higher than average routine skills (relative to incumbents) and lower than average non-routine skills, average skill levels in *both* occupations fall.[23] This will affect both average earnings and earnings dispersion in each occupation.

In the case of routine workers, the quality effect amplifies the impact of the price decline on non-routine wages, further lowering mean earnings in the routine occupation. In addition, wage dispersion in the routine occupation falls, due to the direct impact of price declines and, indirectly, through the compression of worker ability in routine occupations.

By contrast, since workers entering the non-routine occupation are of lower relative quality, self-selection mitigates the direct effect of falling computer prices on non-routine earnings. Although wages per efficiency unit of non-routine labor rise in absolute terms, observed wages could potentially rise or fall due to the offsetting effect of quality change. Earnings dispersion, however, should increase in non-routine occupations.[24]

To summarize our simple conceptual framework, the model implies that a price decline in computer capital lowers the wages of routine occupations and causes their employment to contract. Hence, although input of routine skills – in efficiency units – expands with a fall in the price of computer capital, there is an absolute decline in routine labor supply and demand is satisfied by substitution of computer capital for human labor. Consequently, worker quality in routine

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[22] Recall that $\alpha' = 1$ and $h'(\alpha) > 1$.

[23] A proof of this intuitive result is available from the authors.

occupations declines and earnings dispersion in these occupations decreases.

By contrast, a price decline in computer capital raises the marginal productivity of non-routine occupations and hence the wage per efficiency unit of non-routine labor input. Responding to this price change, labor supply to non-routine occupations expands and worker quality falls. Consequently, average earnings in non-routine occupations may either increase or decrease. Wage dispersion in non-routine occupations unambiguously rises, however.

Many of the details of our model were chosen for simplicity and are inessential 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 well justified by the present state of information technology. A second important assumption is that workers skilled at non-routine activities also have an absolute advantage at routine activities. While we regard this assumption as more controversial than the first, we suspect that it is roughly realistic, particularly in the case of cognitive tasks.

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,[25] it is plausible that changes in final demand could amplify or offset changes in industry level demand for skills. For this reason, we focus our empirical exploration below on the composition of demand at the industry level.

4. Data

Since our approach in this paper is to conceptualize jobs in terms of their component tasks rather than their educational inputs, we require a measure of tasks performed in particular occupations. We draw on information from the Fourth (1977) Edition and Revised Fourth (1991) edition of the U.S.

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[24] A proof is available from the authors.

[25] i.e., β varies by industry.

Department of Labor's *Dictionary of Occupational Titles* (DOT) (U.S. Department of Labor, 1977 and 1991). The DOT rates occupations along 44 dimensions including required training times, worker aptitudes, worker "temperaments," and the occupation's physical demands (see Appendix Table 1). Because an occupation's characteristics can vary across establishments, an occupation is observed and rated in multiple sites. The multiple ratings are then averaged and these average characteristics are published in the DOT.

The DOT has a number of well-known limitations, detailed in 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 information currently available on the skill requirements for detailed occupations economy wide. Researchers who have used the DOT for related analyses include Howell and Wolff (1991) and Wolff (1996), although given our focus on routine versus non-routine activities, our choice of DOT variables is distinct from these studies. In addition, ours is the only study that we are aware of to analyze changes in occupational content between 1977 and 1991 as measured by the DOT's re-evaluation of occupations in the revisions to the Fourth Edition.[26]

Although 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. By drawing on a special version of the 1980 Census in which individuals have been assigned both a 1970 and 1980 occupation code, we were able to overcome the well-known incompatibility between

[26] Spenner (1983) performed an analysis of changes in occupational content over the third and fourth editions of the DOT.

1970 and 1980 COC codes in forming our time series.[27] In addition, we created a crosswalk between the closely related 1960 and 1970 Census occupational coding schemes to permit analysis in the (mostly) pre-computer 1960s era.

While the DOT rates 44 occupational characteristics, many of these characteristics are not germane to the hypothesized effects of computers discussed in Section II. To identify 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 1970 major occupations, we selected four variables that appeared to best approximate our skill constructs. Details of these variables and example tasks from the *Handbook for Analyzing Jobs* are given in Table 1. Means of each variable by major occupation are found in Appendix Table 2, using as weights the occupational distribution of employment in the 1970 Census.

To measure non-routine cognitive tasks, we employ two variables, one to capture non-routine 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 according to our terminology – primarily managerial, professional, and to a lesser degree technical positions. The variable MATH, our second measure of

[27] The actual number varies by Census year and is specified in table notes as relevant. This aggregation was first performed using the occupation codes found in the 1970 Census and published in electronic form in 1981 (National Academy of Sciences, 1981). Researchers then later drew upon a sample of individuals who had been assigned both a 1970 and 1980 occupation code in the 1980 Census to re-weight the DOT variables to reflect DOT characteristics by 1980 Census occupational groupings (England and Kilbourne, 1988). For our analysis, we calculated DOT 1977 Fourth Edition scores by occupation and gender using the original data files developed by the sources cited above. We repeated these steps using an electronic version of the 1991 Revised Fourth Edition of the DOT (ICPSR Study I06100) to produce a set of revised DOT scores by occupation and gender where

non-routine cognitive tasks, codes the quantitative skills required in occupations (ranging from arithmetic to advanced mathematics). 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 information processing. Finally, we identified the variable FINGER as an indicator of routine manual activity. As is clear from the DOT example tasks given in Table 1, there is some overlap between our measures of routine manual and information processing tasks. Although STS is weighted towards routine clerical and numerical tasks such as transcribing and calculating, and FINGER is weighted towards routine manual tasks such as feeding machines and performing repetitive movements, the correlation between the measures is high (0.61 using 1980 CPS weights) and examples of both routine manual and cognitive tasks appear for each measure in the *Handbook for Analyzing Jobs*.[28] A full set of correlations is provided in Appendix Table 3. Given the limitations of the DOT, we believe these variables are appropriate choices. We are, however, examining the sensitivity of our results to reasonable alternative choices and composites.

Using the COC-DOT aggregations described above, we attached the selected DOT occupation characteristics to the Census IPUMS one percent extracts (Ruggles and Sobek, 1997) for 1960 to 1990, to CPS Morg files for 1980, 1990 and 1998, and to the February 1990 CPS.[29] We used all

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differences between 1977 and 1991 are due solely to change in DOT occupational ratings (rather than changes in the relative size of DOT sub-occupations within CIC occupations).

[28] In each observation for an occupation, DCP and STS each appear as a 1 if the DOT Analyst (a trained observer) views the characteristic as part of the occupation and appears as 0 otherwise. The multiple observations of an occupation are then averaged converting the variables to continuous measures with values lying between 0 and 1, which we multiplied by 10 for convenience. The DOT Analyst rated gave each occupation a rating on an inverted scale from 1 to 4 for FINGER and EHF, indicating the extent to which people in the occupation required significantly above average finger dexterity and eye-hand-foot coordination (rating of 1) or whether people in the population with low values of such dexterity and coordination could function effectively in the occupation (rating of 4). We inverted this scale and multiplied the values by 2.5 to place them on the same scale as that used for the other skill indicators.

[29] We include the February 1990 CPS because it is the only CPS survey prior to 1992 that makes use of the new educational attainment codes that were introduced with the 1990 Census. We required the updated codes for 1990 to use in conjunction with the 1998 CPS Morg file to compute changes in educational attainments between 1990 and 1998.

observations on non-institutionalized, employed workers, ages 18-64. For our industry analysis, these individual worker observations were aggregated to three digit industries to provide indicators of average skill requirements by industry for 1960, 1970, 1980, 1990, and 1998. To attain compatibility between the changing Census Industry Codes for 1960 – 1998, we use a crosswalk developed by Autor, Katz, and Krueger (1998) containing 140 consistent CIC industries spanning all sectors of the economy.[30] 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.[31] For analyses of wage differentials associated with DOT skill measures, we further limit our sample to non-self-employed workers with positive earnings and hours.[32]

In measuring changes in job task requirements, we exploit two sources of variation. The first is 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 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). Accordingly, it is likely to provide an increasingly inaccurate picture of changing job task requirements over time.

To (partially) overcome this limitation, 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 also has limitations.

[30] 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.

[31] Usual hours worked per week in the previous year is not available prior to the 1990 Census. 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. Tabulations in Katz and Autor (1999) indicate that most earnings metrics are not sensitive to the choice of hours weights versus raw person weights.

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.[33] Measured 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 nominally identical occupations.

5. Results

a. Trends in skill indicators

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 and 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.[34] As is apparent from Figure 2, while both measures of non-routine cognitive tasks (DCP and Math) 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 (STS) and routine manual (FINGER) tasks both trended *upwards* during the 1960s, before commencing a

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[32] Further details on our samples and data construction will be provided in a detailed data appendix.

[33] 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.

[34] A problem that we faced stemmed from the different coding of educational attainments in the 1990 Census and 1998 MORG as compared to the 1980 and 1970 Census. We used the procedures described in Jaeger (1997) to construct consistent measures of educational attainments. In addition, we used figures from Park (1994) to impute mean years of completed education to individuals in the 1990 IPUMS based upon their highest educational credential, gender and race.

decline in the 1970s that became more rapid in each subsequent decade. As is visible in the second and third columns of each panel of Table 3, these aggregate patterns are also apparent for each gender individually.[35]

Appendix Table 4 also tabulates the DOT tasks measures by major educational group. Two of four skill variables are monotonic in educational attainment, with both measures of non-routine cognitive tasks, interpersonal and analytic, rising in educational attainment. 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.[36] These patterns suggest that despite the limitations of the DOT job content measures, they may provide information about skill requirements that is distinct from education.

b. Shift-share analysis

The trends in job content documented in Table 2 stem both from changes in the occupational mix within industries and changes over time in the percentage of the labor force employed in individual industries. Changes in the organization of work favoring non-routine labor inputs could operate by 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 routine skills that are unrelated to shifts in the within-industry organization of production. Since the focus of our conceptual model and empirical analysis is on changes in industry skill demands, it is important to explore to what degree changes in measured job content are explained by within-industry shifts in task input versus employment shifts across more and less task-intensive sectors.

