# THE SKILL CONTENT OF RECENT TECHNOLOGICAL CHANGE: AN EMPIRICAL EXPLORATION*

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We apply an understanding of what computers do to study how computerization alters job skill demands. We argue that computer capital (1) substitutes for workers in performing cognitive and manual tasks that can be accomplished by following explicit rules; and (2) complements workers in performing nonroutine problem-solving and complex communications tasks. Provided that these tasks are imperfect substitutes, our model implies measurable changes in the composition of job tasks, which we explore using representative data on task input for 1960 to 1998. We find that within industries, occupations, and education groups, computerization is associated with reduced labor input of routine manual and routine cognitive tasks and increased labor input of nonroutine cognitive tasks. Translating task shifts into education demand, the model can explain 60 percent of the estimated relative demand shift favoring college labor during 1970 to 1998. Task changes within nominally identical occupations account for almost half of this impact.

## INTRODUCTION

A wealth of quantitative and case-study evidence documents a striking correlation between the adoption of computer-based technologies and the increased use of college-educated labor within detailed industries, within firms, and across plants within industries.[1] This robust correlation is frequently interpreted as evidence of skill-biased technical change. Yet, as critics point out, this interpretation merely labels the correlation without explain-

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1. Berman, Bound, and Griliches [1994], Autor, Katz, and Krueger [1998], Machin and Van Reenen [1998], Berman, Bound, and Machin [1998, 2000], and Gera, Gu, and Lin [2001] present evidence on industry level demand shifts from the United States, OECD, Canada, and other developed and developing countries. Levy and Murnane [1996], Doms, Dunne, and Troske [1997], and Bresnahan, Brynjolfsson, and Hitt [2002] provide evidence on firm and plant level shifts. Katz and Autor [1999] summarize this literature. Card and DiNardo [2002] offer a critique.


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ing its cause. It fails to answer the question of what it is that computers do—or what it is that people do with computers—that causes educated workers to be relatively more in demand.

This paper proposes an answer to this question. We formalize and test a simple theory of how the rapid adoption of computer technology—spurred by precipitous real price declines—changes the tasks performed by workers at their jobs and ultimately the demand for human skills. Our approach builds on an intuitive set of observations offered by organizational theorists, computer scientists, and most recently economists about what computers do—that is, the tasks they are best suited to accomplish—and how these capabilities complement or substitute for human skills in workplace settings.[2] The simple observations that undergird our analysis are (1) that computer capital substitutes for workers in carrying out a limited and well-defined set of cognitive and manual activities, those that can be accomplished by following explicit rules (what we term "routine tasks"); and (2) that computer capital complements workers in carrying out problem-solving and complex communication activities ("nonroutine" tasks). (See Table I for examples.) Provided that routine and nonroutine tasks are imperfect substitutes, these observations imply measurable changes in the task composition of jobs, which we test below.

To answer the core questions of our paper, the ideal experiment would provide two identical autarkic economies, one facing a dramatic decline in the price of computing power and the other not. By contrasting these economies, it would be straightforward to assess how computerization reshapes the task composition of work and hence the structure of labor demand. Because this experiment is not available, we develop a simple economic model to predict how demand for workplace tasks responds to an economywide decline in the price of computer capital. The model predicts that industries and occupations that are initially intensive in labor input of routine tasks will make relatively larger investments in computer capital as its price declines. These industries and occupations will reduce labor input of routine tasks, for which computer

2. Simon [1960] provides the first treatment of this question with which we are familiar, and his essay introduces many of the ideas explored here. Other early works include Drucker [1954] and Nelson and Winter [1982]. Adler [1986], Orr [1996], and Zuboff [1988] discuss what computers and related technology do in the workplace, but do not consider economic implications. Acemoglu [1998], Goldin and Katz [1998], Bresnahan [1999], Bartel, Ichniowski, and Shaw [2000], Lindbeck and Snower [2000], Lang [2002], and Bresnahan, Brynjolfsson, and Hitt [2002] provide economic analyses of why technology and human capital are complementary.

capital substitutes, and increase demand for nonroutine task input, which computer capital complements. In net, these forces will raise relative demand for highly educated workers, who hold comparative advantage in nonroutine versus routine tasks.

To test these predictions, we pair representative data on job task requirements from the *Dictionary of Occupational Titles (DOT)* with samples of employed workers from the Census and Current Population Survey to form a consistent panel of industry and occupational task input over the four-decade period from 1960 to 1998. A unique virtue of this database is that it permits us to analyze changes in task input within industries, education groups, and occupations—phenomena that are normally unobservable. By measuring the tasks performed in jobs rather than the educational credentials of workers performing those jobs, we believe our study supplies a missing conceptual and empirical link in the economic literature on technical change and skill demand.

Our analysis provides four main pieces of evidence supporting our model.

1) Commencing in the 1970s, labor input of routine cognitive and manual tasks in the U. S. economy declined, and labor input of nonroutine analytic and interactive tasks rose.
2) Shifts in labor input favoring nonroutine and against routine tasks were concentrated in rapidly computerizing industries. These shifts were small and insignificant in the precomputer decade of the 1960s, and accelerated in each subsequent decade.
3) The substitution away from routine and toward nonroutine labor input was not primarily accounted for by educational upgrading; rather, task shifts are pervasive at all educational levels.
4) Paralleling the within-industry task shifts, occupations undergoing rapid computerization reduced input of routine cognitive tasks and increased input of nonroutine cognitive tasks.

We consider a number of economic and purely mechanical alternative explanations for our results. Two supply side factors that we study in particular are the rising educational attainment of the workforce and the rising human capital and labor force attachment of women—both of which could potentially generate shifts in job task composition independent of demand shifts. As we show below, the task shifts that we document—and their associations with the adoption of computer technology—are as pervasive within gender, education, and occupation groups as between, indicating that these supply side forces are not the primary explanation for our results.

We begin by presenting our informal "task model" describing how computerization affects the tasks that workers and machines perform. We next formalize this model in a production framework to develop empirical implications for task demand at the industry and occupation level. Subsequent sections describe our data sources and test the model's main implications. Drawing together the empirical strands, we finally assess the extent to which changes in the task composition can account for recent demand shifts favoring more educated workers. This exercise shows that estimated task shifts are economically large, underscoring the potential of the conceptual model to reconcile key facts.

## I. The Task Model

We begin by conceptualizing work from a "machine's-eye" view as a series of tasks to be performed, such as moving an object, performing a calculation, communicating a piece of information, or resolving a discrepancy. Our model asks: which of these tasks can be performed by a computer? A general answer is found by examining what is arguably the first digital computer, the Jacquard Loom of 1801. Jacquard's invention was a machine for weaving fabrics with inlaid patterns specified by a program punched onto cards and fed into the loom. Some programs were quite sophisticated; one surviving example uses more than 10,000 cards to weave a black and white silk portrait of Jacquard himself.[3] Two centuries later, the electronic descendants of Jacquard's loom share with it two intrinsic traits. First, they rapidly and accurately perform repetitive tasks that are deterministically specified by stored instructions (programs) that designate unambiguously what actions the machine will perform at each contingency to achieve the desired result. Second, computers are "symbolic processors," acting upon abstract representations of information such as binary numbers or, in the loom's case, punched cards.

Spurred by a more than trillionfold decline in the real price of

3. The Jacquard loom was also the inspiration for Charles Babbage's analytical engine and Herman Hollerith's punch card reader, used to process the 1910 United States Census.

computing power [Nordhaus 2001], engineers have become vastly more proficient at applying the loom's basic capabilities—rapid execution of stored instructions—to a panoply of tasks. How does this advance affect the task composition of human work? The answer depends both upon how computers substitute for or complement workers in carrying out specific tasks, and how these tasks substitute for one another. We illustrate these cases by considering the application of computers to routine and nonroutine cognitive and manual tasks.

In our usage, a task is "routine" if it can be accomplished by machines following explicit programmed rules. Many manual tasks that workers used to perform, such as monitoring the temperature of a steel finishing line or moving a windshield into place on an assembly line, fit this description. Because these tasks require methodical repetition of an unwavering procedure, they can be exhaustively specified with programmed instructions and performed by machines.

A problem that arises with many commonplace manual and cognitive tasks, however, is that the procedures for accomplishing them are not well understood. As Polanyi [1966] observed, "We can know more than we can tell [p. 4] . . . The skill of a driver cannot be replaced by a thorough schooling in the theory of the motorcar; the knowledge I have of my own body differs altogether from the knowledge of its physiology; and the rules of rhyming and prosody do not tell me what a poem told me, without any knowledge of its rules [p. 20]." We refer to tasks fitting Polanyi's description as "nonroutine," that is, tasks for which the rules are not sufficiently well understood to be specified in computer code and executed by machines. Navigating a car through city traffic or deciphering the scrawled handwriting on a personal check—minor undertakings for most adults—are not routine tasks by our definition (see Beamish, Levy, and Murnane [1999] and Autor, Levy and Murnane [2002] for examples). The reason is that these tasks require visual and motor processing capabilities that cannot at present be described in terms of a set of programmable rules [Pinker 1997].[4]

Our conceptual model suggests that, because of its declining cost, computer-controlled machinery should have substantially

4. If a manual task is performed in a well-controlled environment, however, it can often be automated despite the seeming need for adaptive visual or manual processing. As Simon [1960] observed, environmental control is a substitute for flexibility.

substituted for workers in performing routine manual tasks. This phenomenon is not novel. Substitution of machinery for repetitive human labor has been a thrust of technological change throughout the Industrial Revolution [Hounshell 1985; Mokyr 1990; Goldin and Katz 1998]. By increasing the feasibility of machine substitution for repetitive human tasks, computerization furthers—and perhaps accelerates—this long-prevailing trend.

The advent of computerization also marks a qualitative enlargement in the set of tasks that machines can perform. Because computers can perform symbolic processing—storing, retrieving, and acting upon information—they augment or supplant human cognition in a large set of information-processing tasks that historically were not amenable to mechanization. Over the last three decades, computers have substituted for the calculating, coordinating, and communicating functions of bookkeepers, cashiers, telephone operators, and other handlers of repetitive information-processing tasks [Bresnahan 1999].

This substitution marks an important reversal. Previous generations of high technology capital sharply increased demand for human input of routine information-processing tasks, as seen in the rapid rise of the clerking occupation in the nineteenth century [Chandler 1977; Goldin and Katz 1995]. Like these technologies, computerization augments demand for clerical and information-processing tasks. But in contrast to its nineteenth century predecessors, it permits these tasks to be automated.

The capability of computers to substitute for workers in carrying out cognitive tasks is limited, however. Tasks demanding flexibility, creativity, generalized problem-solving, and complex communications—what we call nonroutine cognitive tasks—do not (yet) lend themselves to computerization [Bresnahan 1999]. At present, the need for explicit programmed instructions appears a binding constraint. There are very few computer-based technologies that can draw inferences from models, solve novel problems, or form persuasive arguments.[5] In the words of computer scientist Patrick Winston

5. It is, however, a fallacy to assume that a computer must reproduce all of the functions of a human to perform a task traditionally done by workers. For example, Automatic Teller Machines have supplanted many bank teller functions, although they cannot verify signatures or make polite conversation while tallying change. Closely related, computer capital may substitute for the routine components of predominantly nonroutine tasks, e.g., on-board computers that direct taxi cabs. What is required for our conceptual model is that the routine and nonroutine tasks embodied in a job are imperfect substitutes. Consequently, a decline in the price of accomplishing routine tasks does not eliminate demand for nonroutine tasks.

[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."[6]

The implication of our discussion is that because present computer technology is more substitutable for workers in carrying out routine tasks than nonroutine tasks, it is a relative complement to workers in carrying out nonroutine tasks. From a production function standpoint, outward shifts in the supply of routine informational inputs, both in quantity and quality, increase the marginal productivity of workers performing nonroutine tasks that demand these inputs. For example, comprehensive bibliographic searches increase the quality of legal research and timely market information improves the efficiency of managerial decision-making. More tangibly, because repetitive, predictable tasks are readily automated, computerization of the workplace raises demand for problem-solving and communications tasks such as responding to discrepancies, improving production processes, and coordinating and managing the activities of others. This changing allocation of tasks was anticipated by Drucker [1954] in the 1950s: "The technological changes now occurring will carry [the Industrial Revolution] a big step further. They will not make human labor superfluous. On the contrary, they will require tremendous numbers of highly skilled and highly trained men—managers to think through and plan, highly trained technicians and workers to design the new tools, to produce them, to maintain them, to direct them" [p. 22, brackets added].

Table I provides examples of tasks in each cell of our two-by-two matrix of workplace tasks (routine versus nonroutine, manual versus information processing) and states our hypothesis about the impact of computerization for each cell. The next section formalizes these ideas and derives empirical implications.[7]

6. Software that recognizes patterns (e.g., neural networks) or solves problems based upon inductive reasoning from well-specified models is under development. But these technologies have had little role in the "computer revolution" of the last several decades. As one example, current speech recognition software based on pattern recognition can recognize words and short phrases but can only process rudimentary conversational speech [Zue and Glass 2000].

7. Our focus on task shifts in the process of production within given jobs overlooks two other potentially complementary avenues by which technical

TABLE I
PREDICTIONS OF TASK MODEL FOR THE IMPACT OF COMPUTERIZATION ON FOUR CATEGORIES OF WORKPLACE TASKS

| | Routine tasks | Nonroutine tasks |
|---|---|---|
| | Analytic and interactive tasks | |
| Examples | • Record-keeping<br>• Calculation<br>• Repetitive customer service (e.g., bank teller) | • Forming/testing hypotheses<br>• Medical diagnosis<br>• Legal writing<br>• Persuading/selling<br>• Managing others |
| Computer impact | • Substantial substitution | • Strong complementarities |
| | Manual tasks | |
| Examples | • Picking or sorting<br>• Repetitive assembly | • Janitorial services<br>• Truck driving |
| Computer impact | • Substantial substitution | • Limited opportunities for substitution or complementarity |

### *I.A. The Demand for Routine and Nonroutine Tasks*

The informal task framework above implies three postulates about how computer capital interacts with human labor input.

A1. Computer capital is more substitutable for human labor in carrying out routine tasks than nonroutine tasks.

A2. Routine and nonroutine tasks are themselves imperfect substitutes.

A3. Greater intensity of routine inputs increases the marginal productivity of nonroutine inputs.