[35] Hence, the patterns of occupational changes documented by our analyses are not driven primarily by the widespread entry of women into the professional labor force during recent decades (c.f., Weinberg, 2000). Interestingly, in the 1960s, women are more concentrated in both routine manual and routine cognitive tasks than men, and substantially less concentrated in non-routine cognitive and interpersonal tasks. By 1998, women's task distribution looks substantially more similar to men's. Notably, although women start the period higher in routine cognitive tasks than males, they end the period far lower than males.

A decomposition of the growth of task input accounted for by between- and within-industry components provides a measure of the importance of these channels. A standard decomposition of the change in the use of skill j (e.g., DCP, MATH, STS, or FINGER) in aggregate employment between years τ and t ($\Delta S_{jt} = S_{jt} - S_{j\tau}$) into a term reflecting the reallocation of employment across sectors and a term reflecting changes in the skill j input within industries is given by:

(9) $$\Delta S_{jt} = \sum_k(\Delta E_{kt}\gamma_{jk}) + \sum_k(\Delta\gamma_{jkt}E_k) = \Delta S^b_{jt} + \Delta S^w_{jt}$$

where k indexes industries, E_{jkt} is the employment of workers with skill 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, γ_{jkt} is the mean of skill j in industry k in year t, $\gamma_{jk} = (\gamma_{jkt} + \gamma_{jk\tau})/2$, and $E_k = (E_{kt} + E_{k\tau})/2$. The first term ($\Delta S^b_{jt}$) reflects the change in aggregate employment of skill j attributable to changes in employment shares *between* industries that utilize different intensities of skill j. The second term (ΔS^w_{jt}) reflects *within-industry* skill change.

Table 3 presents between- and within-industry decompositions of each of our four DOT measures during each decade from 1960 – 1998 using equation (9). These decompositions present remarkably consistent patterns of task change. For the measure of non-routine cognitive/interactive tasks, DCP, the growth in economy-wide input of this task is entirely a within-industry phenomenon.[37] Moreover, the rate of within-industry growth accelerates sharply in each decade, doubling from the 1960s to the 1970s, and doubling again in the subsequent two decades. Incorporating changes along the intensive margin during 1980 – 1998 (line 6 of Panel 1) increases the estimated annualized rate of growth by an additional 50 percent.

Decomposition estimates for the non-routine cognitive/analytic measure, Math, present a more

[36] This pattern may be taken as supportive evidence for our contention section 1 that education is an imperfect summary statistic for the skills of interest here.

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 the differential importance of between- and within- industry shifts. Specifically, the within- industry component of the trend increase in non-routine/analytic tasks accounts for only one quarter of the overall trend in the 1960s and 70s, and then accelerates thereafter. 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. Interestingly, however, incorporating changes on the intensive margin reduces the measured within-industry acceleration by approximately 40 percent

The time patterns of routine cognitive and routine manual task input are quite comparable. 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 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 over 1970 – 98 while for routine cognitive tasks, the within-industry component accounts for 71 percent. Incorporating changes along the intensive margin for 1980 – 98 approximately *doubles* the rate of reduction of routine cognitive tasks while leaving the results for routine manual tasks largely unaffected.

Although not tabulated here, we find that similar patterns obtain when we operationalize equation (9) for manufacturing and nonmanufacturing sectors separately. Since within-industry shifts dominate the trends in task shifts that we seek to analyze – particularly during the 1970s forward – these findings suggest that an analysis of the determinants of within-industry changes in skill demand has the potential to illuminate the sources of the economy-wide skill changes measured in Table 3.

[37] In fact, 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.

c. Evidence on computer intensity and within-industry task changes: 1960 - 1998

To explore the role that computerization may have played in these task shifts, we examine evidence in this section for whether a number of proxies of industry computer use and computer investment are able to predict the within-industry patterns of changing skill input in found in Table 5. Initially, we estimates model of the form:

$$(10) \qquad \Delta S_{jkt} = \alpha + \beta \Delta C_j + \varepsilon_{jkt}$$

where $\Delta S_{jkt} = S_{jkt} - S_{jk\tau}$ is the change in industry input of skill k between years τ and t and ΔC_j 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 appear to shift their skill input in the directions predicted. In the subsequent section, we use contemporaneous – though less well measured – indicators of computer investment to probe these relationships further.

In estimating (10), we choose the period 1960 – 1998 because it encompasses the recent computer era and, 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 in between 1984 and 1997 – it bears emphasis that the era of rapid computer investment began in the 1970s (Autor, Katz and Krueger, 1998; Bresnahan, 1999).[38] 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

[38] This pattern is documented by.

is not detectable until the 1970s or later, this is more likely to be consistent with a causal relationship.

Table 4 presents initial estimates of (10) for the decades 1960 – 70, 1970 – 80, 1980 – 90 and 1990 – 98. Each dependent variable is ten times the annualized industry level change in the average value of one of the task indicators. In addition, we include for reference comparable models where the dependent variable is the change in industry employment of college graduate labor as a share of total labor input.[39]

The results in Table 4 are substantially consistent with our conceptual model. Industries that computerized relatively rapidly during 1984 – 1997 increased the percentage of jobs requiring high levels of non-routine cognitive/interactive tasks (DCP) more than did other industries in both the 1980s and the 1990s. Interestingly, 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 documented in Table 3.

The patterns for the other three measures of task input are even clearer. Though there is a modest within-industry trend towards increased input of non-routine cognitive/analytic tasks during both the 1960s and 1970s, this trend is essentially uncorrelated with industry patterns of computerization over 1980 – 1997 as is seen in rows A and B of Panel 2. In the 1980s and 1990s, however, the relationship between computerization and increased use of non-routine cognitive/analytic tasks becomes sizable and significant, accounting (in the simplest sense) for all of the observed growth in input of these tasks over both decades.

The relationship between computerization and industry declines in routine cognitive and routine manual activities also provides evidence of task shifts that are not visible in the pre-computer era. In the models of industry input of routine cognitive tasks (STS), the relationship between industry task change and subsequent computerization is small and insignificant in the 1960s. In each subsequent decade, the magnitude of this negative relationship increases in size and statistical significance. As is visible in Panel 4, a comparable pattern is visible for the measure of routine manual task input (FINGER).

d. Contemporaneous changes in computer use and within-industry skill change: 1980 - 1998

While the models in Table 4 indicate that the trends in task content observed in computerizing sectors during the 1970s – 1990s do not for the most part pre-date the computer era, these estimates are limited by the fact that the dependent and independent variables are not temporally aligned. Moreover, they do not incorporate the intensive margin of task change, which was shown to be quite important for two of our four task measures in Table 3.

To improve on the initial estimates, we fit a series of models found in Table 5 in which the dependent variable is the within-industry change between 1980 and 1998 in use of each of our four DOT measures.[40] As above, the explanatory variable is the change in industry computer use between 1984 and 1997 which, in this case, is a contemporaneous measure. We fit two models for each dependent variable. In the first, we examine only changes along the extensive margin (i.e., occupational composition) within industries. In the second, we incorporate the intensive margin by pairing DOT task content measures from the 1977 DOT with the 1980 industry occupational mix and pairing task content measures from the 1991 DOT with the 1998 industry occupational mix.

The results in Table 5 underscore the story of Table 4. 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 (DCP) and cognitive/analytic tasks (Math) between 1980 and 1998 more than did other industries. They also decreased the relative proportion of jobs requiring routine cognitive and manual tasks faster than did other industries. In all cases, the

[39] Our results here are quite comparable to those in Autor, Katz, and Krueger (1998).

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.[41] The intercept of the bivariate regression in the first row of Panel 1 of Table 5, however, is only 0.16. This implies that holding computerization at zero, one would predict that non-routine cognitive/interactive tasks would have only grown by 8 percent (0.16/0.212) of the amount actually observed. Similar calculations imply that computerization can 'account' 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.

Row (b) of the four panels of Table 5 incorporates changes along the intensive margin of occupational task input into each of these estimates. Notably, although the magnitude of the change to be explained increases substantially for two of four task measures (non-routine cognitive/interactive and routine cognitive), the intensive shift is *also* largely explained by computerization in this simple bivariate framework. For example, incorporating the intensive shift in non-routine cognitive/interactive increases the annualized change in this measure from 0.212 to 0.312. Comparing the intercepts in Rows (a) and (b) of Panel 1, however, reveals that both are approximately zero, meaning that the computer measure can account for both the intensive and extensive shift.[42] Interestingly, although the intensive margin of the non-routine cognitive/analytic (Math) measure moves opposite to the extensive margin, the coefficient on computerization is unchanged in the model incorporating the intensive margin and hence the implied magnitude of the

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[40] As above, the explanatory variable is the change between 1984 and 1997 in industry computer use which, in this case, is a contemporaneous measure.
[41] Recall that this variable is scaled from 0 to 10 and begins with a baseline of 2.40 in 1960. Hence, the percentage change over 1980 – 1998 years is 16 percent on the extensive margin, an additional 11 percent on the intensive margin.
[42] Note that this does not follow mechanically. If, for example, the growth in the within component of non-routine cognitive/interactive tasks (DCP) were concentrated in occupations found primarily outside of computer-intensive sectors, the intensive component would *offset* the extensive component in these models, reducing the fraction of the observed change explained by computerization.

task shift due to computerization is unaffected.[43]

e. Computers, capital intensity, and skill changes

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 using data from the National Income and Product Accounts (U.S. Department of Commerce, 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 was 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.[44]

To measure computer investment in the NIPA, we sum data on investment in mainframe and personal computers, computer storage devices, and computer peripherals.[45] To isolate the relationship between computer investment variable and other forms of capital deepening, we also include as a control variable the change in the value of the capital stock per worker over each decade.[46] 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:

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[43] Since there is essentially no shift in the intensive margin of routine manual tasks (FINGER), the two models for this variable are practically identical.
[44] The crosswalk between the CIC and NIPA sectors was 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.
[45] We also experimented with disaggregating computer capital into its various sub-components. Because the measures of sub-components are exceedingly highly correlated, this exercise bore little fruit.
[46] 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 variable since the *level* of the investment variable is a measure of the flow of new computer capital into an industry over the decade. Capital stock measures used here from the Bureau of Economic Analysis' 1997 NIPA revision are preliminary. Final measures were not available as of this writing and hence our computer measures are at present a mixture of revised and non-revised NIPA variables. While we made significant efforts to maintain consistency, our models will be re-estimated when the final NIPA data are released in 2000.

$$(11) \qquad \Delta S_{jkt} = \alpha + \delta_{70-80} + \delta_{80-90} + \delta_{90-98} + \beta CI_{jt} + \phi \Delta K_{jt} + \varepsilon_{jkt}$$

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 $\delta's$ are time dummies equal to one in each of the post-1960s decades corresponding to their subscripts, and α 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 our 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 remarkably comparable to those found in the regressions using the CPS computer measures. The NIPA measure of computer investment consistently predicts relative declines in industry employment of routine tasks and relative growth in employment of non-routine tasks. In all cases, this relationship is statistically significant. Moreover, the estimated coefficient on computer investment is of economically meaningful magnitude. By comparing the decade intercepts in the first column of each panel to the decadal means listed at the bottom of the table, one may calculate that computer investment is able to explain more than 100 percent of the trend increase in both measures of non-routine cognitive tasks (DCP and Math) relative to the 1960s, and 87 and 82 percent respectively of the decline in routine cognitive and manual tasks.[47] The estimates in Panel 5 also indicate that a similar model is able to explain approximately all of the growth in college graduate employment.

A notable pattern in these results is that the estimated impact of capital deepening on changes in industry skill demands is not statistically significant in any of the models, except notably that for change in college graduate employment. Yet the coefficient on computer use is significant in all five

[47] Note that these calculations take the 1960 annualized rate of change in the relevant variable as the baseline since we consider this period the 'pre-computer era.' Changes over 1990-98 are weighted down by 25 percent due to 8 year rather than decadal time span. For example, the calculation for Routine Cognitive (STS) is [(-0.019 – 0.089 +

models that contain the measure of capital deepening. This indicates that there is something distinctive about computer capital's relationship with industry skill demands apart from the well-known pattern of capital-skill complementarity (Griliches, 1969).[48]

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

f. Changes in job content *within* education groups

A natural question raised by these findings is whether the DOT job skill demand measures provide any additional information beyond that which is contained in conventional education measures such as college and high school graduates. To explore this question, we estimate a series of models that measure the relationship between industry computer use 1980 – 1998 and within-industry, *within-education group* changes in job skills. Specifically, we estimate a variant of equation (10) where the dependent variable is the change in the industry mean of each DOT measure *within* high school and college graduate employment groups (rather than within the industry overall).[49] To make this test of our framework as stringent as possible, we ignore for now changes on the intensive margin. We use 1977 DOT task content measures to examine changes in task input proxied by shifts in occupational distributions within education groups within industries. Such changes are of course potentially difficult for our analysis to detect. Because educational levels have risen in essentially all occupations since 1970 and because the DOT measures are only current as of 1977, DOT measures of routine skills will mechanically *rise* and non-routine skills mechanically *fall* among better

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0.027 + (-0.122 – 0.089) +0.032 + ((-0.216 – 0.089) + 0.041)*.8]/([(-0.019 – 0.089 + (-0.122 – 0.089) + (-0.216 – 0.089)*.8] = 0.87

[48] Autor, Katz, Krueger (1998) present a similar finding.

[49] In particular, we replace ΔS_{jkt} in (10) with ΔS_{jklt} where l denotes education groups within industries.

educated workers, patterns that are indeed visible in our data.[50]

Estimates of within-education group models are found in Table 7, with results for high school graduates in Panel A and results for college graduates in Panel B. The weighted means in Panel A indicate that during 1980 – 1998, high school graduates were increasingly employed in occupations high in non-routine cognitive/interactive content, and were increasingly scarce in occupations high in routine cognitive and routine manual tasks and, to a lesser degree, non-routine cognitive/analytic tasks. Estimates of (10) found in rows (1) – (4) reveal that the displacement of high school graduates out of routine tasks was significantly and substantially more pronounced in industries experiencing greater computerization during 1980 – 1997. Similarly, their movement *into* occupations using greater non-routine cognitive/interactive tasks was significantly larger in these same industries. There is no significant relationship between employment of high school graduates in non-routine cognitive/analytic tasks and computerization over this period. Comparison of the estimated intercepts for these models relative to their weighted means indicates that observed employment shifts among high school graduates against routine cognitive and manual skills and favoring non-routine cognitive skills are *entirely driven* by changing employment patterns within computer-intensive sectors during 1980 – 98.

The estimates for college graduates in Panel B provide less striking patterns. None of the estimated coefficients is significant in these models and the standard errors are quite large. Comparing mean changes in occupational task content among college graduates to those among high school graduates indicates that the changes have been much less pronounced for college graduates. Given that almost all college graduate employment in 1980 was found in occupations with extreme values for non-routine and routine tasks (high in the former, low in the latter), it is not particularly surprising that we find little increase (decrease) in these non-routine (routine) measures.

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[50] Hence, it would be unsurprising to find perverse results in the within-education group estimates where college graduates were increasingly hired into ‘routine’ jobs in computerizing sectors.

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

Table 8 presents our estimates of the relationships between changes in computer use within occupations from 1984-1997 and changes in the task content of occupations between 1977 and 1991, as measured by the Fourth Edition of the Dictionary of Occupational Titles (1977) and the Revised Fourth Edition (1991). For each of our skill measures we present the results from four 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. The logic underlying this specification is to test the hypothesis that the coefficient on the computer use variable simply reflects changes in the educational distribution of computer intensive industries. The third specification includes the fraction of workers in the occupation employed in jobs that were re-evaluated in the Revised Fourth edition of the DOT and the interaction of this variable and the computer use variable.

The results are remarkably insensitive to specification, as is evident from the last row of the table which presents the predicted change in the dependent variable due to computerization of the occupation. In occupations that rapidly increased use of computers the use of non-routine cognitive and interactive skills increased more rapidly than in other occupations and the use of routine cognitive and manual skills decreased more rapidly. Moreover the changes accountable by computerization are large. This is consistent with patterns displayed in earlier tables, showing that computerization contributed to changes in skill requirements within industries both by changes in skill content within occupations -- the 'intensive margin' – and changes in the occupational mix – the 'extensive margin.'

h. Relationship of DOT tasks to the demand for college/non-college employment

Since our DOT task input measures do not correspond to conventional measures of skill input such as education, it is logical to ask how changes in job task content demands translate into educational demand. We take up this question briefly in this section.

To translate task demands into education demands, we estimate a linear model of educational employment shares in 1970 occupations using as independent variables our four DOT skill measures in those occupations:

(12) $$S_k = \alpha + X_k \beta + \varepsilon_k$$

where S_k is the employment share (in FTEs) of college graduates in occupation k, X_k is a vector containing the DOT means of our routine and non-routine skill measures, and β is a conformable vector of coefficients. $\hat{\beta}$ is therefore an estimate of college vs. non-college demand as a function of occupational tasks.

We then translate our estimates of changes in job tasks induced by computerization from Tables 5 and 6 into estimates of changes in college vs. non-college demand by calculating:

(13) $$\Delta S_t = \sum_k \hat{\beta}' \Delta \hat{X}_{kt} \gamma_{kt}$$

where $\Delta \hat{X}_{kt}$ is a vector of predicted change in industry $k's$ input of each of our four task measures (due to computerization) between times τ and t from estimates of equation (10) and (11), and γ_{kt} is industry $k's$ average share of employment between τ and t. Similarly, we can incorporate predicted changes on the *intensive* margin of task input over 1980 to 1998 by adding to $\Delta \hat{X}_{kt}$ the predicted change in *within* occupation task content due to computerization as estimated in Table 8.

Two caveats apply to these estimates. First, given the limitations of the DOT discussed earlier, estimates of $\hat{\beta}$ are likely to be biased downward by measurement error. This will reduce our estimates of ΔS_t. Second, equation (13) is a 'fixed coefficients' model of education demand as a function of job tasks that 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 skills, and vice versa for measured demand shifts against routine skills. In fact, it is shown in the subsequent empirical section that both types of price shifts probably occurred during 1970 – 1998.

Detailed calculations of (13) are found in Table 9. Panel 1 performs calculations for 1980 – 1998 using the CPS computerization estimates from Table 5 to estimate $\Delta\hat{X}_{kt}$. Panel 2 performs calculations for 1970 – 1998 using the NIPA estimates from Table 6 to estimate $\Delta\hat{X}_{kt}$. Part 1A of Panel 1A tabulates estimates of $\Delta\hat{X}_{kt}$ for 1980 – 1998 both exclusive and inclusive of changes on the intensive margin. Panel 1B translates these task shifts into demand shifts for college graduate employment using three separate estimates of $\hat{\beta}$, one including all four DOT task measures, a second dropping the non-routine cognitive/analytic measure (Math), and a third dropping the non-routine cognitive/interactive measure (DCP).[51]

Using three estimates of $\hat{\beta}$, we find that computer-induced changes on the extensive margin of task input can explain between 1.2 and 1.8 percentage points of the growth in college vs. non-college employment over 1980 – 1998. Adding to this estimate the impact of changes on the intensive margin, computerization is estimated to have shifted college/non-college demand by 3.8 to 4.8 percentage points.