To develop the formal implications of these assumptions, we write a simple, general equilibrium production model with two

change impacts job task demands. First, innovations in the organization of production reinforce the task-level shifts that we describe above. See Adler [1986], Zuboff [1988], Levy and Murnane [1996], Acemoglu [1999], Bresnahan [1999], Bartel, Ichniowski, and Shaw [2000], Brynjolfsson and Hitt [2000], Lindbeck and Snower [2000], Mobius [2000], Thesmar and Thoenig [2000], Caroli and Van Reenen [2001], Fernandez [2001], Autor, Levy, and Murnane [2002], and Bresnahan, Brynjolfsson, and Hitt [2002] for examples. Second, distinct from our focus on process innovations, Xiang [2002] presents evidence that product innovations over the past 25 years have also raised skill demands.

task inputs, routine and nonroutine, that are used to produce output $Q$, which sells at price one. Because our discussion stresses that computers neither strongly substitute nor strongly complement nonroutine manual tasks, we consider this model to pertain primarily to routine cognitive and routine manual tasks, and nonroutine analytic and nonroutine interactive tasks.

We assume for tractability an aggregate, constant returns to scale Cobb-Douglas production function of the form,

$$Q = (L_R + C)^{1-\beta} L_N^{\beta},\ \beta \in (0,1), \tag{1}$$

where $L_R$ and $L_N$ are routine and nonroutine labor inputs and $C$ is computer capital, all measured in efficiency units. Computer capital is supplied perfectly elastically at market price $\rho$ per efficiency unit, where $\rho$ is falling exogenously with time due to technical advances. The declining price of computer capital is the causal force in our model.[8]

We assume that computer capital and labor are perfect substitutes in carrying out routine tasks. Cobb-Douglas technology further implies that the elasticity of substitution between routine and nonroutine tasks is one, and hence computer capital and nonroutine task inputs are relative complements. While the assumption of perfect substitutability between computer capital and routine task input places assumptions A1 and A2 in bold relief, the only substantive requirement for our model is that computer capital is more substitutable for routine than nonroutine tasks. Observe that routine and nonroutine tasks are $q$-complements; the marginal productivity of nonroutine tasks rises with the quantity of routine task input, consistent with assumption A3.[9]

We assume a large number of income-maximizing workers, each of whom inelastically supplies one unit of labor. Workers have heterogeneous productivity endowments in both routine and nonroutine tasks, with $E_i = [r_i, n_i]$ and $1 \geq r_i, n_i > 0\ \forall\ i$. A given worker can choose to supply $r_i$ efficiency units of routine task input, $n_i$ efficiency units of nonroutine task input, or any convex

8. Borghans and ter Weel [2002] offer a related model exploring how the declining price of computer capital affects the diffusion of computers and the distribution of wages. A key difference is that the tasks performed by computers and workers are inseparable in the Borghans-ter Weel model. Accordingly, computerization alters wage levels but does not directly change the allocation of human labor input across task types. This latter point is the focus of our model and empirical analysis.

9. Specifically, $\partial^2 Q/\partial L_N \partial(L_R + C) = \beta(1 - \beta) L_N^{\beta-1}/(L_R + C)^{\beta} > 0$.

combination of the two. Hence, $L_i = [\lambda_i r_i, (1 - \lambda_i) n_i]$, where $0 \leq \lambda_i \leq 1$. These assumptions imply that workers will choose tasks according to comparative advantage as in Roy [1951]. We adopt the Roy framework because it implies that relative task supply will respond elastically to relative wage levels. If, instead, workers were bound to given tasks, the implications of our model for task productivity would be unchanged, but technical progress, reflected by a decline in $\rho$, would not generate re-sorting of workers across jobs.

Two main conditions govern market equilibrium in this model. First, given the perfect substitutability of routine tasks and computer capital, the wage per efficiency unit of routine task input is pinned down by the price of computer capital:[10]

$$w_R = \rho. \tag{2}$$

Second, worker self-selection among occupations—routine versus nonroutine—clears the labor market.

Define the relative efficiency of individual $i$ at nonroutine versus routine tasks as $\eta_i = n_i / r_1$. Our assumptions above imply that $\eta_i \in (0,\infty)$. At the labor market equilibrium, the marginal worker with relative efficiency units $\eta^*$ is indifferent between performing routine and nonroutine tasks when

$$\eta^* = w_R/w_N. \tag{3}$$

Individual $i$ supplies routine labor ($\lambda_i = 1$) if $\eta_i < \eta^*$, and supplies nonroutine labor otherwise ($\lambda_i = 0$).

To quantify labor supply, write the functions $g(\eta)$, $h(\eta)$, which sum population endowments in efficiency units of routine and nonroutine tasks, respectively, at each value of $\eta$. Hence, $g(\eta) = \Sigma_i r_i \cdot I[\eta_i < \eta]$ and $h(\eta) = \Sigma_i n_i \cdot I[\eta_i \geq \eta]$, where $I[\cdot]$ is the indicator function. We further assume that $\eta_i$ has nonzero support at all $\eta_i \in (0,\infty)$, so that that $h(\eta)$ is continuously upward sloping in $\eta$, and $g(\eta)$ is continuously downward sloping.

Assuming that the economy operates on the demand curve, productive efficiency requires

$$w_R = \frac{\partial Q}{\partial L_R} = (1 - \beta)\theta^{-\beta} \quad \text{and} \quad w_N = \frac{\partial Q}{\partial L_N} = \beta\theta^{1-\beta}, \tag{4}$$

10. We implicitly assume that the shadow price of nonroutine tasks absent computer capital exceeds $\rho$ and hence equation (2) holds with equality. In the precomputer era it is likely that $w_R < \rho$.

where $\theta$ in this expression is the ratio of routine to nonroutine task input in production:

$$\theta \equiv (C + g(\eta^*))/h(\eta^*). \tag{5}$$

These equations provide equilibrium conditions for the model's five endogenous variables $(w_R, w_N, \theta, C, \eta)$. We use them to analyze how a decline in the price of computer capital affects task input, wages, and labor supply, beginning with the wage paid to routine task input.

It is immediate from (2) that a decline in the price of computer capital reduces $w_R$ one-for-one, $\partial(\ln w_R)/\partial(\ln \rho) = 1$, and hence demand for routine task input rises:

$$\frac{\partial \ln \theta}{\partial \ln \rho} = -\frac{1}{\beta}. \tag{6}$$

From the perspective of producers, the rise in routine task demand could be met by either an increase in $C$ or an increase in $L_R$ (or both). Only the first of these will occur, however. Because routine and nonroutine tasks are productive complements (specifically $q$-complements), the relative wage paid to nonroutine tasks rises as $\rho$ declines:

$$\frac{\partial \ln(w_N/w_R)}{\partial \ln \rho} = -\frac{1}{\beta} \quad \text{and} \quad \frac{\partial \ln \eta^*}{\partial \ln \rho} = \frac{1}{\beta}. \tag{7}$$

Consequently, marginal workers will reallocate their labor input from routine to nonroutine tasks. Increased demand for routine tasks must be met entirely by an influx of computer capital.

Hence, an exogenous decline in the price of computer capital raises the marginal productivity of nonroutine tasks, causing workers to reallocate labor supply from routine to nonroutine task input. Although routine labor input declines, an inflow of computer capital more than compensates, yielding a net increase in the intensity of routine task input in production.

### *I.B. Industry Level Implications*

Does this model have testable microeconomic implications? Because the causal force in the model is the price of computer capital, in one sense we have only a single macroeconomic time series available. However, additional leverage may be gained by considering equation (1) as representing the production function of a single industry, with distinct industries $j$ producing outputs $q_j$ that demand different mixes of routine and nonroutine tasks. We write industry $j$'s production function as

$$q_j = r_j^{1-\beta_j} n_j^{\beta_j},\ \beta_j \in (0,1), \tag{8}$$

where $\beta_j$ is the industry-specific factor share of nonroutine tasks, and $r_j$, $n_j$ denote the industry's task inputs. All industries use Cobb-Douglas technology, but industries with smaller $\beta_j$ are more routine task intensive.

We assume that consumer preferences in this economy may be represented with a Dixit-Stiglitz [1977] utility function,

$$U(q_1, q_2, \ldots, q_J) = \left(\sum_j q_j^{1-v}\right)^{1/(1-v)}, \tag{9}$$

where $0 < v < 1$. The elasticity of demand for each good is $-(1/v)$, with the market clearing price inversely proportional to the quantity produced, $p_j(q_j) \propto q_j^{-v}$.

Industry profit maximization yields the following first-order conditions for wages:

$$\rho = n_j^{\beta_j} r_j^{-\beta_j}(1 - \beta_j)(1 - v)(n_j^{\beta_j} r_j^{1-\beta_j})^{-v} \quad \text{and} \tag{10}$$

$$w_N = n^{\beta_j - 1} r^{1-\beta_j} \beta_j (1 - v)(n_j^{\beta_j} r_j^{1-\beta_j})^{-v}.$$

Rearranging to obtain factor demands gives

$$n_j = w_N^{-1/v}(\beta_j(1 - v))^{1/v} \left(\frac{w_N}{\rho} \cdot \frac{(1 - \beta_j)}{\beta_j}\right)^{((1-\beta_j)(1-v))/v} \quad \text{and} \tag{11}$$

$$r_j = \rho^{-1/v}((1 - \beta_j)(1 - v))^{1/v} \left(\frac{w_N}{\rho} \cdot \frac{(1 - \beta_j)}{\beta_j}\right)^{(\beta_j(v-1))/v}.$$

Using these equations, we obtain the following three propositions, which we test empirically below.

P1. Although all industries face the same price of computer capital, $\rho$, the degree to which industries adopt this capital as its price declines depends upon $\beta_j$. For a given price decline, the proportionate increase in demand for routine task input is larger in routine-task-intensive ($\beta_j$ small) industries, as may be seen by taking the cross-partial derivative of routine task demand with respect to $\rho$ and $\beta_j$:

$$\frac{\delta \ln r_j}{\delta \rho} = \frac{\beta_j(1-v)-1}{v\rho} < 0 \quad \text{and} \quad \frac{\delta^2 \ln r_j}{\delta \rho \delta \beta_j} = \frac{1-v}{v\rho} > 0.$$

Although we cannot observe $\beta_j$, a logical proxy for it is the observed industry level of routine task input in the precomputerization era. We therefore test whether industries that were historically (i.e., precomputer era) intensive in routine tasks adopted computer capital to a greater extent than industries that were not.

P2. Due to the complementarity between routine and nonroutine inputs, a decline in the price of computer capital also raises demand for nonroutine task input. This demand increase is proportionately larger in routine-task-intensive industries:

$$\frac{\delta \ln n_j}{\delta \rho} = \frac{(\beta_j - 1)(1-v)}{v\rho} < 0, \quad \frac{\delta^2 \ln n}{\delta \rho \delta b} = \frac{1-v}{v\rho} > 0.$$

Recall, however, that labor supply to routine tasks declines with $\rho$. Rising routine task demand must therefore be satisfied with computer capital. Hence, sectors that invest relatively more in computer capital will show a larger rise in nonroutine labor input and a larger decline in routine labor input.

P3. The previous propositions refer to industry demands. Analogously, we expect that occupations that make relatively larger investments in computer capital will show larger increases in labor input of nonroutine tasks and larger decreases in labor input of routine tasks.

## II. Empirical Implementation

Our analysis requires measures of tasks performed in particular jobs and their changes over time. We draw on information from the Fourth [1977] Edition and Revised Fourth [1991] edition of the U. S. Department of Labor's *Dictionary of Occupational Titles* (DOT). Many of the details of our data construction are provided in the Data Appendix. Here we discuss the most salient features. The U. S. Department of Labor released the first edition of the DOT in 1939 to "furnish public employment offices . . . with information and techniques [to] facilitate proper classification and placement of work seekers" [U. S. Department of Labor 1939;xi, as quoted in Miller et al. 1980]. Although the DOT was updated four times in the ensuing 60 years [1949, 1965, 1977, and 1991], its structure was little altered. Based upon first-hand observations of workplaces, Department of Labor examiners—using guidelines supplied by the *Handbook for Analyzing Jobs* [U. S. Department of Labor 1972]—evaluate more than 12,000 highly detailed occupations along 44 objective and subjective dimensions, including training times, physical demands and required worker aptitudes, temperaments, and interests.[11]

Our DOT data are based on an aggregation of these detailed occupations into three-digit Census Occupation Codes (COC), of which there are approximately 450. We append DOT occupation characteristics to the Census Integrated Public Micro Samples [IPUMS, Ruggles and Sobeck 1997] one percent extracts for 1960, 1970, 1980, and 1990, and to CPS Merged Outgoing Rotation Group (MORG) files for 1980, 1990, and 1998. We use all observations for noninstitutionalized, employed workers, ages 18 to 64. For the industry analysis, these individual worker observations are aggregated to the level of 140 consistent Census industries spanning all sectors of the economy in each year of the sample. All analyses are performed using full-time equivalent hours (FTEs) of labor supply as weights. The latter 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.

We exploit two sources of variation for measuring changing job task requirements. The first consists of changes over time in the occupational distribution of employment, holding constant task content within occupations at the DOT 1977 level. We refer to cross-occupation employment changes as "extensive" margin shifts, which we can measure consistently over the period 1960 to 1998. This variation does not, however, account for changes in task content within occupations [Levy and Murnane 1996], which we label the "intensive" margin. To measure intensive margin shifts, we analyze changes in task content measures within occupations over the period 1977 to 1991, using occupations matched between the Fourth Edition and Revised Fourth Edition of the DOT.

Although the DOT contains the best time-series on job task

11. The Department of Labor's recent successor to the DOT, O*NET, provides potentially more up-to-date information but is not suitable for time-series analysis.

requirements for detailed occupations in the United States, it also has well-known limitations [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. These shortcomings are likely to reduce the precision of our analysis.[12]

### *II.A. Selecting Measures of Routine and Nonroutine Tasks*

To identify variables that best approximate our task constructs, we reduced the DOT variables to a relevant subset using DOT textual definitions, means of DOT measures by occupation from 1970, and detailed examples of DOT evaluations from the *Handbook for Analyzing Jobs*. We selected two variables to measure nonroutine cognitive tasks, one to capture interactive, communication, and managerial skills and the other to capture analytic reasoning skills. The first codes the extent to which occupations involve Direction, Control, and Planning of activities (DCP). It takes on consistently high values in occupations requiring managerial and interpersonal tasks. The second variable, GED-MATH, measures quantitative reasoning requirements. For routine cognitive tasks, we employ the variable STS, which measures adaptability to work requiring Set limits, Tolerances, or Standards. As a measure of routine manual activity, we selected the variable FINGDEX, an abbreviation for Finger Dexterity. To measure nonroutine manual task requirements, we employ the variable EYEHAND, an abbreviation for Eye-Hand-Foot coordination. Definitions and example tasks from the *Handbook for Analyzing Jobs* are provided in Appendix 1.

A limitation of the DOT variables is that they do not have a natural scale and, moreover, cannot confidently be treated as cardinal. To address this limitation, we transformed the DOT measures into percentile values corresponding to their rank in the 1960 distribution of task input. We choose 1960 as the base period for this standardization because it should primarily reflect the distribution of tasks prior to the computer era. Consequently, all of our outcome measures may be interpreted as levels or

12. Researchers who have used the DOT to analyze changing job skill requirements include Rumberger [1981], Spenner [1983, 1990], Howell and Wolff [1991], Wolff [1996, 2002], Handel [2000], and Ingram and Neumann [2000]. What is unique to our work is the focus on routine and nonroutine tasks, and the joint analyses of the effect of computerization on task changes between and within occupations.

changes in task input relative to the 1960 task distribution, measured in "centiles."[13]

## II.B. A Predictive Test

As an initial check on our data and conceptual framework, we test the first proposition of our theoretical model: industries historically intensive in routine tasks should have adopted computer capital relatively rapidly as its price fell. To operationalize this test, we form an index of industry-level routine task intensity during the precomputer era. Using the 1960 Census data paired to our selected DOT task measures, we calculate the percentage share of routine task input in industry $j$'s total task input as, Routine Task Share$_{j,1960}$ = $100 \times r_{j,1960}/(r_{j,1960} + n_{j,1960})$, where all task measures are standardized with equal mean and variance. The numerator of this index is the sum of industry routine cognitive and routine manual task inputs, while the denominator is the sum of all five task inputs: routine cognitive and manual; nonroutine analytic, interactive, and manual. This index, which has mean 40.0 and standard deviation 5.0, should roughly correspond to $(1 - \beta_j)$ in our model.

To proxy computer adoption after 1960, we use the Current Population Survey to calculate industries' percentile rank of computer use in 1997. Although we do not have a measure of industry computer use in 1960, this was likely close to zero in all cases. Consequently, the 1997 measure should closely reflect post-1960 computer adoption.

We fit the following equation:

$$\text{(12)}\quad \text{Computer adoption}_{j,1960\text{–}1997} = \underset{(19.18)}{-24.56} + \underset{(0.48)}{1.85} \times \text{Routine Task Share}_{j,1960} \quad (n = 140, R^2 = 0.10).$$

The point estimate of 1.85 (standard error 0.48) for the routine task share variable confirms that an industry's routine task intensity in 1960 is strongly predictive of its subsequent computer adoption. Comparing two industries that in 1960 were 10 percentage points (2 standard deviations) apart in routine task input, the model predicts that by 1997, these industries would be 19 percentage points apart in the distribution of computer adop-

13. An earlier version of this paper [Autor, Levy, and Murnane 2001] employed raw DOT scores rather than the percentile measures used here. Results were qualitatively identical.

tion—approximately 13 percentage points apart in on-the-job computer use.

We have estimated many variations of this basic model to verify its robustness, including specifying the dependent variable as the level or percentile rank of industry computer use in 1984, 1997, or the average of both; scaling the routine task share measure in percentiles of the 1960 task distribution; calculating the routine task share index using task percentiles rather than task levels; and replacing the routine task index with its logarithm. These many tests provide robust support for the first proposition of our theoretical model: demand for computer capital is greatest in industries that were historically routine task intensive.

## III. Trends in Job Task Input, 1960–1998

Our model implies that the rapidly declining price of computer capital should have reduced aggregate demand for labor input of routine tasks and increased demand for labor input of nonroutine cognitive tasks. This section analyzes the evidence for such shifts.

### *III.A. Aggregate Trends*

Figure I illustrates the extent to which changes in the occupational distribution over the period 1960 to 1998 resulted in changes in the tasks performed by the U. S. labor force. This figure is constructed by pairing the selected DOT 1977 task measures with Census and CPS employment data for each decade. By construction, each task variable has a mean of 50 centiles in 1960. Subsequent points depict the employment-weighted mean of each assigned percentile over each decade.[14]

As is evident in the figure, the share of the labor force employed in occupations that made intensive use of nonroutine analytic and nonroutine interactive tasks increased substantially during the last four decades. Although both of these measures of nonroutine tasks increased in the 1960s—that is, during the

14. We do not impose an adding-up constraint across task measures—whereby total task allocation must sum to one within jobs or time periods—since this structure is not intrinsic to the DOT. It is therefore possible for the economywide average of total task input to either rise or fall. This over-time variation is modest in practice. The mean of all five task measures, equal to 50 by construction in 1960, rose slightly to 52.5 in 1980, and fell to 51.2 in 1998.

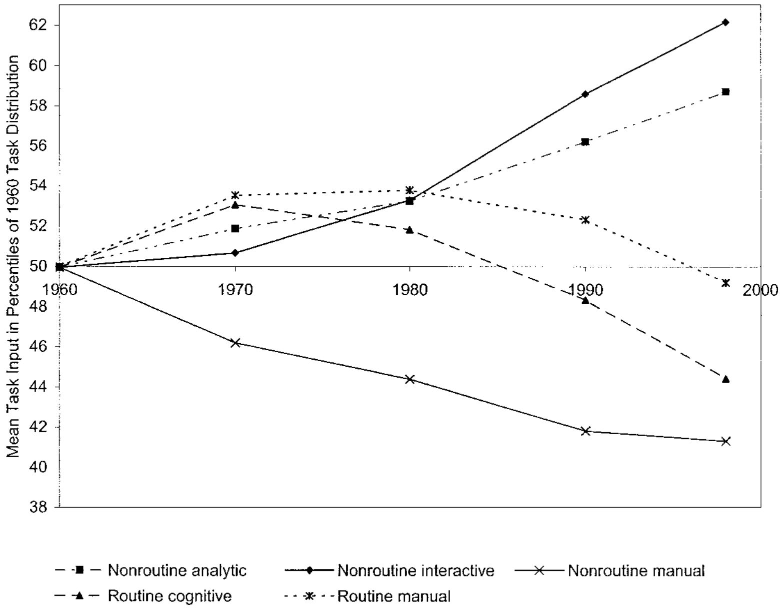


FIGURE I

Trends in Routine and Nonroutine Task Input, 1960 to 1998

Figure I is constructed using *Dictionary of Occupational Titles* [1977] task measures by gender and occupation paired to employment data for 1960 and 1970 Census and 1980, 1990, and 1998 Current Population Survey (CPS) samples. Data are aggregated to 1120 industry-gender-education cells by year, and each cell is assigned a value corresponding to its rank in the 1960 distribution of task input (calculated across the 1120, 1960 task cells). Plotted values depict the employment-weighted mean of each assigned percentile in the indicated year. See Table I and Appendix 1 for definitions and examples of task variables.

precomputer era—the upward trend in each accelerated thereafter. By 1998, nonroutine analytic task input averaged 6.8 centiles above its 1970 level and nonroutine interactive input averaged 11.5 centiles above its 1970 level.

By contrast, the share of the labor force employed in occupations intensive in routine cognitive and routine manual tasks declined substantially. Between 1970 and 1998, routine cognitive tasks declined 8.7 centiles and routine manual tasks declined by 4.3 centiles. Notably, these declines reversed an upward trend in both forms of routine task input during the 1960s. For routine cognitive tasks, this trend reversed in the 1970s, and for routine manual tasks, the trend halted in the 1970s and reversed in the 1980s.

Finally, the share of the labor force employed in occupations intensive in nonroutine manual tasks showed a secular decline across all decades. This decline was most rapid in the 1960s, and slowed considerably in subsequent decades.

Panel A of Table II provides the corresponding means of task input by decade, both in aggregate and by gender. For both males and females, there are pronounced shifts against routine cognitive, routine manual, and nonroutine manual task inputs, and pronounced shifts favoring nonroutine analytic and interactive inputs. These shifts, however, are numerically larger for females. Given the rapid entry of women into the labor force in recent decades, it appears plausible that demand shifts for workplace tasks would impact the stock of job tasks more rapidly for females than males [Goldin 1990; Weinberg 2000; Blau, Ferber, and Winkler 2002, Chapter 4]. To assess the importance of these gender differences, we estimated all of our main results separately for males and females. Because we found quite similar results for both genders, we focus below on the pooled gender samples.

To complete the picture provided by the decadal means, Figure II depicts smoothed changes in the density of the two routine and two nonroutine cognitive task measures between 1960 and subsequent decades. Three series are plotted for each task measure. Two depict extensive margin task shifts at approximately twenty-year intervals. These are measured using the 1977 DOT task measures paired to the 1960, 1980, and 1998 employment data. The third series adds intensive margin task shifts by pairing the 1991 DOT task measures with the 1998 employment data. By construction, task input is uniformly distributed across all percentiles in 1960. Hence, the height of each line in the figure represents the difference in the share of overall employment in 1980 or 1998 at each centile of 1960 task input.[15] To conserve space, we do not provide a plot of the nonroutine manual measure, since it is not the subject of subsequent analysis.

As shown in panels A and B of the figure, the distribution of nonroutine analytic and nonroutine interactive task input shifted markedly rightward after 1960. In particular, there was substantial growth in the share of employment requiring nonroutine task input above the 1960 median and a corresponding decline below

15. We apply an Epanechnikov kernel with bandwidth $h = 0.90\sigma n^{-1/5}$, where $n$ is the number of observations and $\sigma$ is the standard deviation. For our samples, this yields bandwidths between 5 and 7 centiles.

TABLE II

MEANS OF TASK INPUT BY DECADE AND DECOMPOSITION INTO WITHIN AND BETWEEN INDUSTRY COMPONENTS, 1960–1998

A. Weighted means of economywide task input by decade (percentiles of 1960 task distribution)

| | 1. Nonroutine analytic | | | 2. Nonroutine interactive | | | 3. Routine cognitive | | | 4. Routine manual | | | 5. Nonroutine manual | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | All | Male | Fem | All | Male | Fem | All | Male | Fem | All | Male | Fem | All | Male | Fem |
| 1960 (Census) | 50.0 | 54.6 | 37.0 | 50.0 | 58.4 | 26.4 | 50.0 | 48.6 | 53.8 | 50.0 | 43.2 | 69.2 | 50.0 | 56.5 | 31.6 |
| 1970 (Census) | 52.5 | 57.5 | 41.5 | 51.1 | 61.7 | 27.5 | 52.2 | 49.8 | 57.5 | 54.0 | 44.9 | 74.4 | 46.9 | 54.1 | 30.8 |
| 1970 (Census) | 51.9 | 56.4 | 41.8 | 50.7 | 60.8 | 28.1 | 53.1 | 50.8 | 58.2 | 53.5 | 44.7 | 73.3 | 46.2 | 53.2 | 30.7 |
| 1980 (Census) | 54.9 | 58.2 | 49.2 | 55.4 | 63.3 | 41.8 | 52.9 | 50.0 | 58.0 | 55.1 | 44.6 | 73.3 | 44.0 | 53.2 | 28.1 |
| 1980 (CPS) | 53.2 | 56.6 | 47.9 | 53.3 | 61.4 | 40.4 | 51.8 | 50.0 | 54.8 | 53.8 | 43.3 | 70.4 | 44.4 | 55.0 | 27.5 |
| 1990 (CPS) | 56.2 | 57.4 | 54.6 | 58.6 | 62.7 | 53.0 | 48.3 | 48.1 | 48.6 | 52.3 | 42.8 | 65.5 | 41.8 | 53.1 | 26.3 |
| 1998 (CPS) | 58.7 | 59.3 | 58.0 | 62.2 | 63.9 | 59.9 | 44.4 | 46.6 | 41.6 | 49.2 | 41.5 | 59.3 | 41.3 | 52.6 | 26.5 |

B. Decomposition of task shifts into between and within industry components for combined genders (10 × annual changes in mean task percentile)

| | Total | Btwn | Wthn | Total | Btwn | Wthn | Total | Bwtn | Wthn | Total | Btwn | Wthn | Total | Btwn | Wthn |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1960–1970 | 2.57 | 1.74 | 0.83 | 1.15 | −0.34 | 1.49 | 2.20 | 1.14 | 1.06 | 4.01 | 2.39 | 1.62 | −3.03 | −2.28 | −0.74 |
| 1970–1980 | 3.02 | 1.54 | 1.48 | 4.68 | 0.26 | 4.42 | −0.14 | 0.33 | −0.47 | 1.63 | 0.79 | 0.84 | −2.25 | −1.00 | −1.25 |
| 1980–1990 | 2.97 | 0.92 | 2.05 | 5.31 | 0.52 | 4.79 | −3.48 | −1.42 | −2.07 | −1.47 | −0.16 | −1.31 | −2.58 | −1.27 | −1.31 |
| 1990–1998 | 3.12 | 0.67 | 2.45 | 4.48 | 0.54 | 3.94 | −4.88 | −1.31 | −3.57 | −3.88 | −0.38 | −3.50 | −0.63 | −0.31 | −0.31 |

*Sources: Dictionary of Occupational Titles* [1977], and all employed workers ages 18–64, Census IPUMS 1960, 1970, 1980, CPS MORG 1980, 1990, and 1998. Samples used for decadal changes in panel B are 1960–1970, 1960 and 1970 Census; 1970–1980, 1970 and 1980 Census; 1980–1990, 1980 and 1990 CPS MORG; 1990–1998, 1990 and 1998 CPS MORG. Two Census 1970 samples are used in panels A and B, one coded for consistency with the 1960 Census occupation codes and a second coded for consistency with the 1980 Census occupation codes. Data are aggregated to 1120 industry-gender-education cells by year and each cell is assigned a value corresponding to its rank in the 1960 distribution of task input (calculated across the 1120, 1960 task cells). Panel A contains the employment-weighted mean of each assigned percentile in the indicated year. Panel B presents a decomposition of the aggregate change in task input over the indicated years into within and between industry components for 140 consistent Census Industry Code (CIC) industries (59 in manufacturing, 81 in nonmanufacturing). See Table I and Appendix 1 for definitions and examples of task variables.

the 1960 median. These shifts are visible from 1960 to 1980 and become even more pronounced by 1998. Adding variation along the intensive margin augments the rightward shift, particularly for the nonroutine interactive measure.

Panels C and D of Figure II plot the corresponding densities for routine cognitive and routine manual task input. Consistent with the theoretical model, the distribution of labor input of both routine cognitive and routine manual tasks shifted sharply leftward after 1960—opposite to the case for nonroutine tasks. The shift is particularly pronounced for the routine cognitive task measure, and becomes even more apparent when the intensive margin is added. As suggested by Figure I, the decline in the input of routine manual tasks is less dramatic, though still visible.

In sum, the evidence in Figures I and II supports our model's primary macroeconomic implications. Between 1970 and 1998 there were secular declines in labor input of routine cognitive and routine manual tasks and corresponding increases in labor input of nonroutine analytic and interactive tasks. We next analyze the sources of these task shifts at the industry level.