For reference, these estimates can be compared directly to the growth of college employment (in FTEs) over this time period, which we estimate at 6.83 percentage points using our CPS samples. However, this is not the most appropriate comparison since trends in college employment are likely to be driven primarily by secular trends in the production of college graduates rather than shifts in demand per se. Hence, we also tabulate changes in log relative demand for college vs. non-college labor over the same time period estimated by Autor, Katz, and Krueger (1998) and updated to 1998 for this exercise. These estimates are based on a constant elasticity of substitution framework using an estimated elasticity of substitution between college and non-college equivalent workers of 1.4, a

[51] Because these task measures are highly correlated, we are interested in to the extent to which each can individually explain changes in educational demand.

figure that receives wide support in the empirical labor demand literature (Katz and Murphy, 1992; Katz and Autor, 1999). Comparison of the predicted change in college demand to the estimated figure of 6.69 log points over 1980 – 1998 indicates that changes in task content can explain a sizable share of the shift (approximately 40 percent).

Panel 2 of Table 9 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, i.e., taking the 1960 trends in occupational task content as the baseline against which estimated computerization-induced changes over the subsequent three decades are to be compared. Using three estimates of $\hat{\beta}$, we find that task content shifts can explain approximately 0.3, 0.9, and 0.9 percentage points of the *increase* in college/non-college demand relative to the 1960s level in the 1970s, 1980s, and 1990s respectively (Panel 2B). It is particularly noteworthy that computerization is estimated to accelerate growth in demand for college labor in the 1970s and further again in the 1980s and 1990s relative to the 1960s trend.[52]

The final column of Panel 2B adds changes in the intensive margin over 1980 – 1998 to these calculations. As with the previous estimates, the intensive changes contribute quite substantially to the total. In net, the DOT task shift measures are estimated to explain a sizable share (close to 30 percent) of the shift in log relative demand favoring college educated labor between 1970 – 1998 and are consistent with an acceleration of relative demand for college labor in the 1980s and 1990s relative to previous decades.[53]

[52] As Mishel, Bernstein and Schmitt (1997) and Autor, Katz and Krueger (1998) emphasize, if computerization has contributed to increased skill demand, it must have done so by accelerating the growth in relative demand for college labor beyond trends visible during the 1940 – 1970 period.

[53] 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.

i. Routine and Non-Routine Tasks and Wages

In the final empirical section we explore whether the relative wages associated with the tasks affected by computerization changed systematically during 1960 to 1998. Table 10 presents trends in log hourly earnings differentials for our DOT task measures using Census and CPS samples. Each decadal trend is estimated from cross-section log hourly earnings regressions using wage samples for the first and last year of each decade. Due to non-comparabilities in sample frames and education measures among data sets, we present estimates using the most closely comparable data sets for each decade under study. Columns A – D present changes over each decadal interval. For the 1980s we present one set of estimates in which 1977 DOT skill measures were used with both the 1980 and 1990 samples and a second set in which the 1977 DOT skill measures were used with the 1980 sample and the 1991 DOT values were used with the 1990 sample. For the 1990s, we present one set of estimates in which 1977 DOT values were attached to both the 1990 and 1998 samples and one set in which 1991 DOT values were attached to both samples. Column E presents cumulative log changes for the entire period.[54] Sample coefficients from the earnings regressions underlying Table 10 are found in Appendix Table B and C, and additional details of the estimation methods are found in the table notes. We note briefly that, except in the case of routine cognitive tasks, estimated earnings differentials for the DOT task measures are statistically significant and of meaningful economic magnitude at the start of our sample.[55]

In interpreting the coefficients in Table 10 it is important to keep two things in mind. First, the two measures of non-routine skills (DCP and MATH) are quite highly correlated. A consequence is

[54] We also tabulate in Appendix D estimated earnings differentials for college and high school graduates to confirm that our wage models conform to documented trends. These differentials show familiar trends. The college/high school earnings differential was smaller in 1980 than in 1970, a consequence primarily of the rapid growth during the 1970s in the supply of college-educated workers (Freeman, 1976; Katz and Murphy, 1992). The college/high school earnings differential grew markedly during the 1980s, and somewhat more slowly during the 1990s. Over the 1970s, 1980s, and 1990s, the differential between the earnings of high school graduates and those of school dropouts grew modestly.

[55] This finding reinforces our claim that the DOT measures contain meaningful variation in both job content and earnings independent of education measures.

that when we fit wage models containing all four skill measures, our estimates indicate a declining payoff to DCP over the period 1960-98. Had we omitted MATH from the model, our estimates would have indicated an increase in the payoff to DCP. For this reason in discussing trends in the payoff to cognitive skills we concentrate on the pattern for the MATH variable. Second, the entry into the labor market in the 1960s and especially in the 1970s of the large, well educated baby boom cohorts dramatically increased the supply of cognitive skills (MATH and DCP). This dampened the impact on wage differentials of growth in the demand for skills during the 1970s.

The estimates in Column E of Table 9 indicate substantial changes in the relative wage differentials associated with routine and non-routine tasks during recent decades. The wage differential associated with MATH increased enormously, while wage differentials for routine cognitive and routine manual information processing tasks fell considerably. Relative to baseline estimates in 1960 (Appendix Table b), the premium to non-routine cognitive/analytic skills more than doubled while the premium to routine cognitive and manual tasks fell cumulatively by more than 200 percent. It bears emphasis, however, that these trends are estimated with substantial imprecision and we do not place great confidence in them.

Several patterns appear clear, however. Changes in the wage premium to non-routine cognitive tasks (MATH) track changes in the overall premium to education reasonably closely. After rising in the 1960s the payoff to MATH remained quite stable in the 1970s (a decade in which the premium to education declined markedly), increased dramatically in the 1980s, and grew more slowly during the 1990s. The estimated growth in the payoff to MATH over the four decade period is about 20 percent larger when the changes in the intensive margin are taken into account. Not surprisingly, the predicted increase in the payoff to MATH over the four decades is about half as large when estimated from models that include education controls (Panel B) as it is when estimated from models without education controls (Panel A). It is striking, however, than the payoff to math skills more than doubled over the period 1960-98 when estimated from models that take account of the rising payoff to formal education (Panel B).

Of particular interest is the large drop in the premium to both routine manual and cognitive tasks. When estimated from models that used the 1991 DOT to take account of changes in skill content within occupations, the wage premium to routine tasks falls in each decade. Over the four decades, the wage premium associated with routine manual skills fell by more than 100 percent and the wage premium associated with routine cognitive tasks fell by almost 200 percent. Moreover, the declines are approximately three-quarters as large when controls for educational attainment are included in the models.[56]

The substantial declines in routine tasks premiums appear to confirm our model's prediction that computerization depresses these task differentials. One caveat, however, is that the premium to both measures of routine tasks not only fell during the decades in which computerization took place; it also fell sharply during the 1960s, prior to the advent of computerization and prior to the observed decline in routine task input.

6. Conclusions

Consistent with our conceptual framework, there have been substantial economy-wide declines over the period 1960-1998 in the percentage of the U.S. labor force engaged in routine cognitive tasks and routine manual tasks, and an increase in the percentage engaged in non-routine cognitive tasks. These compositional changes in employment are primarily driven by within-industry shifts in employment patterns starting in the 1970s. Models of the determinants of employment patterns within detailed industries indicates that proxies of computer usage and investment are able to "explain" a substantial share of the observed shifts favoring routine over non-routine tasks starting in the 1970s. This is even true among workers with the same educational attainments. It is also the case that changes in computer use within occupations predict changes in skill requirements within

[56] These changes remain significant whether or not educational measures are included in the wage models.

occupations over the period 1977-1991. Translating the compositional shifts and the within-occupation changes in skills back into educational units, our task framework explains about 40 percent of the growth in relative demand for college graduates since 1980, and about 30 percent of the growth in the relative demand for college graduates since 1970. Analysis of the labor market prices of routine and non-routine tasks provides less clear-cut results, however. While task prices move in the direction predicted by our model, limited statistical precision prevents us from drawing sharp inferences.

In several respects our task-based analysis recapitulates findings in the economic literature documenting a positive correlation between technology investments and task upgrading. However, we also present evidence that our task framework is able to explain changes in job tasks *within* education groups and within occupations, contributions that distinguish it from the existing literature. We recognize that our reliance on the Dictionary of Occupational Titles places limitations on the certainty and precision of our analysis. At the same time, we suspect that, computerization will exert an increasing influence on the shape of labor demand. For that reason, it becomes increasingly important to understand the detailed mechanisms at work. We hope that this paper represents a step in that direction.

References

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

Acemoglu, Daron. "Technical Change, Inequality, and the Labor Market." MIT Mimeo, July 2000.

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

Babbage, Henry P. "The Analytical Engine." *Proceedings of the British Association*, 1888.

Berman, Eli, John Bound, and Zvi Griliches, "Changes in the Demand for Skilled Labor within U.S. Manufacturing Industries: Evidence from the Annual Survey of Manufactures," *Quarterly Journal of Economics*, 109 (1994), 367-97.

Berman, Eli, John Bound, and Stephen Machin, "Implications of Skill-Biased Technological Change: International Evidence," *Quarterly Journal of Economics*, CXIII (1998), 113 (1998), 1245-79.