*III.B. Task Changes within and between Industries*

The changes in economywide labor input of routine and nonroutine tasks documented in Figure I and Table II could stem from substitution of computer capital for routine labor inputs within detailed industries, as our model suggests. Alternatively, they could stem from changes in the composition of final demand. Since much of our detailed analysis focuses on changes in task input at the industry level, we explore briefly the extent to which changes in job content are due to within-industry task shifts.

Panel B of Table II presents a standard decomposition of task changes into within- and between-industry components.[16] This decomposition shows quite consistent patterns of task change.

16. We decompose the use of task $k$ in aggregate employment between years $t$ and $\tau$ ($\Delta T_{k\tau} = T_{k\tau} - T_{kt}$) into a term reflecting the reallocation of employment across sectors and a term reflecting changes in task $j$ input within industries using the equation $\Delta T_{k\tau} = \Sigma_j(\Delta E_{j\tau}\gamma_{jk}) + \Sigma_j(\Delta\gamma_{jk\tau}E_j) = \Delta T^b_{k\tau} + \Delta T^w_{k\tau}$, where $j$ indexes industries, $E_{jk\tau}$ is the employment of workers in task $k$ in industry $j$ in year $\tau$ as a share of aggregate employment in year $\tau$, $E_{jt}$ is total employment (in FTEs) in industry $j$ in year $\tau$, $\gamma_{jk\tau}$ is the mean of task $k$ in industry $j$ in year $\tau$, $\gamma_{jk} = (\gamma_{jk\tau} + \gamma_{jkt})/2$, and $E_j = (E_{j\tau} + E_{jt})/2$. The first term ($\Delta T^b_{kt}$) reflects the change in aggregate employment of task $k$ attributable to changes in employment shares between industries that utilize different intensities of task $k$. The second term ($\Delta T^w_{kt}$) reflects within-industry task change.

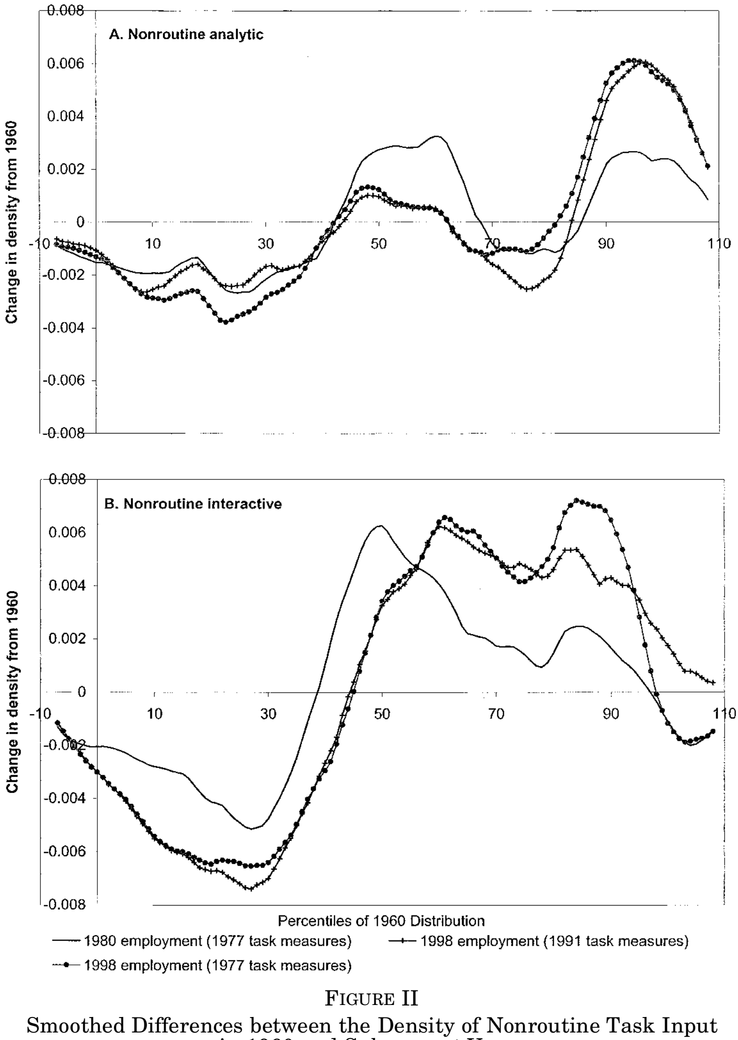


FIGURE II

Smoothed Differences between the Density of Nonroutine Task Input in 1960 and Subsequent Years

Figure II is constructed using *Dictionary of Occupational Titles* (DOT) task measures by gender and occupation paired to employment data from 1960, 1980, and 1998 Census and Current Population Survey samples. Plots depict the change in the share of employment between 1960 and the indicated year at each 1960 percentile of task input. All series use DOT 1977 data paired to employment data for the indicated year except for series marked "1991 task measures," which use task data from 1991 DOT. See Table I and Appendix 1 for definitions and examples of task variables.

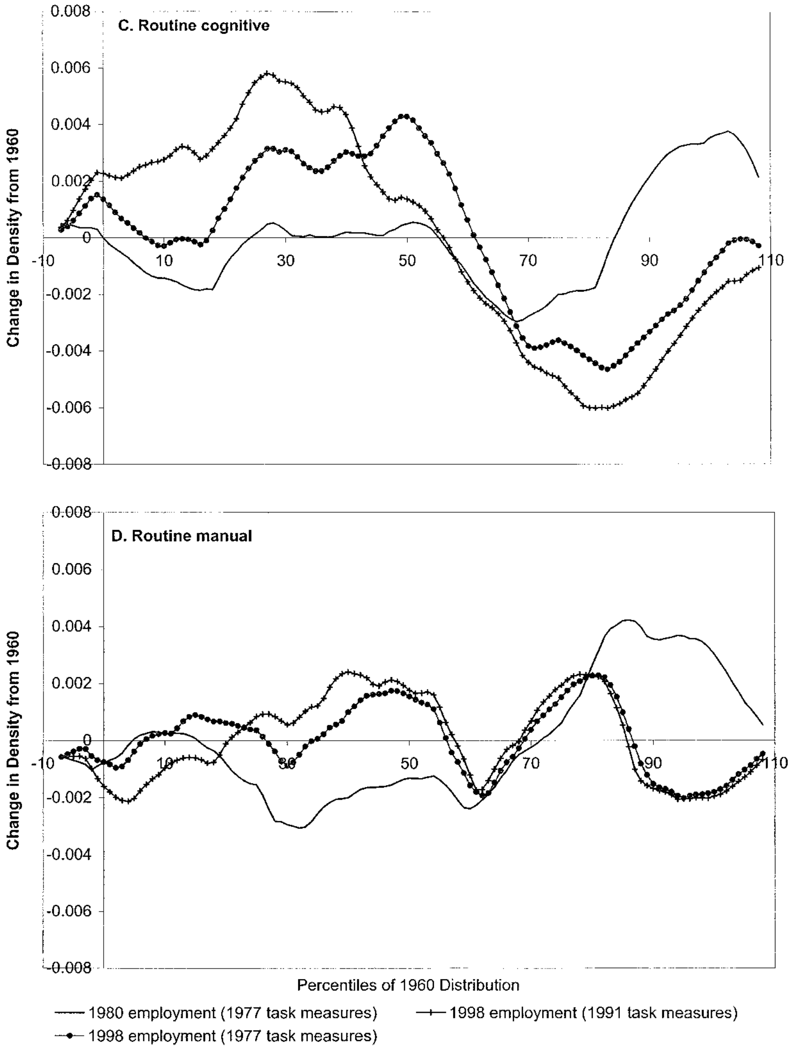


FIGURE II (CONTINUED)

Both the nonroutine analytic and nonroutine interactive task measures show strong within-industry growth in each decade following the 1960s. Moreover, the rate of within-industry growth of each input increases in each subsequent decade. Although, as noted above, nonroutine analytic input also increased during the 1960s, Table II shows that this was primarily a cross-industry phenomenon—i.e., due to sectoral shifts. After the 1960s, by contrast, the growth in nonroutine task input was dominated by within-industry task shifts.

Trends in both routine cognitive and routine manual tasks show a similarly striking pattern. Both types of routine task input increased during the 1960s, due to a combination of between- and within-industry shifts. In the decades following, however, input of both routine cognitive and routine manual tasks sharply declined, and the bulk of these declines was due to within-industry shifts. Moreover, the rate of within-industry decline increased in each subsequent decade.

As distinct from the other four task measures, we observe steady within- and between-industry shifts against nonroutine manual tasks for the entire four decades of our sample. Since our conceptual framework indicates that nonroutine manual tasks are largely orthogonal to computerization, we view this pattern as neither supportive nor at odds with our model.

In summary, the trends against routine cognitive and manual tasks and favoring nonroutine cognitive tasks that we seek to analyze are dominated by within-industry shifts, particularly from the 1970s forward. We next analyze whether computerization can explain these task shifts.[17] Because our model makes no prediction for how computerizing industries will adjust demand for nonroutine manual tasks, we do not include this variable in our industry-level analysis below (see Autor, Levy, and Murnane [2001] for detailed analysis).

## IV. Computerization and Task Change: Industry Level Relationships

As industries adopt computer technology, our model predicts that they will simultaneously reduce labor input of routine cognitive and manual tasks and increase labor input of nonroutine cognitive tasks. We test these hypotheses below.

17. Our model also implies that the expenditure shares of routine-task-intensive industries should have increased as $\rho$ declined. By contrast, the prediction for the employment share of routine-task-intensive industries is ambiguous since these industries should have differentially substituted computer capital for labor input. Because our data measure employment, not expenditures, we are unable to test the implication for expenditure shares. Closely related, computer-intensive industries should have experienced relatively larger gains in labor productivity as $\rho$ declined. Stiroh [2002] presents evidence that this occurred in the 1990s.

### IV.A. Industry Computerization and Task Trends over Four Decades

We begin by estimating a model for the within-industry relationship between computer adoption and task change over four decades. Specifically, we fit the equation

$$\Delta T_{jk\tau} = \alpha + \phi \Delta C_j + \varepsilon_{jk\tau}, \tag{13}$$

where $\Delta T_{jk\tau} = T_{jk\tau} - T_{jkt}$ is the change in industry $j$'s input of task $k$ between years $t$ and $\tau$ and $\Delta C_j$ is the annual change in the percentage of industry workers using a computer at their jobs between 1984 and 1997 (estimated from the October Current Population Survey supplements). While our model predicts that computer adoption should be highly correlated with industry task change during the computer era, we would not anticipate a similar relationship for the precomputer era of the 1960s. Accordingly, we estimate equation (13) separately for each of the four decades in our sample. This allows us to confirm that the relationship between computerization and industry task change in the 1970s–1990s does not reflect trends that predate the computer era.[18]

Estimates of equation (13) for each of the four task measures are given in Table III. The first two panels show that during the 1970s, 1980s, and 1990s, rapidly computerizing industries raised their input of nonroutine analytic and interactive tasks significantly more than others. For example, the point estimate of 12.04 (standard error of 4.74) in column 1 of panel A indicates that between 1990 and 1998, a 10 percentage point increase in computer use was associated with a 1.2 centile annualized increase in labor input of nonroutine analytic tasks. To evaluate the magnitude of this relationship, note that the mean annualized industry level rise in nonroutine analytic task input during 1990–1998, tabulated immediately below the regression estimate, was 2.5 percentiles. By comparison, the intercept of the bivariate regression for this period is 0.1. Hence, almost the entirety of the observed within-industry change in nonroutine analytic input is "explained" by the computerization measure. Similar comparisons confirm that the relationship between industry computerization and rising input of nonroutine interactive and analytic

18. As noted by Autor, Katz, and Krueger [1998] and Bresnahan [1999], the era of rapid computer investment began in the 1970s. Desktop computing became widespread in the 1980s and 1990s.

TABLE III
COMPUTERIZATION AND INDUSTRY TASK INPUT, 1960–1998
DEPENDENT VARIABLE: 10 × ANNUAL WITHIN-INDUSTRY CHANGE IN TASK INPUT, MEASURED IN PERCENTILES OF 1960 TASK DISTRIBUTION

| | | 1. 1990–1998 | 2. 1980–1990 | 3. 1970–1980 | 4. 1960–1970 |
|---|---|---|---|---|---|
| A. Δ Nonroutine analytic | Δ Computer use 1984–1997 | 12.04 | 14.02 | 9.11 | 7.49 |
| | | (4.74) | (4.97) | (4.17) | (5.28) |
| | Intercept | 0.07 | −0.66 | −0.26 | −0.55 |
| | | (1.00) | (1.03) | (0.86) | (1.05) |
| | $R^2$ | 0.04 | 0.05 | 0.03 | 0.01 |
| | Weighted mean Δ | 2.45 | 2.05 | 1.48 | 0.83 |
| B. Δ Nonroutine interactive | Δ Computer use 1984–1997 | 14.78 | 17.21 | 10.81 | 7.55 |
| | | (5.48) | (6.32) | (5.71) | (6.64) |
| | Intercept | 1.02 | 1.46 | 2.35 | 0.10 |
| | | (1.15) | (1.31) | (1.17) | (1.32) |
| | $R^2$ | 0.05 | 0.05 | 0.03 | 0.01 |
| | Weighted mean Δ | 3.94 | 4.79 | 4.42 | 1.49 |
| C. Δ Routine cognitive | Δ Computer use 1984–1997 | −17.57 | −13.94 | −11.00 | −3.90 |
| | | (5.54) | (5.72) | (5.40) | (4.48) |
| | Intercept | −0.11 | 0.63 | 1.63 | 1.78 |
| | | (1.17) | (1.19) | (1.11) | (0.89) |
| | $R^2$ | 0.07 | 0.04 | 0.03 | 0.01 |
| | Weighted mean Δ | −3.57 | −2.07 | −0.47 | 1.06 |
| D. Δ Routine manual | Δ Computer use 1984–1997 | −24.72 | −5.94 | −6.56 | 4.15 |
| | | (5.77) | (5.64) | (4.84) | (3.50) |
| | Intercept | 1.38 | −0.16 | 2.09 | 0.85 |
| | | (1.22) | (1.17) | (0.99) | (0.70) |
| | $R^2$ | 0.12 | 0.01 | 0.01 | 0.01 |
| | Weighted mean Δ | −3.50 | −1.31 | 0.84 | 1.62 |

*n* is 140 consistent CIC industries. Standard errors are in parentheses. Each column of panels A–D presents a separate OLS regression of ten times the annual change in industry-level task input between the endpoints of the indicated time interval (measured in centiles of the 1960 task distribution) on the annual percentage point change in industry computer use during 1984–1997 (mean 0.193) and a constant. Computer use is the fraction of industry workers using a computer at their jobs, estimated from the October 1984 and 1997 CPS samples. Estimates are weighted by mean industry share of total employment in FTEs over the endpoints of the years used to form the dependent variable. Samples used are Census 1960, 1970, and 1980 and CPS MORG 1980, 1990, and 1998. See Table I and Appendix 1 for definitions and examples of task variables.

tasks is economically large and statistically significant at conventional levels in each of the three most recent decades.

Panels C and D of the table provide analogous estimates for the two routine task measures. As predicted by the conceptual model, the relationships between industry computerization and changes in routine task input are uniformly negative in the 1970s, 1980s, and 1990s. These relationships are also economically large and in most cases statistically significant. For example, the computerization measure explains the entirety of the within-industry decline in routine task input during the 1990s, and more than explains this decline in the 1980s and 1970s.

A notable pattern for all four task measures is that the relationship between computerization and industry task change tends to become larger in absolute magnitude with each passing decade. This suggests a secularly rising relationship between computerization and task change. The final column of Table III tests for this rise by estimating equation (13) for the 1960s, a decade during which computerization is unlikely to have strongly influenced task demands. Reassuringly, there are no significant relationships between computerization and task change in this decade. And in one case, the coefficient is of the opposite sign as in later decades. Hence, these estimates suggest that the relationship between industry task shifts and computer adoption either commenced or substantially accelerated during the computer era, and not before.[19]

### IV.B. *Using Composite DOT Variables*

Though we view the selected task measures as the most appropriate available from the DOT, we are sensitive to the concern that the choice of variables could be viewed as arbitrary. One way to test their appropriateness is to use alternative composite variables. We used principal components analyses (PCA) to pool variation from each selected DOT task measure with several other plausible alternatives and estimated equation (13) using these composites.[20] The details of our compositing exercise are provided in the Data Appendix, and the results of the composite estimation are found in Appendix 2. A limitation of this exercise is that the variables used in the composites do not in our view

19. We also estimated the models in Table III separately by gender and for manufacturing and nonmanufacturing sectors. The pattern of results is similar in all cases. For both genders, computer investment is a significant predictor of reductions in routine labor input of cognitive and manual tasks and increases in nonroutine analytic input. For females the relationship between computerization and nonroutine interactive tasks is positive but insignificant. The magnitude of the relationship between computerization and nonroutine tasks is somewhat larger in manufacturing than nonmanufacturing, and the reverse is true for routine tasks. Further details are available from the authors.

20. The PCA extracts eigenvectors that maximize common variation among selected measures, each of which is standardized with mean zero and variance one, subject to the constraint that the sum of squared weights in the eigenvector equals one. It can be shown that if measurement error in the selected variables is classical (i.e., white noise), the PCA extracts maximal nonerror variation.

correspond as closely to the intended construct as our primary measures.

As visible in the table, the qualitative trends in the composite relationships are comparable to those using our preferred measures in Table III. In particular, industry computerization is associated with sharp declines in routine cognitive and manual labor inputs and growth in nonroutine analytic and interactive labor inputs. Moreover, these relationships typically become stronger in successive decades. Contrary to expectations, however, the composite measure for routine cognitive input is only significant in the most recent decade and the composite measure for nonroutine interactive input is statistically significant in the 1960s. Thus, while our results are generally robust to variable choice, this exercise underscores that variable choice does matter. A data source specifically designed to measure changes in workplace input of routine and nonroutine cognitive tasks over a long time horizon would clearly provide a more complete test of the model. Given the absence of such a data source for the United States, we view the evidence provided by the DOT as uniquely informative.[21]

### *IV.C. Employing Contemporaneous Measures of Computer and Capital Investment*

A limitation of the CPS computer measure used so far is that it is only available for the 1980s and 1990s. To provide more comprehensive measures of computer and capital investment available for the entire 1959–1998 period, we draw on the National Income and Product Accounts (NIPA), which provides detailed data on capital stocks across 42 major industries excluding government [U. S. Department of Commerce 2002a, 2002b]. As a measure of industry computerization, we calculated the log of real investment in computer hardware, software and peripherals per full-time equivalent employee (FTE) over the course of each decade. To distinguish the relationship between task change and computerization from overall capital-skill complementarity [Griliches 1969], we construct two variables to control for capital

21. Spitz [2003] studies the predictions of our task model using German data from 1979–1999, which contains far more detailed and precise information on workplace tasks than is available from the DOT. Consistent with the predictions of the model, Spitz reports that computer capital substitutes for repetitive manual and repetitive cognitive skills and complements analytical and interactive skills. See also Bartel, Ichniowski, and Shaw [2000] and Ichniowski and Shaw [2003] for quantitative and case study evidence.

deepening: the log of capital investment flow per worker and the log capital to labor ratio.

Using these data, we fit stacked first-difference industry task shift models of the form,

$$\Delta T_{jk\tau} = \alpha + \delta_{70-80} + \delta_{80-90} + \delta_{90-98} + \varphi CI_{j\tau} + \theta KI_{j\tau} + \varepsilon_{jk\tau}, \tag{14}$$

where $CI_{j\tau}$ is industry $j$'s real log investment in computer capital per FTE over the contemporaneous decade in industry, $KI_{j\tau}$ is the analogous measure for real capital investment, the δ's are time dummies equal to one in each of the decades post-1960 corresponding to their subscripts, and α is a common intercept. In this equation, the δ's measure the trend change in industry task input in the 1970s, 1980s, and 1990s relative to the base period of the 1960s.

Estimates of equation (14) are found in Table IV. Two sets of Huber-White standard errors are tabulated for each model. Those in parentheses account for the fact that the NIPA capital measures are observed at a more aggregate level than the dependent variables measured from the CPS and Census (42 sectors versus 123 sectors for this exercise). The standard errors in brackets additionally account for potential serial correlation in industry task changes over succeeding decades (cf. Bertrand, Duflo, and Mullainathan [2004]).

As is visible in the table, the NIPA measure of computer investment consistently predicts relative declines in industry input of both routine cognitive and manual tasks and growth in input of nonroutine analytic and interactive tasks. How large are these relationships? We can gauge the model's explanatory power by comparing the magnitude of the estimated δ's conditional on computer investment with the unconditional within-industry trends in task input observed for each decade. To facilitate this comparison, the bottom panel of Table IV tabulates the unconditional decadal trends. As with the Table III estimates, we find that industries making relatively greater investments in computer capital are responsible for the bulk of the observed substitution away from routine cognitive and manual tasks and toward nonroutine analytic and interactive tasks. Holding computer investment constant, we can explain more than 100 percent of the overall trend increase in nonroutine cognitive/analytic task input, a substantial part of the trend increase in nonroutine cognitive/interactive input, and substantial parts of the trend decreases in routine cognitive and routine manual inputs.

TABLE IV
COMPUTER INVESTMENT, CAPITAL INTENSITY, AND TASK INPUT IN THREE-DIGIT INDUSTRIES 1960–1998: STACKED FIRST-DIFFERENCE ESTIMATES
DEPENDENT VARIABLE: 10 × ANNUAL CHANGE IN QUANTILES OF TASK MEASURE, MEASURED IN PERCENTILES OF 1960 TASK DISTRIBUTION

| | A. Δ Nonroutine analytic | | B. Δ Nonroutine interactive | | C. Δ Routine cognitive | | D. Δ Routine manual | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (1) | (2) | (1) | (2) | (1) | (2) |
| Log(*Cl/L*) | 6.65 | 6.76 | 11.59 | 10.03 | −8.27 | −8.30 | −9.11 | −8.20 |
| | (4.13) | (3.97) | (3.21) | (3.31) | (3.63) | (3.26) | (2.57) | (2.29) |
| | [6.36] | [5.90] | [3.97] | [4.50] | [4.74] | [3.76] | [3.27] | [2.86] |
| Log(*Kl/L*) | 1.22 | | −3.41 | | −2.93 | | −2.42 | |
| | (4.36) | | (4.58) | | (4.76) | | (3.95) | |
| | [6.36] | | [4.45] | | [7.31] | | [5.87] | |
| Δ Log(*K/L*) | | 0.24 | | 3.01 | | −1.32 | | −3.89 |
| | | (2.35) | | (2.24) | | (2.12) | | (1.92) |
| | | [2.36] | | [2.19] | | [2.18] | | [2.38] |
| 1970–1980 dummy | −0.64 | −0.54 | 1.38 | 2.49 | −0.32 | −0.84 | 0.68 | −0.80 |
| | (1.08) | (1.29) | (1.50) | (1.62) | (1.31) | (1.58) | (0.96) | (1.17) |
| | [1.02] | [1.23] | [2.07] | [2.12] | [1.13] | [0.93] | [0.94] | [1.03] |
| 1980–1990 dummy | −0.34 | −0.25 | 0.58 | 1.83 | −1.62 | −2.14 | −1.32 | −2.90 |
| | (1.57) | (1.60) | (1.81) | (1.70) | (1.56) | (1.86) | (1.11) | (1.38) |
| | [1.43] | [1.67] | [1.58] | [1.46] | [1.33] | [1.35] | [0.86] | [1.07] |
| 1990–1998 dummy | −1.19 | −1.13 | −1.91 | −0.90 | −1.33 | −1.71 | −1.15 | −2.36 |
| | (1.55) | (1.62) | (1.83) | (1.70) | (1.66) | (1.64) | (1.32) | (1.47) |
| | [1.77] | [1.93] | [1.85] | [1.88] | [1.93] | [1.63] | [0.95] | [1.13] |
| Intercept | 8.89 | 8.23 | 12.40 | 11.30 | −9.29 | −7.09 | −9.62 | −5.55 |
| | (4.08) | (4.42) | (4.25) | (3.59) | (4.12) | (3.63) | (3.14) | (2.67) |
| | [5.45] | [6.38] | [4.76] | [4.80] | [4.48] | [4.36] | [3.75] | [3.30] |
| $R^2$ | 0.06 | 0.06 | 0.11 | 0.12 | 0.14 | 0.14 | 0.20 | 0.21 |

| | Weighted mean of dependent variable | | | |
|---|---|---|---|---|
| 1960–1970 | 1.16 | 1.74 | 1.30 | 1.63 |
| 1970–1980 | 1.23 | 4.59 | −0.20 | 0.98 |
| 1980–1990 | 2.07 | 4.69 | −2.05 | −1.74 |
| 1990–1998 | 2.15 | 3.76 | −3.03 | −2.82 |

$n = 492$. Robust standard errors in parentheses are heteroskedasticity consistent and account for clustering of errors within 42 consistent NIPA sectors in each decade (168 clusters). Standard errors in brackets additionally account for potential serial correlation within sectors (42 clusters). Each column presents a separate OLS regression of ten times annual industry changes in task input on the indicated covariates. Sample is 123 consistent CIC industries, with four observations per industry. 1960–1970 and 1970–1980 changes use Census IPUMS samples, and 1980–1990 and 1990–1998 use CPS MORG samples. Estimates are weighted by mean industry share of total employment (in FTEs) over the endpoints of the years used to form the dependent variable. All capital measures are in millions of real 1996 dollars.

Log(*Cl/L*) and Log(*Kl/L*) are, respectively, one-tenth the log of annual computer investment per FTE and total capital investment per FTE between the two end years used to form the dependent variable. Means of Log(*Cl/L*) are −1.08, −0.95, −0.87, and −0.73 in 1960–1970, 1970–1980, 1980–1990, and 1990–1998, respectively. Means of Log(*Kl/L*) are −0.57, −0.54, −0.54, and −0.52 in the corresponding years.

Δ Log(*K/L*) is ten times the annual change in log capital/FTE over the two end years used to form the dependent variable. Means are 0.43, 0.10, 0.10, and 0.24 in the corresponding years.

A notable pattern in Table IV is that the coefficients on the capital investment and capital intensity variables are economically small and in most cases insignificant. This indicates that aggregate capital deepening—apart from computer investment—explains little of the observed change in task input.[22] We have also explored a large number of variations of these models including estimating separate models for manufacturing and nonmanufacturing industries and for male and female task input; subdividing capital investment into equipment and structures investment; subdividing computer investment into hardware and software investment; and controlling for industries' log output, capital-output ratios, and import and export penetration. These tests confirm the overall robustness of our results.

## V. Task Change within Education Groups and Occupations

The analyses above establish that industries undergoing rapid computerization reduced labor input of routine cognitive and manual tasks and increased labor input of nonroutine interactive and analytic tasks. Since better educated workers are likely to hold a comparative advantage in nonroutine versus routine tasks, one interpretation of these results is that they confirm the established pattern of increasing relative educational intensity in computerizing industries over the past several decades. While we do not disagree with this interpretation, our task framework makes a broader claim, namely that changes in the demand for workplace tasks, stemming from technological change, are an underlying cause—not merely a reflection—of relative demand shifts favoring educated labor. To test this broader implication, we exploit the unique features of the DOT to analyze two novel margins of task change: changes within education groups and changes within occupations.

### *V.A. Within-Industry Task Shifts by Education Group: 1980–1998*

We showed in Tables III and IV that increased industry computerization predicts increased nonroutine cognitive activity and reduced routine cognitive and manual activities. Why does

22. This pattern echoes the findings of Berman, Bound, and Griliches [1994], Autor, Katz, and Krueger [1998], and Bresnahan, Brynjolfsson, and Hitt [2002] for skill upgrading.

this occur? One possibility is that as industries purchase computer capital, they hire better educated workers who specialize in these tasks. Alternatively, industries may change the task assignments of workers with given educational attainments, reducing their allocation to routine tasks and raising it to nonroutine tasks. We explore the relative importance of these two channels by estimating a variant of equation (13) for within-industry task upgrading by education group. Specifically, we estimate the model,

$$\Delta T_{ijk\tau} = \alpha_i + \phi_i \Delta C_j + \varepsilon_{ijk\tau}, \tag{15}$$

where the dependent variable is the within-industry change in the mean of each DOT task, measured in centiles of the 1960 distribution, among workers of the same educational attainment. In this equation, $i$ indexes each of four education groups—high school dropouts, high school graduates, some-college completers, and college graduates—and subscripts $j$, $k$, and $\tau$ refer to industries, tasks and time periods as above. We estimate this model using industry task data for 1980–1998 to exploit the (almost) contemporaneous industry computer use data for 1984–1997.

To establish a baseline for comparison, we initially estimate equation (15) for aggregate within-industry task changes over 1980–1998 (i.e., incorporating both between- and within-education group task shifts). Consistent with earlier findings, these estimates in panel A of Table V show striking correlations between industry computerization, rising labor input of routine cognitive and manual tasks, and declining labor input of nonroutine interactive and analytic tasks.