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

Bresnahan, Timothy F. "Computerization and Wage Dispersion: An Analytical Reinterpretation" *Economic Journal*, 1999**.**

Bresnahan, Timothy F., Erik Brynjolfsson, and Lorin M. Hitt "Information Technology, Workplace Organization and the Demand for Skilled Labor: Firm-Level Evidence", NBER Working Paper 7136, May 1999.

Bresnahan, Timothy F. and Manuel Trajtenberg, "General Purpose Technologies: 'Engines of Growth'?" *Journal of Econometrics*, 65 (1995), 83 – 108.

Bryjolfsson, Erik and Lorin M. Hitt, "Beyond Computation: Information Technology, Organizational Transformation and Business Performance" *Journal of Economic Perspectives*, forthcoming.

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

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

Doms, Mark, Timothy Dunne, and Kenneth R. Troske, "Workers, Wages, and Technology," *Quarterly Journal of Economics*, CXII (1997), 253-90.

England, Paula and Barbara Kilbourne (Principal Investigators), Occupational Measure from the Dictionary of Occupational Titles for 1980 Census Detailed Occupations. ICPSR #8942, Ann Arbor Michigan, 1988.

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

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

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

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

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

Heckman, James J., "Policies to Foster Human Capital", Cambridge, MA. National Bureau of Economic Research, Working Paper # 7288, August1999.

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

Hounshell, David A., *From the American System to Mass Production, 1800-1932 : The Development of Manufacturing Technology in the United States*, Baltimore: Johns Hopkins University Press, c1984.

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

Juhn, Chinhui; Murphy, Kevin M; Pierce, Brooks. "Wage Inequality and the Rise in Returns to Skill. *Journal of Political Economy*. Vol. 101 (3). June 1993, p. 410-42.

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

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

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

Lee, David S. "Wage Inequality in the United States during the 1980s: Rising Dispersion or Falling Minimum Wage?" *Quarterly Journal of Economics*. Vol. 114 (3). August 1999. p 977-1023.

Levy, Frank, Anne Beamish, Richard J. Murnane and David H. Autor, "Computerization and Skills: Examples from a Car Dealership", mimeo, MIT Department of Urban Studies and Planning, November 3, 1999.

Levy, Frank and Murnane, Richard J. "U.S. Earnings Levels and Earnings Inequality: A Review of Recent Trends and Proposed Explanations." *Journal of Economic Literature*. Vol. 30 (3). September 1992, p 1333-81.

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

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

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

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

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

Murnane, Richard J, Frank Levy and David H. Autor: "Technological Change, Computers and Skill Demands: Evidence from the Back Office of a Large Bank," mimeo, Harvard University Graduate School of Education, July 1999.

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

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

Park, Jin Heum, "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 1994.

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

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

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

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

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

Simon, Herbert A. “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, Inc.), 1960, 17 – 55.

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

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

U.S. Department of Commerce, *Fixed reproducible tangible wealth of the United States, 1925–1979*. NCN-0229 (Washington, DC: U.S. Department of Commerce, Economics and Statistics Administration, Bureau of Economic Analysis), 1999.

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

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

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

Weinberg, Bruce A. “Computer Use and the Demand for Female Workers” *Industrial and Labor Relations Review*, 55(2), 2000, 290 – 308.

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

Wolff, Edward N. “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, 1996.

Wood, Adrian, *North-South Trade, Employment, and Inequality* (Oxford: Clarendon Press, 1994).

Wood, Adrian, “Globalisation and the Rise in Labour Market Inequalities,” unpublished paper, Institute of Development Studies, University of Sussex, 1998.

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

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

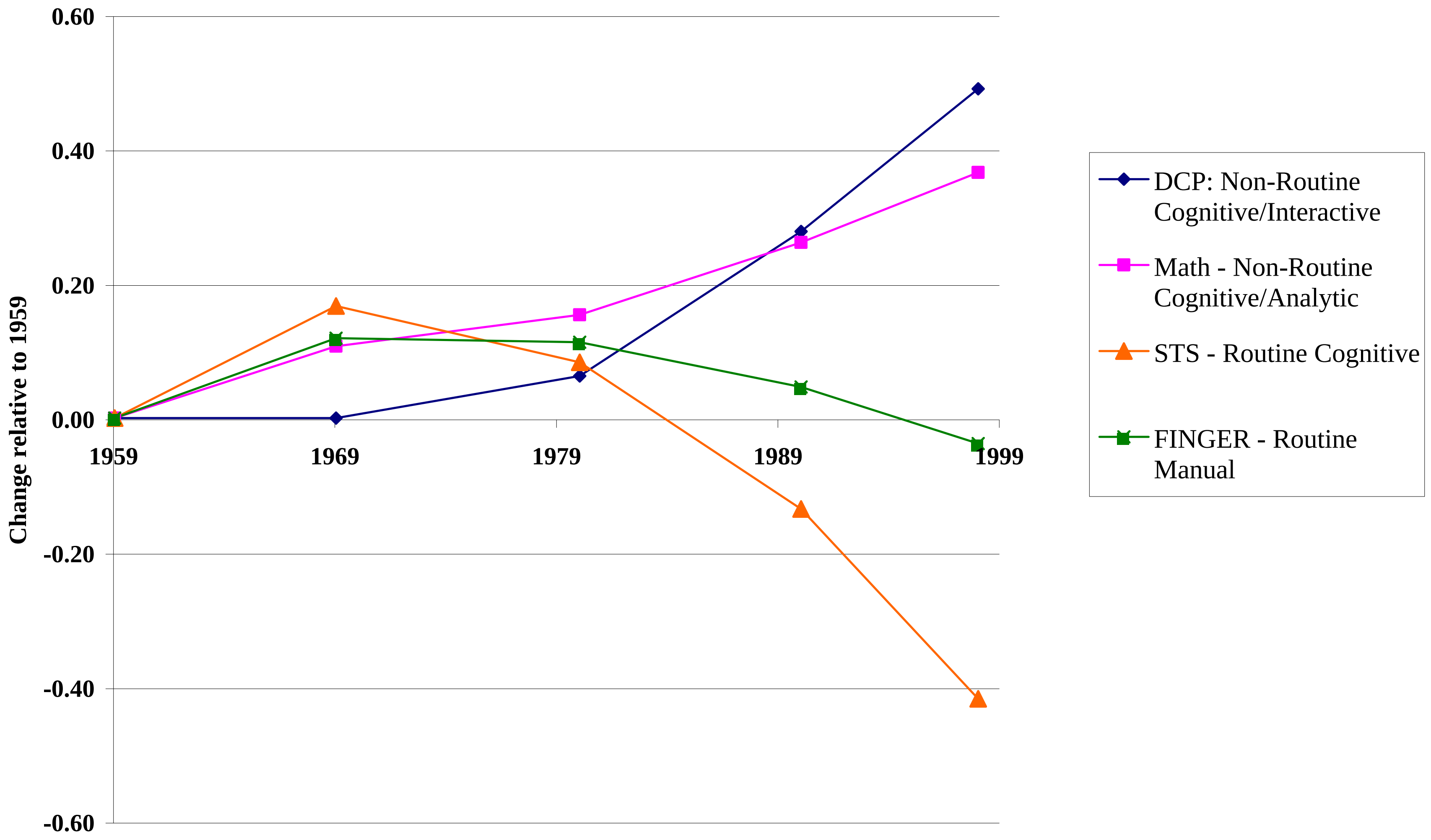

Table 1. Definitions of skill measures employed from the 1977 Dictionary of Occupational Titles.

Variable	DOT Definition	Task Framework Interpretation	Example Tasks from 1972 *Handbook for Analyzing Jobs*
1. DCP	Adaptability to accepting Responsibility for the Direction, Control, or Planning of an activity.	*Job requiring non-routine cognitive/interactive skills.*	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. GED-Math	General Educational Development - Mathematics.	*Job requiring non-routine cognitive/analytic skills.*	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. STS	Adaptability to situations requiring the precise attainment of Set limits, Tolerances, or Standards.	*Job requiring routine information processing.*	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 records.
4. FINGER	Ability to move fingers, and manipulate small objects with fingers, rapidly or accurately.	*Job requiring routine manual activity.*	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.

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

Table 2: Means of Dictionary of Occupational Titles Job Content Measures
Overall and by Gender: 1970 - 1998.

	A. DCP *(Non-Routine Cognitive/Interactive)*			C. STS *(Routine Cognitive)*		
Extensive margin only:	**All**	**Males**	**Females**	**All**	**Males**	**Females**
Census 1960 - DOT 77	2.40	2.82	1.20	4.53	4.43	4.81
Census 1970 - DOT 77	2.40	2.91	1.27	4.70	4.51	5.12
CPS 1980 - DOT 77	2.46	2.94	1.71	4.61	4.47	4.84
CPS 1990 - DOT 77	2.68	2.99	2.25	4.40	4.36	4.45
CPS 1998 - DOT 77	2.89	3.10	2.62	4.11	4.24	3.95
Extensive + Intensive margin:						
CPS 1990 - DOT 91	2.81	3.04	2.49	3.90	4.18	3.51
CPS 1998 - DOT 91	3.08	3.18	2.94	3.71	4.06	3.25

	B. Math *(Non-Routine Cognitive/Analytic)*			D. Finger *(Routine Manual)*		
Extensive margin only:	**All**	**Males**	**Females**	**All**	**Males**	**Females**
Census 1960 - DOT 77	3.61	3.81	3.05	3.78	3.60	4.29
Census 1970 - DOT 77	3.72	3.93	3.23	3.90	3.64	4.48
CPS 1980 - DOT 77	3.76	3.95	3.46	3.90	3.62	4.34
CPS 1990 - DOT 77	3.87	3.99	3.70	3.83	3.60	4.14
CPS 1998 - DOT 77	3.97	4.07	3.84	3.75	3.58	3.97
Extensive + Intensive margin:						
CPS 1990 - DOT 91	3.81	3.94	3.65	3.82	3.59	4.14
CPS 1998 - DOT 91	3.91	4.00	3.79	3.75	3.58	3.97

Sources: All employed workers ages 18 - 64, Census IPUMS 1960 and 1970, CPS MORG 1980, 1990, and 1998, and Dictionary of Occupational Titles 1977 and 1991.

Table 3. Between- and Within- Industry Decomposition of the Change in Skill Use: 1970 - 1998.
(Dependent Variable: 10 * Annualized Change in DOT Measure)

1. DCP - *Non-Routine Cognitive/Interactive*

		Btwn	*Wthin*	*Total*
A. **1960 - 70**	***Census-Census***	-0.056	0.061	0.005
B. **1970 - 80**	***Census-Census***	0.002	0.112	0.114
C. **1980 - 90**	***CPS-CPS***	0.017	0.198	0.215
D. **1990 - 98**	***CPS-CPS***	0.028	0.238	0.266
Annualized changes over 1980 - 1998:				
E. **Intensive margin only**		0.025	0.212	0.238
F. **Intensive + extensive margin**		0.029	0.312	0.341

2. Math - *Non-Routine Cognitive/Analytic*

		Btwn	*Wthin*	*Total*
A. **1960 - 70**	***Census-Census***	0.078	0.029	0.107
B. **1970 - 80**	***Census-Census***	0.069	0.026	0.095
C. **1980 - 90**	***CPS-CPS***	0.040	0.068	0.108
D. **1990 - 98**	***CPS-CPS***	0.025	0.105	0.130
Annualized changes over 1980 - 1998:				
E. **Intensive margin only**		0.035	0.082	0.118
F. **Intensive + extensive margin**		0.034	0.049	0.083

3. STS - *Routine Cognitive Activity*

		Btwn	*Wthin*	*Total*
A. **1960 - 70**	***Census-Census***	0.088	0.077	0.166
B. **1970 - 80**	***Census-Census***	0.033	-0.033	0.000
C. **1980 - 90**	***CPS-CPS***	-0.100	-0.118	-0.219
D. **1990 - 98**	***CPS-CPS***	-0.100	-0.253	-0.353
Annualized changes over 1980 - 1998:				
E. **Intensive margin only**		-0.101	-0.177	-0.278
F. **Intensive + extensive margin**		-0.099	-0.403	-0.503

4. Finger - *Routine Manual Activity*

		Btwn	*Wthin*	*Total*
A. **1960 - 70**	***Census-Census***	0.068	0.051	0.119
B. **1970 - 80**	***Census-Census***	0.024	-0.010	0.014
C. **1980 - 90**	***CPS-CPS***	-0.001	-0.066	-0.067
D. **1990 - 98**	***CPS-CPS***	-0.009	-0.097	-0.105
Annualized changes over 1980 - 1998:				
E. **Intensive margin only**		-0.005	-0.079	-0.084
F. **Intensive + extensive margin**		-0.003	-0.079	-0.082

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). Rows A - E uses DOT 1977 occupational content measures paired to Census and CPS occupation codes. Row F uses DOT 1977 occupational content measures paired to 1980 CPS MORG file and DOT 1991 occupational content measures paired to 1998 CPS MORG file.

Table 4. 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 **DCP**	**A. 1960-70**	-0.066	0.532	0.03	0.061
(Non-Routine Cognitive/Interactive)		(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)		
2. D **MATH**	**A. 1960-70**	0.016	0.055	0.00	0.029
(Non-Routine Cognitive/Analytic)		(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)		
3. D **STS**	**A. 1960-70**	0.114	-0.152	0.00	0.077
(Routine Cognitive)		(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 **FINGER**	**A. 1960-70**	0.038	0.055	0.00	0.051
(Routine manual)		(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 **College-Plus**	**A. 1960-70**	0.012	0.013	0.00	0.015
Employment share		(0.005)	(0.021)		
	B. 1970-80	0.027	0.072	0.04	0.044
		(0.008)	(0.028)		
	C. 1980-90	0.013	0.098	0.06	0.038
		(0.009)	(0.034)		
	D. 1990-98	-0.017	0.162	0.10	0.024
		(0.012)	(0.042)		

Notes. n is 140 consistent CIC industries. Standard errors are in parentheses. Weighted mean of Δ computer use 1984 - 1997 is 0.252 (using 1990 MORG weights). 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. 1960-70 and 1970-80 use Census 60, 70, and 80 IPUMS 1% samples. 1980 - 90 and 1990-98 changes use CPS MORG 80, 90 and 98 samples. Change in college-plus employment for 1990-98 in panel 5 uses Feb 1990 CPS and MORG 1998 samples.

Table 5. OLS First-Difference Estimates of Changes in Industry Task Input 1980 - 98 and Change in Industry Computer Use 1984 - 97 Incorporating Extensive and Intensive Margin of Task Change. (Dependent variables: 10 * Annual Changes)

Dep. Variable:		Intercept	D Computer Use '84-'97	R-Squared	Wtd. Mean of Dep. Var.
1. D **DCP** ***(Non-Routine Cognitive/ Interactive)***	(a) Extensive Margin Only	0.016 (0.056)	1.008 (0.268)	0.093	0.212
	(b) Intensive and Extensive Margins	-0.002 (0.079)	1.613 (0.379)	0.116	0.312
2. D **Math** ***(Non-Routine Cognitive/Analytic)***	(a) Extensive Margin Only	0.004 (0.032)	0.400 (0.154)	0.046	0.082
	(b) Intensive and Extensive Margins	-0.029 (0.035)	0.398 (0.166)	0.040	0.049
3. D **STS** ***(Routine Cognitive)***	(a) Extensive Margin Only	0.043 (0.067)	-1.128 (0.321)	0.082	-0.177
	(b) Intensive and Extensive Margins	-0.075 (0.080)	-1.682 (0.386)	0.121	-0.403
4. D **FINGER** ***(Routine Manual)***	(a) Extensive Margin Only	0.000 (0.029)	-0.402 (0.137)	0.058	-0.079
	(b) Intensive and Extensive Margins	-0.009 (0.039)	-0.359 (0.186)	0.026	-0.079

Notes. n is 140 consistent CIC industries. Standard errors are in parentheses. Dependent variables formed from CPS MORG 1980 and 1998 samples. Model (a) uses DOT 1977 job content measures with 1980 MORG file and DOT 1991 job content measures with MORG 1998 file. Model (b) uses DOT 1977 job content measures throughout. Weighted mean of change in computer use 1984-97 is 0.198, estimated as change in mean fraction of industry workers using a computer at their jobs in 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 6. OLS Stacked First-Difference Estimates of the Relationship between Computer Investment, Capital Intensivity, and Task Input in Three-Digit Industries 1960 - 1998. (10 * Annual Changes)

	1. D **DCP**		2. D **MATH**		**3.** D **STS**		**4.** D **FINGER**		**5.** D **College Employment**	
	(Non-routine Cog./Interactive)		*(Non-routine Cog./Analytic)*		*(Routine Cognitive)*		*(Routine manual)*			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Log(CI/L)	0.854	0.827	0.228	0.210	-0.676	-0.671	-0.328	-0.293	0.081	0.067
	(0.244)	(0.251)	(0.091)	(0.103)	(0.204)	(0.184)	(0.086)	(0.073)	(0.020)	(0.016)
D **Log(K/L)**		0.059		0.038		-0.012		-0.075		0.030
		(0.140)		(0.058)		(0.115)		(0.046)		(0.011)
1970-80 dummy	0.002	0.024	-0.027	-0.012	-0.040	-0.044	-0.019	-0.048	0.020	0.032
	(0.067)	(0.080)	(0.035)	(0.040)	(0.094)	(0.105)	(0.022)	(0.026)	(0.004)	(0.005)
1980-90 dummy	-0.132	-0.104	-0.032	-0.014	-0.002	-0.008	-0.024	-0.060	-0.001	0.014
	(0.117)	(0.111)	(0.048)	(0.054)	(0.116)	(0.121)	(0.031)	(0.036)	(0.006)	(0.008)
1990-98 dummy	-0.141	-0.118	-0.035	-0.019	-0.041	-0.046	-0.012	-0.042	-0.028	-0.016
	(0.108)	(0.109)	(0.047)	(0.055)	(0.111)	(0.112)	(0.039)	(0.040)	(0.008)	(0.009)
Intercept	0.473	0.435	0.152	0.126	-0.236	-0.228	-0.102	-0.053	0.055	0.035
	(0.119)	(0.132)	(0.050)	(0.063)	(0.116)	(0.110)	(0.044)	(0.036)	(0.009)	(0.009)
R-squared	0.172	0.174	0.061	0.063	0.145	0.145	0.285	0.298	0.009	0.214
Mean D Dep. Variable										
1960-70		0.064		0.042		0.089		0.055		0.016
1970-80		0.151		0.038		-0.019		0.003		0.044
1980-90		0.195		0.080		-0.122		-0.070		0.040
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. (1990-98 change in college employment uses Feb. 90 CPS and 98 CPS MORG). 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. OLS First-Difference Estimates of the Relationship between Industry Task Input within Education Groups 1980 - 1998 and Industry Computer Use 1984 - 1997 (Dependent Variables: 10 * Annual Changes)

A. High School Graduates

Dependent Variable:	**Intercept**	**D Computer Use '84-'97**	**R^2**	**Wtd. Mean of Dep. Var.**
1. D **DCP**	-0.036	0.790	0.061	0.118
(Non-routine Cog./Interactive)	(0.054)	(0.260)		
2. D **Math**	-0.073	-0.027	0.000	-0.082
(Non-routine Cog./Analytic	(0.034)	(0.163)		
3. D **STS**	0.201	-2.302	0.197	-0.286
(Routine Cognitive)	(0.083)	(0.397)		
4. D **FINGER**	0.019	-0.835	0.176	-0.144
(Routine Manual)	(0.032)	(0.154)		