Panels B through E of Table V present analogous models estimated separately for the four education groups. Here, measured changes in task input stem solely from within-education group shifts in occupational distributions within industries. These estimates reveal that industry-level computerization is strongly predictive of shifts toward nonroutine and against routine tasks within essentially all education groups. For the two groups at the middle of the education distribution—high school graduates and those with some college—changing employment patterns within rapidly computerizing sectors entirely account for observed task shifts. More precisely, holding computer adoption fixed, our estimates would not predict any significant within-industry task change for either education group.

For the education groups at the bottom and top of the distri-

TABLE V
COMPUTERIZATION AND INDUSTRY TASK INPUT 1980–1998:
OVERALL AND BY EDUCATION GROUP
DEPENDENT VARIABLE: 10 × ANNUAL CHANGE IN QUANTILES OF TASK MEASURE,
MEASURED IN PERCENTILES OF 1960 TASK DISTRIBUTION

| | 1. Δ Nonroutine analytic | 2. Δ Nonroutine interactive | 3. Δ Routine cognitive | 4. Δ Routine manual |
|---|---|---|---|---|
| | A. Aggregate within-industry change | | | |
| Δ Computer use 1984–1997 | 12.95 | 15.97 | −15.84 | −14.32 |
| | (3.68) | (4.32) | (4.73) | (4.73) |
| Intercept | −0.33 | 1.27 | 0.38 | 0.54 |
| | (0.77) | (0.90) | (0.99) | (0.99) |
| Weighted mean task Δ | 2.20 | 4.39 | −2.71 | −2.25 |
| | B. Within industry: High school dropouts | | | |
| Δ Computer use 1984–1997 | 4.64 | 11.92 | −2.64 | −8.85 |
| | (6.07) | (8.73) | (7.95) | (6.76) |
| Intercept | −2.51 | −4.39 | 0.02 | 1.11 |
| | (1.26) | (1.82) | (1.66) | (1.41) |
| Weighted mean task Δ | −1.61 | −2.07 | −0.49 | −0.62 |
| | C. Within industry: High school graduates | | | |
| Δ Computer use 1984–1997 | 0.04 | 13.49 | −28.18 | −25.50 |
| | (4.17) | (5.40) | (6.13) | (6.05) |
| Intercept | −1.49 | 1.07 | 1.55 | 0.48 |
| | (0.87) | (1.13) | (1.28) | (1.26) |
| Weighted mean task Δ | −1.48 | 3.70 | −3.95 | −4.49 |
| | D. Within industry: Some college | | | |
| Δ Computer use 1984–1997 | 7.95 | 18.14 | −15.68 | −17.77 |
| | (5.03) | (5.54) | (5.27) | (5.61) |
| Intercept | −1.88 | −0.58 | 0.35 | 1.39 |
| | (1.05) | (1.15) | (1.10) | (1.17) |
| Weighted mean task Δ | −0.33 | 2.96 | −2.71 | −2.08 |
| | E. Within industry: College graduates | | | |
| Δ Computer use 1984–1997 | 1.61 | 5.57 | −0.78 | −4.46 |
| | (3.42) | (3.35) | (4.85) | (5.70) |
| Intercept | 0.25 | 0.10 | −0.96 | −0.12 |
| | (0.71) | (0.70) | (1.01) | (1.19) |
| Weighted mean task Δ | 0.57 | 2.22 | −1.48 | −1.98 |
| | F. Decomposition into within and between education group components | | | |
| Explained task Δ | 2.52 | 3.11 | −3.09 | −2.79 |
| Within educ groups (%) | 23.7 | 77.9 | 91.7 | 111.1 |
| Between educ groups (%) | 76.3 | 22.1 | 8.3 | −11.1 |

*n* in panels A–E is 140, 139, 140, 140, and 139 consistent CIC industries. Standard errors are in parentheses. Each column of panels A–E presents a separate OLS regression of ten times the annual change in industry-level task input for the relevant education group (measured in centiles of the 1960 task distribution) during 1980–1998 on the annual percentage point change in industry computer use during 1984–1997 (weighted mean 0.198) and a constant. Estimates are weighted by mean industry share of total employment (in FTEs) in 1980 and 1988. Industries with no employment in the relevant educational category in either 1980 or 1998 are excluded. Data sources are CPS MORG 1980 and 1998 and DOT 77 job task measures. The "explained" component in Panel F is the within-industry change in the task measure predicted by computerization in regression models in Panel A. See Table I and Appendix 1 for definitions and examples of task variables.

bution—college graduates and high school dropouts—similar patterns prevail, but they are less precisely estimated. In all cases, the estimates are of the expected sign, but none is statistically significant. For college graduates, this is likely to reflect "topping out," since this education group was already at the extreme of the distribution for all tasks. We are less certain why the relationships are weaker for high school dropouts, but one possibility is that this group has insufficient human capital to be effectively redeployed to alternative job tasks.

To assess whether these within-education group shifts are a quantitatively important component of the overall change in industry task content, panel F of Table V presents a decomposition of industry task changes into within and between education group components. This exercise shows that in every case, within-education group task upgrading explains a substantial share, 24 to 111 percent, of total task upgrading over these two decades. For example, the annual within-industry change in nonroutine interactive tasks over the period 1980–1998 is 4.4 centiles per decade, of which 3.1 centiles (71 percent) is accounted for by contemporaneous industry computerization. Within-education group task changes explain the bulk of these shifts: 78 percent of the explained component and 55 percent of the total. Subdividing the explained within-education group component further, 59 percent is due to changes in task assignment among high school graduates and those with some college, and the rest is equally accounted for by task shifts among college graduates and high school dropouts.

This exercise demonstrates that within-education group shifts in task content are the primary channel through which the structure of workplace tasks has shifted over the past two decades. Furthermore, a large portion of the within-education group changes are accounted for by cross-industry patterns of computer adoption. This suggests to us that task change is antecedent to educational upgrading, rather than merely a reflection of it.

### V.B. *Task Shifts within Occupations*

The analyses above exploit shifts in occupational composition—the extensive margin—to quantify changes in task input. This approach is imperfect since it assumes that the tasks performed within occupations are static, which is unlikely to be accurate over long time intervals. Moreover, our task framework implies that this assumption should be violated in a specific manner: occupations undergoing rapid computerization should differentially reduce labor input of routine cognitive and manual tasks and increase labor input of nonroutine cognitive tasks. To provide one example, the 1976 edition of the Department of Labor's *Occupation Outlook Handbook* described the job of Secretary as: ". . . Secretaries relieve their employers of routine duties so they can work on more important matters. Although most secretaries type, take shorthand, and deal with callers, the time spent on these duties varies in different types of organizations" [U. S. Department of Labor 1976, p. 94]. In 2000 the entry for Secretary reads: "As technology continues to expand in offices across the Nation, the role of the secretary has greatly evolved. Office automation and organizational restructuring have led secretaries to assume a wide range of new responsibilities once reserved for managerial and professional staff. Many secretaries now provide training and orientation to new staff, conduct research on the Internet, and learn to operate new office technologies" [U. S. Department of Labor 2000, p. 324].

To test whether this example captures a pervasive phenomenon, we match occupations from the 1977 and 1991 revisions of the DOT to estimate the following equation:

$$\Delta T_{mk\tau} = \alpha + \xi \Delta C_m + \varepsilon_{mk\tau}. \tag{16}$$

Here, $\Delta T_{mk\tau}$ is the change in occupational input of task $k$ between 1977 and 1991 in three-digit COC occupation $m$, and $\Delta C_m$ is the change in occupational computer penetration measured by the CPS. To provide a clean test, our data set is constructed using only the subset of occupations appearing in the 1977 DOT, which was used to create our original occupation crosswalk. Accordingly, the variation used to estimate equation (16) stems exclusively from DOT examiners' reevaluation of the task content of individual occupations between 1977 and 1991.[23]

Table VI presents three estimates for each task measure. The first column of each panel presents a bivariate regression of the within-occupation change in task content on occupational computerization and a constant. These estimates provide striking

23. The weighted fraction of employment reevaluated between 1978 and 1990 in our data is 73 percent. Occupations were chosen for reevaluation by DOT examiners partly on the expectation that their content had changed. Hence, this is not a random sample. We assume that occupations that were not revised between the 1977 and 1991 DOT experienced no task change. Provided that these occupations did not experience offsetting shifts, our approach will provide a lower bound on the extent of task change.

TABLE VI
COMPUTERIZATION AND CHANGES IN JOB TASK CONTENT WITHIN OCCUPATIONS 1977–1991
DEPENDENT VARIABLE: 10 × ANNUAL WITHIN-OCCUPATION CHANGE IN QUANTILE OF TASK MEASURE, MEASURED IN PERCENTILES OF 1984 TASK DISTRIBUTION

| | A. Δ Nonroutine analytic | | | B. Δ Nonroutine interactive | | | C. Δ Routine cognitive | | | D. Δ Routine manual | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (1) | (2) | (3) | (1) | (2) | (3) | (1) | (2) | (3) |
| Δ Computer use | 2.94 | 3.57 | 4.02 | 5.70 | 5.86 | 7.08 | −18.18 | −16.56 | −18.48 | 1.74 | 0.83 | 0.37 |
| 1984–1997 | (1.84) | (1.92) | (2.06) | (1.88) | (1.97) | (2.11) | (3.29) | (3.41) | (3.65) | (2.89) | (3.01) | (3.23) |
| Δ College grad emp. | | −4.79 | −4.83 | | −4.47 | −4.58 | | 22.59 | 22.76 | | −16.07 | −16.03 |
| 1984–1997 | | (5.54) | (5.54) | | (5.68) | (5.67) | | (9.86) | (9.85) | | (8.70) | (8.71) |
| Δ HS grad emp. | | 2.83 | 3.09 | | −0.19 | 0.52 | | 16.97 | 15.86 | | −10.42 | −10.70 |
| 1984–1997 | | (3.78) | (3.81) | | (3.88) | (3.90) | | (6.73) | (6.77) | | (5.94) | (5.99) |
| Δ Female emp. | | | −2.37 | | | −6.47 | | | 10.14 | | | 2.47 |
| 1984–1997 | | | (3.94) | | | (4.03) | | | (6.99) | | | (6.19) |
| Intercept | −0.92 | −0.91 | −0.95 | −0.46 | −0.42 | −0.52 | 0.56 | 0.14 | 0.30 | 0.42 | 0.70 | 0.74 |
| | (0.40) | (0.41) | (0.41) | (0.41) | (0.42) | (0.42) | (0.71) | (0.72) | (0.73) | (0.63) | (0.64) | (0.64) |
| $R^2$ | 0.01 | 0.01 | 0.01 | 0.02 | 0.02 | 0.03 | 0.06 | 0.08 | 0.08 | 0.00 | 0.01 | 0.01 |
| Weighted mean Δ | | −0.39 | | | 0.58 | | | −2.76 | | | 0.74 | |

$n$ is 470 consistent three-digit Census Occupation Code (COC) occupations. Standard errors are in parentheses. Each column presents a separate OLS regression of ten times the annual change in the occupational task measure (measured in centiles of the 1984 distribution) between the 1977 and 1991 DOT revisions. Computer use, college graduate, high school graduate, and female employment shares are measured as ten times the annual change in the relevant measure from the 1984 and 1997 CPS. Weighted means are 0.183, 0.017, −0.015, and 0.017, respectively. Omitted education categories are some college and high school dropout. Estimates are weighted by the average occupational share of U. S. employment in 1984 and 1997. See Table I and Appendix 1 for definitions and examples of task variables.

confirmation of the predicted relationships between computerization and task change. Occupations making relatively large increases in computer use saw relatively greater increases in labor input of nonroutine cognitive analytic and interactive tasks and larger declines in labor input of routine cognitive skills. Each of these relationships is significant at the 10 percent level or greater, and is of sizable magnitude: for all three cognitive task measures, the computerization variable more than fully accounts for the observed change in occupational task input. Only in the case of routine manual tasks, where the point estimate is close to zero, do we fail to find the expected relationship.

To examine whether intra-occupational task changes are implicitly captured by shifts in the educational and gender distribution of employees within an occupation, we add controls for the contemporaneous change in the percentage of workers in an occupation who are college graduates, high school graduates, and females.[24] As is visible in specifications 2 and 3, the relationship between computerization and within-occupation task change is surprisingly insensitive to these controls. In fact, standard measures of educational and gender composition are poor proxies for changes in job tasks observed by DOT examiners. In net, these findings demonstrate that shifts in job content away from routine tasks and toward nonroutine cognitive tasks are a pervasive feature of the data and are concentrated in industries and occupations that adopted computer technology most rapidly.

## VI. Quantifying the Magnitude of Task Structure Changes

What is the economic significance of the change in the tasks performed by the U. S. labor force during the last three decades? The answer is not immediately apparent since units of task input do not have a familiar scale. To quantify task shifts in concrete economic terms, we draw together task changes within industries, education groups, and occupations to calculate their potential contribution to the demand for college-educated labor during 1970 to 1998. This analysis proceeds in three steps.

We begin by estimating a "fixed coefficients" model of educa-

24. For consistency of measurement, we employ CPS computerization, education, and gender means by occupation for 1984 to 1997. We cannot perform an analogous exercise using the NIPA investment measures since they are not available for occupations.

tion requirements in industries and occupations as a function of their task inputs:

$$(17) \qquad \text{College Share}_j = \alpha + \sum_{k=1}^{4} \pi_k \cdot T_j^k + \varepsilon_j.$$

In this equation, College Share$_j$ is the college-equivalent share of employment (in FTEs) in industry or occupation $j$ at the midpoint of our samples, and the $T_j^k$'s measure industry or occupation task input in centiles during the same period.[25] The coefficients, $\hat{\pi}_k$, obtained from (17) provide an estimate of college-equivalent labor demand as a function of industry or occupation task inputs. We estimate this model separately for industry and occupation task demands, using employment data from our CPS samples from 1980 and 1984 paired to the 1977 DOT job task measures.[26]

We refer to equation (17) as a fixed coefficients model because it neglects the impact of task prices on task demands—or equivalently, assumes that the elasticity of substitution between college and noncollege equivalent workers is zero. This is an imperfect approximation: if the market price of nonroutine relative to routine tasks has risen, this calculation will understate demand shifts favoring nonroutine tasks and, by implication, college graduate employment.

The second step of our methodology is to translate task shifts into predicted changes in college employment. We first assemble changes in our four key task measures over 1970 to 1998, $\Delta T^k_{1970-1998}$. We then apply these task shift measures to the "fixed coefficients" estimated from equation (17) to calculate

$$(18) \qquad \tilde{\Delta}\text{College Share}_{1970-1998} = \sum_{k=1}^{4} \tilde{\pi}_k \cdot \Delta T^k_{1970-1998}.$$

Here, $\tilde{\Delta}$College Share$_{1970-1998}$ is the change in the college share of aggregate employment predicted by task shifts over 1970–1998.