B. College Graduates

Dependent Variable:	**Intercept**	**D Computer Use '84-'97**	**R^2**	**Wtd. Mean of Dep. Var.**
1. D **DCP**	-0.009	0.496	0.012	0.088
(Non-routine Cog./Interactive)	(0.081)	(0.388)		
2. D **Math**	0.000	-0.069	0.000	-0.013
(Non-routine Cog./Analytic	(0.073)	(0.352)		
3. D **STS**	-0.160	0.395	0.007	-0.083
(Routine Cognitive)	(0.083)	(0.396)		
4. D **FINGER**	-0.007	-0.154	0.009	-0.037
(Routine Manual)	(0.028)	(0.135)		

Notes. n is 137 consistent CIC industries with both College and 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 8. OLS First-Difference Estimates of Dictionary of Occupational Titles Task Content Measures within Detailed Occupations 1977 - 1991 and Occupational Computerization 1984 - 1997

	1. D **DCP** *(Non-Routine Cognitive/Interactive)*			**2.** D **MATH** *(Non-Routine Cognitive/Analytic)*			**3.** D **STS** *(Routine Cognitive)*			**4.** D **FINGER** *(Routine Motor)*		
	(a)	**(b)**	**(c)**	**(a)**	**(b)**	**(c)**	**(a)**	**(b)**	**(c)**	**(a)**	**(b)**	**(c)**
D **Computer Use 84-97**	1.22 (0.46)	1.22 (0.46)	-2.10 (1.28)	0.25 (0.13)	0.27 (0.13)	-1.03 (0.36)	-2.50 (0.59)	-2.60 (0.59)	6.72 (1.60)	-0.05 (0.13)	-0.03 0.127	-1.04 (0.35)
D **College Grad Emp. Share 84-97**		0.137 (1.21)			-0.51 (0.35)			2.72 (1.56)			-0.36 (0.33)	
D **Computer Use * Fraction of Jobs Reevaluated**			4.56 (1.70)			1.84 (0.48)			-12.92 (2.13)			1.38 (0.47)
Fraction of Jobs Reevaluated			-0.39 (0.48)			-0.50 (0.14)			2.14 (0.60)			-0.21 (0.13)
Intercept	-0.09	-0.09	0.18	-0.09	-0.08	0.25	0.01	-0.03	-1.46	-0.01	0.00	0.14
$\mathbf{R^2}$	0.01	0.01	0.03	0.01	0.01	0.03	0.03	0.04	0.11	0.00	0.00	0.02
Wtd. Mean Dep. Var.	0.20	0.20	0.20	-0.03	-0.03	-0.03	-0.59	-0.59	-0.59	-0.02	-0.02	-0.02
Implied D **due to computerization**	**0.30**	**0.29**	**0.30**	**0.06**	**0.06**	**0.08**	**-0.60**	**-0.63**	**-0.67**	**-0.01**	**-0.01**	**-0.01**

Notes. n is 470 consistent 3-digit CIC occupations. Dependent variable is the change the occupational DOT skill content measure between the DOT 1977 and DOT 1991 revisions. Fraction of jobs re-evaluated is the weighted share of DOT sub-occupations within the CIC occupation re-evaluated by DOT job analysts between 1977 and 1991 (mean 0.717). Within-occupation Δ Computer Use and Δ College Employment variables are estimated from the October 1984 and 1997 CPS files (means 0.241 and 0.024 respectively). Models are weighted by the mean occupational share of employment (in FTEs) in 1980 and 1990 Census IPUMS.

Table 9. Fixed Coefficient Demand Shift Calculations: Change in College vs. Non-College Employment due to Task Shifts Induced by Computerization: 1970 - 1998

1. 1980 - 1998 Using Change in Computer Use 1984 - 1997

1A. Change in DOT skill input measures predicted by computerization (from Tables 5 & 8)		
Variable	**Extensive Margin 1980 - 98**	**Extensive + Intensive Margin 1980 - 98**
DCP *(N.R. Cog./Interactive)*	0.353	0.655
MATH *(N.R. Cog./Analytic)*	0.140	0.218
STS *(Routine cognitive)*	-0.396	-1.063
FINGER *(Routine manual)*	-0.142	-0.147
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	0.74	2.06
2. Non-routine tasks	1.01	1.54
3. All four tasks	1.74	3.60
Observed D **College emp.**	6.83	6.83
1C. 100 *Estimated shifts in log (College/Non-College) demand		
Shift implied by DOT task D's	1.01	2.03
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 skill input measures predicted by computerization (from Tables 6 & 8)				
	Extensive Margin			**Extensive + Intensive Margin**
Variable	**1970 - 80**	**1980 - 90**	**1990 - 98**	**1980 - 98**
DCP *(N.R. Cog./Interactive)*	0.086	0.263	0.266	0.831
MATH *(N.R. Cog./Analytic)*	0.023	0.070	0.071	0.219
STS *(Routine cognitive)*	-0.068	-0.208	-0.211	-1.087
FINGER *(Routine manual)*	-0.033	-0.101	-0.102	-0.208
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	0.12	0.38	0.39	2.08
2. Non-routine tasks	0.16	0.49	0.49	1.52
3. All four tasks	0.28	0.87	0.88	3.60
Observed D **College emp.**	5.74	4.27	2.56	6.83
1D. 100 *Estimated shifts in log (College/Non-College) demand				
Shift implied by DOT task D's	0.23	0.51	0.46	2.03
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 5 and 6. Predicted changes in intensive margin (within-occupation) of DOT job skills for 1980-98 are based on Table 8. 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.

Table 10. Trends in DOT Skill Premiums, 1960 - 1998:
100 * Decadal Log Changes in Estimated Earnings Differentials

	A. 1960 - 1970 Census - Census	B. 1970 - 1980 Census - Census	C. 1980 - 1990 CPS Morg - CPS Morg		D. 1990 - 1998 Feb CPS - CPS Morg		E. Cumulative Log Change: 1960 - 1998	
	DOT '77 - DOT '77	DOT '77-DOT '77	DOT '77-DOT '77	DOT '77-DOT '91	DOT '77-DOT '77	DOT '77-DOT '91	DOT '77-DOT '77	DOT '77-DOT '91
A. No Education Controls								
	(1)	(1)	(1)	(2)	(1)	(2)	(1)	(2)
DCP ***(Non-routine Cog./Interactive)***	-0.432	-0.808	0.434	0.138	-0.170	-0.141	-0.942	-1.215
MATH ***(Non-routine Cog./Analytic)***	0.803	0.035	3.484	4.327	0.745	0.891	4.918	5.878
STS ***(Routine Cognitive)***	-0.714	-0.205	-0.638	-0.687	-0.504	-0.350	-1.960	-1.886
FINGER ***(Routine manual)***	-1.189	-1.643	0.328	-0.734	0.202	-0.673	-2.342	-4.104
B. Education Controls								
	(1)	(1)	(1)	(2)	(1)	(2)	(1)	(2)
DCP ***(Non-routine Cog./Interactive)***	-0.551	-0.468	-0.304	-0.699	-0.298	-0.283	-1.621	-1.944
MATH ***(Non-routine Cog./Analytic)***	0.533	-0.015	2.023	2.859	0.054	0.041	2.595	3.410
STS ***(Routine Cognitive)***	-0.555	-0.176	-0.305	-0.606	-0.320	-0.135	-1.356	-1.445
FINGER ***(Routine manual)***	-1.110	-1.661	-0.578	0.053	0.142	-0.803	-3.207	-3.361

Notes. Wage premiums for DOT measures are estimated from cross-section earnings regressions that include a quartic in potential experience, part-time dummy, black race, and other race dummies, 3 region dummies, a female dummy, and interactions between the female dummy, the experience quartic, the part-time dummy, and the race dummies. In addition, estimates in panel B include 3 education category dummies (high school dropout, some college, college-plus) All estimates are weighted by individual labor supply (sampling weight * hours worked in previous week * [for Census samples only] weeks worked in previous year). Estimates in column D panel B use CPS February 1990 and CPS Morg 1998 file for educational comparability.

Appendix Table 1. The DOT Occupational Characteristics Coded, 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

Definitions:

DCP - Non-routine cognitive/interpersonal activity
MATH - Non-routine cognitive/technical activity
STS - Routine cognitive activity
FINGER - Routine manual activity

	Years of Schooling	DCP	MATH	STS	EHF	FINGER	D Computer Use '84-'97	Share of Employed
1. Executive, administrative and	14.12	7.97	5.61	1.94	0.36	2.76	0.35	12.4%
2. Professional specialty occupations	15.93	4.45	5.98	3.23	1.32	4.02	0.36	12.5%
3. Technicians and related support occupations	13.70	1.69	5.77	7.69	1.15	4.88	0.24	3.0%
4. Sales occupations	13.00	2.31	4.19	1.74	0.31	3.54	0.32	9.5%
5. Administrative support occupations, including	12.62	0.86	3.51	7.51	0.15	5.01	0.30	16.3%
6. Private household occupations	9.76	0.50	1.66	0.03	1.40	2.50	0.03	0.3%
7. Protective service occupations	12.68	1.12	1.71	0.23	2.91	2.55	0.27	1.7%
8. Service occupations, except protective and	11.24	0.69	2.25	2.74	1.52	3.40	0.08	8.2%
9. Precision production, craft and repair	11.06	5.66	3.74	1.90	2.36	2.87	0.07	3.0%
10. Machine operators, assemblers, and inspectors	11.62	2.13	3.95	8.47	1.92	4.57	0.15	14.2%
11. Transportation and material moving	10.83	0.16	2.00	8.31	1.29	4.41	0.13	9.8%
12. Handlers, equipment cleaners, helpers and	11.03	0.48	1.54	2.80	4.38	2.77	0.13	5.0%
13. Farming, forestry and fishing occupations	10.75	0.09	1.36	2.68	1.44	3.27	0.11	3.9%

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

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.

Definitions:

DCP - Non-routine cognitive/interpersonal activity
MATH - Non-routine cognitive/technical activity
STS - Routine cognitive activity
FINGER - Routine manual activity

Correlations:	**DCP**	**STS**	**FIN-GER**	**MATH**	**Yrs. Ed.**	**< HS**	**HS Grad**	**Sm. Clg.**	**Clg. +**	**D Comp. Use '84-'97**
DCP	1.00									
STS	-0.31	1.00								
FINGER	-0.31	0.61	1.00							
MATH	0.59	0.04	0.27	1.00						
Yrs. Educ'n	0.40	-0.23	0.05	0.68	1.00					
< HS	-0.29	0.13	-0.10	-0.58	-0.91	1.00				
HS Grad	-0.46	0.32	0.16	-0.49	-0.51	0.16	1.00			
Sm. Clg.	0.07	-0.03	0.12	0.37	0.53	-0.75	0.07	1.00		
Clg. +	0.51	-0.30	-0.06	0.66	0.91	-0.68	-0.77	0.20	1.00	
D Comp. Use '84-'97	0.16	-0.13	0.13	0.53	0.59	-0.49	-0.39	0.32	0.54	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.

	All	Males	Females	All	Males	Females
	A. DCP (Non-routine cognitive/interpersonal)			C. STS (Routine cognitive)		
Overall	2.46	2.94	1.71	4.61	4.47	4.84
HS Dropouts	1.32	1.55	0.84	4.93	5.25	4.26
HSGraduates	1.75	2.17	1.20	5.30	5.14	5.50
Some College	2.45	2.97	1.68	4.87	4.38	5.58
College Plus	4.76	5.30	3.69	2.86	2.86	2.87
	B. Math (Non-routine cognitive/analytic)			D.Finger (Routine manual)		
Overall	3.76	3.95	3.46	3.90	3.62	4.34
HS Dropouts	2.55	2.76	2.11	3.72	3.59	4.00
HSGraduates	3.34	3.45	3.20	4.09	3.69	4.61
Some College	3.97	4.07	3.82	4.02	3.62	4.61
College Plus	5.36	5.67	4.75	3.57	3.52	3.67

Sources: CPS MORG 1998, all employed workers ages 18 - 64 and Dictionary of Occupational Titles, 1977.

Appendix Table 5. By Gender OLS First-Difference Estimates of the Relationship between Industry Skill Use 1980 - 98 and Industry Computer Use 1984 - 97

Dep. Variable:		Intercept	D Computer Use '84-'97	R^2	Wtd. Mean of Dep. Var.
1. D **DCP**	*(a) Males*	-0.181	1.585	0.143	0.128
(Non-routine		(0.069)	(0.330)		
info. Proc *					
interactions)	*(b) Females*	0.442	0.843	0.023	0.606
		(0.097)	(0.465)		
2. D **Math**	*(a) Males*	-0.068	0.317	0.023	-0.006
(Non-routine		(0.037)	(0.177)		
info. proc.)					
	(b) Females	0.056	0.397	0.023	0.133
		(0.046)	(0.223)		
3. D **STS**	*(a) Males*	-0.129	0.070	0.000	-0.115
(Routine info.		(0.073)	(0.348)		
proc.)					
	(b) Females	-0.686	-1.630	0.026	-1.003
		(0.177)	(0.850)		
4. D **FINGER**	*(a) Males*	0.074	-0.442	0.042	-0.012
(Routine		(0.037)	(0.180)		
Manual)					
	(b) Females	-0.207	-0.174	0.003	-0.241
		(0.058)	(0.279)		

Notes. n is 137 consistent CIC industries. Employment in 1980 and 1998. Standard errors are in parentheses. 1980-98 change uses CPS MORG 80 and 98 samples. 1980 levels use DOT 77 job content measures and 1998 levels use DOT 1991 job content 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).

Appendix Table 6a. Log Earnings Differentials for DOT Measures (using DOT 77 Values) by Decade, *Excluding* Educational Attainment

	A. 1960 - 1970		B. 1970 - 1980		C. 1980 - 1990		D. 1990 - 1998	
	Census 1960	Census 1970	Census 1970	Census 1980	CPS Morg 1980	CPS Morg 1990	CPS Feb 1990	CPS Morg 1998
DCP	0.033	0.028	0.023	0.015	0.005	0.010	0.009	0.008
(Non-Routine Cognitive/Interactive	(0.008)	(0.008)	(0.007)	(0.007)	(0.005)	(0.007)	(0.007)	(0.006)
MATH	0.055	0.063	0.069	0.069	0.068	0.103	0.101	0.107
(Non-Routine Cognitive/Analytical	(0.017)	(0.013)	(0.011)	(0.010)	(0.008)	(0.010)	(0.011)	(0.008)
STS	0.011	0.004	0.004	0.002	0.007	0.001	-0.002	-0.006
(Routine Cognitive)	(0.007)	(0.006)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)
FINGER	0.036	0.024	0.012	-0.004	-0.009	-0.013	-0.008	-0.006
(Routine Manual	(0.018)	(0.015)	(0.013)	(0.012)	(0.009)	(0.012)	(0.014)	(0.011)
n	456,188	540,550	540,550	771,693	183,935	176,696	14,654	138,336
Occupation clusters	202	203	408	491	408	500	449	445

Notes. Standard errors in parentheses are heteroskedasticity consistent and are adjusted for clustering of DOT variables at the 3-digit CIC occupation level. In addition to DOT variables, regressions also include 3 education category dummies (high school dropout, some college, college-plus) a quartic in experience, part-time dummy, black race, and other race dummies, 3 region dummies, a female dummy, and interactions between the female dummy, the experience quartic, the part-time dummy, and the race dummies. All estimates are weighted by individual labor supply (sampling weight * hours worked in previous week * [for Census samples only] weeks worked in previous year).

Appendix Table 6b. Log Earnings Differentials for DOT Measures (using DOT 77 Values) by Decade, *Including* Educational Attainment

	A. 1960 - 1970		B. 1970 - 1980		C. 1980 - 1990		D. 1990 - 1998	
	Census 1960	Census 1970	Census 1970	Census 1980	CPS Morg 1980	CPS Morg 1990	CPS Feb 1990	CPS Morg 1998
DCP	0.027	0.021	0.019	0.014	0.012	0.008	0.009	0.006
(Non-Routine Cognitive/Interactive	(0.008)	(0.008)	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)	(0.004)
MATH	0.022	0.027	0.031	0.031	0.039	0.059	0.060	0.060
(Non-Routine Cognitive/Analytical	(0.015)	(0.012)	(0.008)	(0.008)	(0.007)	(0.008)	(0.009)	(0.006)
STS	0.017	0.011	0.013	0.011	0.014	0.011	0.008	0.005
(Routine Cognitive)	(0.006)	(0.005)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)
FINGER	0.033	0.022	0.013	-0.004	-0.009	-0.014	-0.012	-0.011
(Routine Manual	(0.017)	(0.013)	(0.011)	(0.009)	(0.008)	(0.009)	(0.011)	(0.008)
n	456,188	540,550	540,550	771,693	183,935	176,696	14,654	138,336
Occupation clusters	202	203	408	491	408	500	449	445

Notes. Standard errors in parentheses are heteroskedasticity consistent and are adjusted for clustering of DOT variables at the 3-digit CIC occupation level. In addition to DOT variables, regressions also include 3 education category dummies (high school dropout, some college, college-plus) a quartic in experience, part-time dummy, black race, and other race dummies, 3 region dummies, a female dummy, and interactions between the female dummy, the experience quartic, the part-time dummy, and the race dummies. All estimates are weighted by individual labor supply (sampling weight * hours worked in previous week * [for Census samples only] weeks worked in previous year).

Appendix Table 6c. Log Educational Earnings Differentials 1960 - 1998.

	A. 1960 - 1970		A. 1970 - 1980		B. 1980 - 1990		C. 1990 - 1998	
	Census 1960	Census 1970	Census 1970	Census 1980	CPS Morg 1980	CPS Morg 1990	CPS Feb 1990	CPS Morg 1998
A. Estimated Log Educational Differentials by Decade								
College/HS Wage Premium	0.376	0.447	0.447	0.390	0.337	0.496	0.470	0.529
	(0.042)	(0.033)	(0.032)	(0.024)	(0.021)	(0.023)	(0.025)	(0.021)
HS Grad/Dropout Wage Premium	0.211	0.207	0.207	0.219	0.184	0.237	0.227	0.297
	(0.030)	(0.021)	(0.016)	(0.011)	(0.013)	(0.015)	(0.019)	(0.018)
Years of Schooling	0.067	0.074	0.074	0.071	0.064	0.090	0.076	0.104
	(0.009)	(0.006)	(0.005)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)
n	456,188	540,550	540,550	771,693	183,935	176,706	14,654	138,336

Notes. Standard errors in parentheses are heteroskedasticity consistent. Models also include a quartic in experience, part-time dummy, black race, and other race dummies, 3 region dummies, a female dummy, and interactions between the female dummy, the experience quartic, the part-time dummy, and the race dummies. Education category regressions contain high school dropout, some college, and college-or-greater dummies. All estimates are weighted by individual labor supply (sampling weight * hours worked in previous week * [for Census samples only] weeks worked in previous year).