25. We follow Autor, Katz, and Krueger [1998] and Murphy, Romer, and Riddell [1998] in defining college equivalent workers as all those with a college degree or greater plus half of those with some college. Results using exclusively college graduates are quite similar.

26. The industry task demand model is estimated using the 1980 MORG employment data, which is at the midpoint of our sample. The occupation task demand model is estimated using the 1984 CPS sample, which is at the midpoint of our occupation sample. For completeness, estimates of equation (17) also control for input of nonroutine manual tasks. Inclusion or exclusion of this covariate has no substantive impact.

The intuition for this calculation is that industries and occupations that are high in nonroutine cognitive task input, and low in routine manual and routine cognitive task input, employ college graduates relatively intensively. Consequently, secular increase in nonroutine cognitive task input and declines in nonroutine cognitive and manual task input over 1970–1998 will cause equation (18) to predict corresponding growth in the college graduate share of aggregate employment.

Table VII summarizes the changes in job task input due to cross-occupation (extensive margin) and within-occupation (intensive margin) shifts documented by our earlier analyses. Panel A presents observed economywide shifts in task input during the period 1970 to 1998. Panel B presents analogous numbers where in place of observed task changes, we tabulate changes in task input predicted by computerization. Specifically, we use estimates of equations (14)–(16), corresponding to the models in Tables IV–VI, to calculate the predicted mean change in each task measure due to contemporaneous industry or occupation computerization. A limitation of this approach is that it treats computerization as an exogenous determinant of industry and occupation task change. Since, as stressed above, we view computer adoption and task change as simultaneously determined, we view this exercise as primarily illustrative.

We implement these calculations in panels C and D. Panel C uses equation (18) to estimate the extent to which rising input of nonroutine tasks and declining input of routine tasks raised the college share of aggregate employment over 1970–1998. As seen in columns 1–4, observed cross-occupation (extensive margin) task changes raised college employment by 2.1 percentage points per decade between 1970 and 1998. Three-quarters of this contribution (1.5 percentage points) is due to shifts favoring nonroutine cognitive tasks. The remainder is explained by shifts against routine cognitive and manual tasks.

Columns 5–7 perform analogous calculations for 1980 to 1998. Here we add within-occupation (intensive) margin task change for 1977 to 1991. In net, shifts favoring nonroutine over routine tasks contributed 2.5 percentage points growth per decade to college-equivalent employment over these eighteen years.[27]

27. Observed intensive margin shifts did not contribute to this demand growth, however, due to the offsetting effects of routine cognitive and nonroutine analytic tasks. This stands in contrast to within-occupation task changes predicted by computerization, where intensive margin shifts are economically large.

TABLE VII
SHIFTS IN COLLEGE-EQUIVALENT LABOR DEMAND IMPLIED BY CHANGES IN JOB TASKS, 1970–1998

| | 1. 1970–1980 extensive margin | 2. 1980–1990 extensive margin | 3. 1990–1998 extensive margin | 4. 1970–1998 extensive margin | 5. 1980–1998 extensive margin | 6. 1980–1998 intensive margin | 7. 1980–1998 extensive + intensive |
|---|---|---|---|---|---|---|---|
| | A. 10 × observed annual changes in DOT task measures (percentile changes relative to 1960 task distribution) | | | | | | |
| Nonroutine analytic | 3.02 | 2.97 | 3.12 | 3.04 | 3.05 | −0.39 | 2.67 |
| Nonroutine interactive | 4.68 | 5.31 | 4.48 | 4.84 | 4.85 | 0.58 | 5.43 |
| Routine cognitive | −0.14 | −3.48 | −4.88 | −3.03 | −4.26 | −2.76 | −7.02 |
| Routine manual | 1.63 | −1.47 | −3.88 | −1.44 | −2.81 | 0.74 | −2.07 |
| | B. 10 × predicted annual changes in DOT task measures (percentile changes relative to 1960 task distribution) | | | | | | |
| | NIPA computer input measure | | | | CPS computer use measure | | |
| Nonroutine analytic | 0.84 | 1.35 | 2.30 | 1.55 | 2.56 | 0.54 | 3.10 |
| Nonroutine interactive | 1.47 | 2.36 | 4.01 | 2.70 | 3.16 | 1.04 | 4.20 |
| Routine cognitive | −1.05 | −1.68 | −2.86 | −1.92 | −3.14 | −3.32 | −6.46 |
| Routine manual | −1.15 | −1.86 | −3.15 | −2.12 | −2.84 | 0.32 | −2.52 |
| | C. 10 × predicted annual changes in college-equivalent share of employment in percentage points, due to observed task shifts (panel A) | | | | | | |
| Nonroutine tasks | 1.53 | 1.40 | 1.63 | 1.51 | 1.53 | −0.36 | 0.83 |
| Routine tasks | −0.20 | 0.66 | 1.17 | 0.50 | 0.97 | 0.27 | 0.87 |
| All tasks | 1.33 | 2.06 | 2.80 | 2.01 | 2.49 | −0.09 | 2.40 |

Panel A: Observed extensive margin task shifts are defined as the change in economywide input of each task (in percentiles of the 1960 task distribution) estimated using DOT 1977 occupational task measures applied to Census and CPS samples for 1970 to 1998 and summarized in Table II. Intensive margin shifts are measured as change in mean of DOT occupational task input (measured in centiles of the 1977 task distribution) between 1977 and 1991 DOT revisions, using the 1980 and 1998 occupational distributions of employment from the CPS MORG samples. See Table I and Appendix 1 for definitions and examples of task variables.

Panel B: Predicted task changes are calculated as the weighted mean of the NIPA computer investment measure or CPS computer use measure (as noted) multiplied by the coefficient from a regression of changes in industry or occupation task input on the relevant computer measure. NIPA coefficient estimates correspond to specification (1) of Table IV. CPS extensive margin computer task estimates correspond to Panel A of Table V. CPS intensive margin computer task estimates correspond to specification (1) of Table VI. (A negligible interaction term is ignored.)

TABLE VII
(CONTINUED)

| | 1. 1970–1980 extensive margin | 2. 1980–1990 extensive margin | 3. 1990–1998 extensive margin | 4. 1970–1998 extensive margin | 5. 1980–1998 extensive margin | 6. 1980–1998 intensive margin | 7. 1980–1998 extensive + intensive |
|---|---|---|---|---|---|---|---|
| | D. 10× annual changes in college-equivalent share of employment in percentage points, predicted by impact of computerization on task input (panel B) | | | | | | |
| | NIPA computer investment measure | | | | CPS computer use measure | | |
| Nonroutine tasks | 0.40 | 0.65 | 1.10 | 0.69 | 1.41 | 0.40 | 1.81 |
| Routine tasks | 0.29 | 0.48 | 0.81 | 0.51 | 0.80 | 1.04 | 1.84 |
| All tasks | 0.70 | 1.12 | 1.91 | 1.19 | 2.21 | 1.44 | 3.65 |
| | E. Estimated log demand shifts for college-equivalent/noncollege-equivalent labor 1970–1998 (100 × annual log changes) | | | | | | |
| | Using constant-elasticity of substitution model to estimate changes in college demand | | | | | | |
| $\sigma = 0.0$ | 4.99 | 2.53 | 2.25 | 3.33 | | | 2.41 |
| $\sigma = 1.4$ | 3.95 | 4.65 | 2.76 | 3.86 | | | 3.81 |
| $\sigma = 2.0$ | 3.50 | 5.56 | 2.98 | 4.09 | | | 4.41 |
| | Using task model to predict changes in college demand | | | | | | |
| Total task Δ (panel C) | 1.23 | 1.29 | 1.43 | 1.31 | 1.56 | −0.06 | 1.51 |
| Predicted by computerization (panel D) | 0.64 | 0.70 | 0.98 | 0.76 | 1.39 | 0.91 | 2.29 |

Panels C and D: Implied employment share changes for college-equivalent labor (in percentage points) are calculated as the inner product of observed or predicted changes in task input from panels A and B and the coefficient vector from a fixed coefficient model of educational input. For extensive margin task shifts, this coefficient vector is estimated from a regression of college equivalent employment (in FTEs) in 140 consistent CIC industries on the five DOT measures of industry task input (in centiles) and a constant using the 1980 MORG sample. For intensive margin task shifts, the coefficient vector is estimated from a regression of college equivalent employment in 470 COC occupations on the five DOT measures of occupational task input (in centiles) and a constant using the 1984 CPS sample. College-equivalents labor is defined as all workers with college or greater education plus half of those with some college.

Panel E: Fixed coefficients log relative demand shifts are calculated as the change in the log ratio of college-equivalent/noncollege-equivalent employment using the initial (1970, 1980, or 1990) college-equivalent/equivalent employment share in full-time equivalents and the implied percentage point change in this share from Panels C and D.

Constant Elasticity of Substitution (CES) implied relative demand shifts for college-equivalent labor are calculated following Autor, Katz, and Krueger [1998] using a CES aggregate production function with two inputs, college and high school equivalents, and an elasticity of substitution denoted by $\sigma$. See Table II of Autor, Katz, and Krueger for details.

We next estimate the contribution of task changes attributable to computerization to growth in college graduate employment. These estimates, shown in panel D, implement equation (18) using the within-industry and within-occupation task shifts predicted by computerization (panel B). The estimates of the "computer-induced" changes in college employment are comparable in magnitude to, and in some cases larger than, the analogous estimates based on observed task inputs. We find, for example, that computer-induced task changes along the extensive margin contributed 1.2 percentage points per decade to growth in college employment during 1970 to 1998, and 2.2 percentage points during 1980 to 1998. Adding intensive margin task changes raises this estimate considerably. In net, we estimate that task shifts attributable to computerization increased college employment by 3.7 percentage points per decade from 1980 to 1998.

The final step of our estimation is to benchmark employment changes induced by shifting task demands against conventional estimates of demand for college labor calculated for the same period. For this benchmarking exercise, we use the familiar constant elasticity of substitution (CES) framework with two factors of production—college equivalent and high school equivalent labor—to estimate log relative demand shifts favoring college labor during 1970 to 1998. Under the assumptions that the economy operates on the demand curve and that factors are paid their marginal products, the CES model calculates the implied shift in college/noncollege relative demand consistent with observed shifts in relative employment and earnings of college versus noncollege workers.[28] This procedure also requires us to assume an elasticity of substitution, $\sigma$, between college and high school equivalent workers. Following a large literature, we use values of $\sigma$, ranging from 0 to 2, with a consensus estimate of $\sigma = 1.4$.

Panel E of the table presents the benchmark CES estimates for the period 1970 to 1998. We calculate that relative demand for

28. The demand model is $Q_t = [\alpha_t(a_t N_{ct})^\rho + (1 - \alpha_t)(b_t N_{ht})^\rho]^{1/\rho}$, where $Q$ is aggregate output, $N_{ct}$, $N_{ht}$ are quantities of employed college and high school equivalent labor, $a_t$, $b_t$ are factor-augmenting technological parameters, $\alpha$ is an index of the share of work activities allocated to college versus high school labor, and the elasticity of substitution is given by $\sigma = 1/(1 - \rho)$. The demand index is $D_t = \sigma \ln(\alpha_t/[1 - \alpha_t]) + (\sigma - 1)\ln(a_t/b_t)$. Katz and Murphy [1992], Johnson [1997], Murphy, Romer, and Riddell [1999], and Acemoglu [2002] implement similar models. Our estimates are based on Table II of Autor, Katz, and Krueger [1998] and updated in 1998 (from 1996) for this analysis. Unlike these authors, we also include estimates for $\sigma = 0$ since our fixed coefficients model incorporates this assumption.

college-educated labor grew rapidly between 1970 and 1998. Using the consensus value of $\sigma = 1.4$, we estimate that demand for college labor rose by 3.9 log points annually. If we instead assume that $\sigma = 0$, we obtain a smaller—though still quite rapid—demand shift of 3.3 log points annually.[29]

In the bottom of panel E we finally compare our task-based demand estimates with the CES-based numbers. To facilitate comparison, we convert predicted changes in the college employment level (panels C and D) into changes in log relative college-equivalent/noncollege employment. As noted above, this task-based calculation ignores wage changes and hence corresponds to an elasticity of substitution of $\sigma = 0$. It is therefore useful to compare the task-based demand estimates to the corresponding CES numbers using both the consensus elasticity of $\sigma = 1.4$ and the more comparable, albeit less realistic, value of $\sigma = 0$.

As is visible in panel E, the task model explains a sizable share—25 to 65 percent—of the estimated growth in college-equivalent/noncollege-equivalent demand in each decade. Consistent with the accelerating rate of task change shown in Figure I, the smallest share of the overall demand shift is explained by task shifts in the 1970s and the largest share in the 1990s.

Comparing task changes potentially attributable to computerization to the CES demand index for these three decades, we find that these extensive margin task changes explain 20 to 25 percent of the estimated demand shift for college versus noncollege labor during 1970 to 1998. If we focus on only the two most recent decades and include both intensive and extensive margin changes, the task model can explain a large fraction—60 to 90 percent—of the estimated increase in relative demand for college employment. Notably, almost 40 percent of the computer contribution to rising educational demand in the last two decades is due to shifts in task composition within nominally unchanging occupations.

In net, these illustrative calculations demonstrate that changes in task demands accompanying workplace computerization are economically large and—with caveats noted—could have contributed substantially to relative demand shifts favoring educated labor in the United States since 1970.

29. The estimated demand shift is smaller in the latter calculation because a higher value of $\sigma$ places greater weight on relative wage changes, and the relative earnings of college graduates rose rapidly after 1980.

## VII. Conclusion

What is it that computers do—or what is it that people do with computers—that appears to increase demand for educated workers? This paper formalizes and tests an intuitive answer to this question that has been informally articulated by scholars in a number of disciplines over several decades. Computer technology substitutes for workers in performing routine tasks that can be readily described with programmed rules, while complementing workers in executing nonroutine tasks demanding flexibility, creativity, generalized problem-solving capabilities, and complex communications. As the price of computer capital fell precipitously in recent decades, these two mechanisms—substitution and complementarity—have raised relative demand for workers who hold a comparative advantage in nonroutine tasks, typically college-educated workers.

Our task framework emphasizes that the causal force by which advancing computer technology affects skill demand is the declining price of computer capital—an economywide phenomenon. We developed a simple model to explore how this price decline alters task demand within industries and occupations. This model predicts that industries that were intensive in labor input of routine tasks in the precomputer era would make relatively larger investments in computer capital. Simultaneously, they would reduce labor input of routine tasks, for which computer capital substitutes, and increase demand for nonroutine task input, which computer capital complements.

Employing consistent, representative, time series observations on the task composition of jobs from the *Dictionary of Occupational Titles,* we affirm these predictions across several margins of task change and estimate that they may have contributed substantially to demand shifts favoring educated labor over the past three decades. We also considered several alternative explanations for our findings, most significantly the rising human capital and labor force attachment of women. We find that the documented task shifts, and their associations with the adoption of computer technology, are as evident *within* gender, education, and occupation groups as between them. The pervasiveness of these shifts suggests to us that changes in job task content—spurred by technological change—may plausibly be viewed as an underlying factor contributing to recent demand shifts favoring educated labor.

APPENDIX 1: DEFINITIONS OF TASK MEASURES FROM THE 1977 DICTIONARY OF OCCUPATIONAL TITLES

| Variable | DOT definition | Task interpretation | Example tasks from *Handbook for Analyzing Jobs* |
|---|---|---|---|
| 1. GED Math (MATH) | General educational development, mathematics | Measure of nonroutine analytic tasks | Lowest level: Adds and subtracts 2-digit numbers; performs operations with units such as cup, pint, and quart. Midlevel: 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 oversees analyses of aerodynamic and thermodynamic systems . . . to determine suitability of design for aircraft and missiles. |
| 2. Direction, Control, Planning (DCP) | Adaptability to accepting responsibility for the direction, control, or planning of an activity | Measure of nonroutine interactive tasks | Plans and designs private residences, office buildings, factories, and other structures; applies principles of accounting to install and maintain operation of general accounting system; conducts prosecution in court proceedings . . . gathers and analyzes evidence, reviews pertinent decisions . . . appears against accused in court of law; commands fishing vessel crew engaged in catching fish and other marine life. |
| 3. Set Limits, Tolerances, or Standards (STS) | Adaptability to situations requiring the precise attainment of set limits, tolerances, or standards | Measure of routine cognitive tasks | Operates a billing machine to transcribe from office records data; calculates degrees, minutes, and second of latitude and longitude, using standard navigation aids; measures dimensions of bottle, using gauges and micrometers to verify that setup of bottle-making conforms to manufacturing specifications; prepares and verifies voter lists from official registration records. |
| 4. Finger Dexterity (FINGDEX) | Ability to move fingers, and manipulate small objects with fingers, rapidly or accurately | Measure of routine manual tasks | Mixes and bakes ingredients according to recipes; sews fasteners and decorative trimmings to articles; feeds tungsten filament wire coils into machine that mounts them to stems in electric light bulbs; operates tabulating machine that processes data from tabulating cards into printed records; packs agricultural produce such as bulbs, fruits, nuts, eggs, and vegetables for storage or shipment; attaches hands to faces of watches. |
| 5. Eye Hand Foot Coordination (EYEHAND) | Ability to move the hand and foot coordinately with each other in accordance with visual stimuli | Measure of nonroutine manual tasks | Lowest level: Tends machine that crimps eyelets, grommets; next level: attends to beef cattle on stock ranch; drives bus to transport passengers; next level: pilots airplane to transport passengers; prunes and treats ornamental and shade trees; highest level: performs gymnastic feats of skill and balance. |

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

APPENDIX 2: COMPUTERIZATION AND INDUSTRY TASK INPUT, 1960–1998: USING COMPOSITE TASK MEASURES
DEPENDENT VARIABLE: 10 × ANNUAL WITHIN-INDUSTRY CHANGE IN TASK INPUT, MEASURED IN PERCENTILES OF 1960 TASK DISTRIBUTION

| | | 1. 1990–1998 | 2. 1980–1990 | 3. 1970–1980 | 4. 1960–1970 |
|---|---|---|---|---|---|
| A. Δ Nonroutine analytic | Δ Computer use 1984–1997 | 8.21 | 12.09 | 6.50 | 8.57 |
| | | (4.55) | (4.55) | (4.21) | (5.74) |
| | Intercept | 0.64 | −0.67 | 0.07 | −0.07 |
| | | (0.96) | (0.94) | (0.86) | (1.14) |
| | $R^2$ | 0.02 | 0.05 | 0.02 | 0.02 |
| | Weighted mean Δ | 2.26 | 1.67 | 1.32 | 1.51 |
| B. Δ Nonroutine interactive | Δ Computer use 1984–1997 | 9.83 | 9.93 | 5.67 | 10.45 |
| | | (4.39) | (4.74) | (3.47) | (5.00) |
| | Intercept | 0.54 | 0.53 | 1.42 | 0.00 |
| | | (0.92) | (0.98) | (0.71) | (1.00) |
| | $R^2$ | 0.04 | 0.03 | 0.02 | 0.03 |
| | Weighted mean Δ | 2.48 | 2.45 | 2.51 | 1.93 |
| C. Δ Routine cognitive | Δ Computer use 1984–1997 | −13.40 | −4.59 | −4.76 | −7.02 |
| | | (4.44) | (5.58) | (3.70) | (4.75) |
| | Intercept | 0.23 | −0.39 | 0.56 | −0.05 |
| | | (0.94) | (1.16) | (0.76) | (0.95) |
| | $R^2$ | 0.06 | 0.00 | 0.01 | 0.02 |
| | Weighted mean Δ | −2.41 | −1.28 | −0.35 | −1.35 |
| D. Δ Routine manual | Δ Computer use 1984–1997 | −23.17 | −15.27 | −13.25 | 3.98 |
| | | (6.99) | (6.86) | (5.34) | (4.13) |
| | Intercept | −0.52 | −0.80 | 1.97 | 1.35 |
| | | (1.47) | (1.42) | (1.09) | (0.82) |
| | $R^2$ | 0.07 | 0.03 | 0.04 | 0.01 |
| | Weighted mean Δ | −5.09 | −3.76 | −0.56 | 2.09 |

*n* is 140 consistent CIC industries. Standard errors are in parentheses. Each column of panels A–D presents a separate OLS regression of ten times the annual change in industry-level task input between the endpoints of the indicated time interval (measured in centiles of the 1960 task distribution) on the annual percentage point change in industry computer use during 1984–1997 (mean 0.193) and a constant. Computer use is the fraction of industry workers using a computer at their jobs, estimated from the October 1984 and 1997 CPS samples. Estimates are weighted by mean industry share of total employment in FTEs over the endpoints of the years used to form the dependent variable. Samples used are Census 1960, 1970, and 1980 and CPS MORG 1980, 1990, and 1998. See the Data Appendix for details on construction of the composite task variables. See Table I for definitions and examples of task variables.

## DATA APPENDIX

### *A.1. Samples Used from Current Population Survey and Census of Populations*

To calculate occupational and education distributions economywide and within industries for 1960 to 1998, we used observations on all noninstitutionalized, employed workers ages

18–64 from the Census PUMS one percent samples for 1960, 1970, 1980, and 1990 [Ruggles and Sobek, 1997] and the Merged Outgoing Rotation Groups of the Current Population Survey for the years 1980, 1990, and 1998. All individual and industry level analyses are performed using as weights full-time equivalent hours of labor supply, which is the product of the individual Census or CPS sampling weight times hours of work in the sample reference week divided by 35 and, for Census samples, weeks of work in the previous year. Because hours are not reported for the self-employed in the CPS prior to 1994, we assigned self-employed workers in all CPS samples the average labor hours in their industry-education-year cell. In cases where industry hours supplied by education category were unavailable (due to an empty industry-education-year cell), we assigned weekly hours as the mean of workers' education-year cells.

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

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

To compute DOT Task Means for 1970 CIC Occupations, we used the April 1971 CPS Monthly File issued by the National Academy of Sciences [1981] in which experts assigned individual DOT occupation codes and associated DOT measures to each of 60,441 workers. Because Census occupation categories are significantly coarser than DOT occupation categories, the 411 1970 census occupation codes represented in the 1971 CPS were assigned a total of 3886 unique 1977 DOT occupations. We used the CPS sampling weights to calculate means of each DOT task measure by occupation. Because the gender distribution of DOT occupations differs substantially within COC occupation cells, we performed this exercise separately by gender. In cases where a COC cell contained exclusively males or females, we assigned the cell mean to both genders. This provided a set of 822 DOT occupation means by 1970 COC and gender.

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

It was not possible to develop a bridging crosswalk between 1970 and 1980 COC occupations due to the substantial differences between these classifications. Instead, we employed a Census sample prepared for the Committee on Occupational Classification and Analysis chaired by Donald Treiman and provided to us by Michael Handel. This file contains 122,141 observations from the 1980 Census that are individually dual coded with both 1970 and 1980 COC occupation codes based on occupational and other demographic information supplied by Census respondents. To calculate DOT means by 1980 occupation, we merged the 1970 COC-DOT means (above) to the Treiman file by gender and 1970 COC occupation, achieving a 97 percent match rate. We appended to the Treiman file consistent occupation codes for the years 1980 to 1998 developed by Autor, Katz, and Krueger [1998], and calculated weighted means of each DOT measure within occupation-gender categories. This yielded DOT means by gender for each of 485 DOT occupations.

### *A.3. Computing DOT Task Means by Consistent 1960–1998 Industry*

To compute DOT task means overall, by industry, and by industry-education cell for 1960–1998, we assigned the consistent DOT occupational task means for 1960–1998 by gender and occupation to each observation in our Census and CPS samples for 1960–1998. Using labor supply in FTEs as weights, we calculated means of each DOT measure for each occupation-industry-education-year cell. These means provide the primary outcome measures for our analysis. To attain compatibility between changing Census Industry Codes for 1960–1998, we use a crosswalk developed by Autor, Katz, and Krueger [1998] providing 140 consistent CIC industries spanning all sectors of the economy. This crosswalk includes all CIC industries and attains consistency by aggregating where necessary to the lowest common level of consistent industry definition among 1970, 1980, and 1990 CIC standards.

### *A.4. Composite Task Indicators from the DOT*

To verify that our results are robust to plausible alternative selections of DOT variables, we formed composite indicators of our intended constructs using Principal Components Analysis. We chose a short list of alternative DOT variables that appeared relevant to each of our conceptual categories. These choices are Nonroutine Analytic Tasks: GED-MATH, GED-REASON, NUMBER, MVC; Nonroutine Interactive Tasks: DCP, GED-LANGUAGE, DEPL, VARCH; Routine Cognitive Tasks: STS, COLORDIS, REPCON, VOCPREP; Routine Manual Tasks: FINGDEX, MOTOR, FORM, MANUAL. Definitions and representative examples of these variables are found in U. S. Department of Labor [1972]. Using 1980 employment as weights, we performed principal components analysis for each set of variables to identify the linear combinations that maximized common variation subject to the constraint that the sum of squared vector weights is equal to one. In each case, we used the first principal component.

### *A.5. Calculating DOT Quantiles*

To convert DOT measures into percentiles of the 1960 task distribution, we used DOT 1977 task measures paired to the 1960 Census to form an employment-weighted empirical cumulative distribution function of task input for each task measure across 1120 industry-education-gender cells: 140 industries, two gender, and four education levels (high school dropout, high school graduate, some college, and college graduate). We applied a small amount of interpolation to remove flat spots in the distribution. We inverted this empirical distribution and applied it to all DOT task measures in subsequent years by industry-education-gender and year. These centile values are the unit of measure for all later analyses. A limitation of this methodology is that DOT values after 1960 may potentially lie outside the support of the 1960 distribution, leading to truncation. In practice, this issue affects at most 4 percent of the distribution of each task in any year. An earlier version of this paper [Autor, Levy, and Murnane, 2001] employed raw DOT scores rather than the percentile measures used here. Results were qualitatively identical.

*A.6. Calculating within-Occupation Changes in DOT Task Measures: 1977–1991*

To measure within-occupation changes in task content, we employed the 1991 Revised Fourth Edition of the *Dictionary of Occupational Titles,* available in electronic form from the National Academy of Sciences [1981]. Based on a study of select industries to determine which jobs had undergone the most significant occupational changes since the 1977 publication of the DOT fourth edition, DOT analysts introduced, revised, and eliminated occupational definitions for occupations that were observed to have most substantively changed between 1977 and 1991. A total of 2452 occupations were reviewed, updated, or were added; 646 nominal titles were revised; 136 titles were combined; and 75 were deleted. To provide a conservative measure of total task change, we assume that any occupation that was not revised in the 1991 DOT experienced no task change.

We used documentation from the North Carolina Employment Security Commission [1992a, 1992b] to construct a crosswalk between the 1991 DOT and 1997 DOT occupation codes. With this crosswalk, we applied DOT 1991 task variables to our 1971 CPS file, yielding a match rate of 99.9 percent. Of these matched occupations, 73 percent (weighted by employment) had been updated between 1977 and 1991 by DOT examiners. We then calculated DOT means by 1970 and 1980 COC occupations and gender using a procedure identical to that described in A.3, to obtain 1991 DOT task means for the 1977 occupations. The within-occupation variation that we exploit over 1977–1991 stems exclusively from reevaluation of occupational content by DOT examiners, rather than from changes in the relative size of DOT suboccupations within CIC occupations.

We assigned the 1977 DOT and 1991 DOT task measures to 470 consistent COC occupations in the 1984 and 1998 CPS samples (corresponding to the years of our CPS computer measure).

As with the industry data, we transformed the DOT task measures into percentiles of the base year distribution, in this case using occupational employment shares from 1984 to form employment weights.

### *A.7. Computer Usage Data from the Current Population Survey*

Industry computer use frequencies were calculated from the October 1984 and 1997 School Enrollment Supplements to the Current Population Survey (CPS) as the weighted fraction of currently employed workers ages 18–65 who answered yes to the question, "Do you use a computer directly at work?" within consistent CIC industries. A computer is defined as a desktop terminal or PC with keyboard and monitor and does not include an electronic cash register or a handheld data device. To calculate these frequencies in 1984 and 1997, 61,712 and 56,247 observations were used, respectively.

### *A.8. Computer and Capital Investment Measures from the National Income and Products Accounts*

We used data on industry capital stocks and flows of equipment, structures, and computers from the National Income and Product Accounts [U. S. Department of Commerce, 2002a, 2002b] for the years 1950–1998. All NIPA stock and investment variables are measured in real 1996 dollars. Investment variables measure cumulated real investment in the relevant asset over the prior ten years, except in 1998 where we use 1.25 times cumulated investment over the previous eight years. Deflation of NIPA measures is performed by the Bureau of Economic Analysis using primarily Producer Price Indexes (PPIs). PPIs for computer investment are based on quality adjustment, price linking, and hedonic regression methods. As denominators for capital/FTE and computer investment/FTE variables, we used Census and CPS samples to calculate FTEs by industry by year. Computer investment is calculated as the sum of investment in mainframe computers, personal computers, packaged and custom software, printers, terminals, storage devices, and other integrated devices. Structures and equipment variables are defined in the NIPA.

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

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