Computerization and Skill Bifurcation:

The Role of Task Complexity in Creating Skill Gains and Losses

by

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Does computerization increase or reduce the extent of skills that workers are required to have? Autor, Levy and Murnane (2003) show empirically that adoption of computer-based technologies (CBT) was greater in industries historically intensive in routine tasks, and that computerization increased complex problem-solving and communication activities and reduced routine cognitive and manual activities. We extend this argument and argue that the effects of CBT are neither universal nor uniform, but a *bifurcation* emerges: occupations that historically (pre-computerization) required low skills and entailed low-complexity tasks do not experience a lot of CBT in their environment, or if they do, they remain low skill (or *in extremis* become less skilled) occupations, whereas historically high-skill occupations that entailed high complexity see much CBT as well as increases in the skills they require. We test these propositions in a unique dataset that includes measures of the degree of computerization and changes attendant to computerization in the level of seven skills of core employees (content, complex problem-solving, etc.) for a sample of 819 firms in 2000. We link this dataset by core employees' occupation to US occupation-level data on three dimensions of task complexity (with respect to data, people and things) in 1971 (pre-CBT). We find that: (1) higher pre-CBT task complexity is associated with subsequent adoption and intensity of CBT; and (2) for occupations that were historically characterized by complex tasks, CBT affects most skills positively, but for simple tasks, CBT does not affect skills or affects them negatively. We replicate our analyses with the dataset and measures used by Autor, Levy and Murnane (2003) and obtain similar results. Our results shed light on the skill-based technological change and skilling-deskilling debates and suggest that the relationships are contingent in more nuanced ways than the literature has suggested.

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I. INTRODUCTION

Skill-biased technological change (SBTC) is the proposition that technological change in the form of computer-based technology (CBT) entails an increase in the skill content of jobs performed by skilled workers (Machin, 2001). Less-skilled workers, who do not possess the necessary skills to work with CBT, are being left behind, with diminishing skills and the accompanying wage stagnation or decline, and damaged labor market prospects. Empirically, the SBTC hypothesis has been supported by a documented positive correlation between the adoption of CBT and the increased employment and wages of skilled workers (Katz and Autor, 1999 and Levy and Murnane, 1992 survey this literature). Yet, as DiNardo and Pischke (1997) suggest, rather than reflecting returns to computer use or computer skills, relative increases in employment and wages of CBT users may indicate that "computer users possess unobserved skills which might have little to do with computers but which are rewarded in the labor market, or that computers were first introduced in higher paying occupations" (p. 292).

The unobserved skills have been identified by Autor, Levy, and Murname (2003) (henceforth ALM) as complex problem-solving skills and complex communication skills. ALM explain how the SBTC proposition actually works: computers take over the execution of *routine* manual and cognitive tasks—tasks that can be *routinized* or readily described with programmed rules—making redundant workers who previously carried out such tasks; at the same time, computers complement the efforts of workers to carry out *nonroutine* cognitive tasks, entailed by complex problem-solving and communication activities. ALM show that indeed CBT adoption was greater in industries historically intensive in routine tasks, and that the increased computerization predicts increased complex problem-solving and communication activities and reduced routine cognitive and manual activities. These trends are present within occupations, industries and education groups. Therefore, ALM's claim is broader than the SBTC hypothesis: the use of CBT complements the employment and skills not only of more-skilled but also of less-skilled workers.

The recent economics literature favors the skilling approach, as did the sociological literature in the tradition of Blauner (1964). That technological change may stimulate demand for more skilled workers is also implied by the notion of learning-by-doing (Arrow, 1962). More educated employees are better able to evaluate and adopt innovations and learn faster new functions and

routines than less educated ones (Nelson and Phelps, 1966). In contrast, theories of occupational downgrading or deskilling, most forcefully stated by Braverman (1974, 1975), emphasized the desire of employers to acquire control over the work process by reducing the skill level of their workers. In a similar vein, product life cycle models (Vernon, 1966) emphasize the constant pressure to routinize new technology so that it becomes less reliant on skilled labor. The skilling approach tends to rely on forces external to the organization, basing its evidence on changes in the distribution of employment, whereas the deskilling approach relies on forces internal to the firm (management strategy) and changes within individual jobs. Other researchers, agnostic on overall historical trends, adopted a "contingency" or "mixed effects" position, asserting that situational factors such as labor costs or employee bargaining power are important in determining the utility of any technology or system of work organization (Wood, 1982; Spenner, 1983; Hirschhorn, 1984; Form, Kauffman, Parcel, and Wallace, 1988; Zuboff, 1988).

In this paper we extend ALM's ideas by arguing that enhancements in complex problem-solving and complex communication skills are neither suitable for all workers nor profitable for all occupations. We propose that the initial (historic) task attributes of a job or occupation and the related skill content influence the subsequent degree of computerization as well as its posterior skill effects. We claim that a *bifurcation* emerges such that occupations that historically (pre-CBT) required low skills and entailed low-complexity tasks do not see much CBT in their environment, or if they do, they remain low skill (or *in extremis* become less skilled). In contrast, workers in historically *skilled and complex jobs* see much CBT as well as increases in the skills they need to possess. We suggest that CBT does not only automate the gathering and storage of information but also generates information that can be analyzed by workers who possess the required skills and abilities (Zuboff, 1980). So the greatest gain from CBT has likely occurred in firms that pre-CBT had a lot of routine tasks, as shown by ALM, and those that had a lot of complex tasks so that CBT could complement the efforts of workers and makes them more productive. To formalize these propositions, we develop a simple model of skill accumulation that shows that the path of skill accumulation depends on the extent of initial skill, and exhibits bifurcation of the kind discussed above.

We test our hypotheses using firm-level information obtained from a survey administered in 2000 to more than 800 firms headquartered and operating in Minnesota in a broad cross-section of industries. We examine the impact of CBT on seven sets of skills of *core employees*, the non-managerial employees that are directly involved in making a firm's main products. We find considerable support for the existence of bifurcation in our data for Minnesota firms. We use a replication of ALM's dataset and measures and find that a bifurcation is present also in the broader sample of industries and occupations that they use.

The rest of the paper is organized as follows. In Section II we put forth our theoretical framework and hypotheses. In Section III we describe the various datasets used in the paper. Section IV contains the empirical work, first concerning the adoption of CBT and next the effects of CBT on various skills. In Section V we explore the differences in our results as compared to ALM's, evaluating the alternative characterization of tasks, and replicating ALM's principal analyses and augmenting them with elements of our models. Section VI concludes.

II. THEORY AND HYPOTHESES

In order to understand the effects of CBT on skills we need to understand first why CBT is adopted. The two parts are clearly related, so the full argument concerning the "why" question can be understood more fully after the explanation of the effects of CBT.

II.1. CBT adoption and use

What factors facilitate the adoption of CBT and the degree of reliance on them? ALM (2003) found that industries that historically (pre-CBT) were intensive in routine tasks or tasks that can be accomplished by following explicit rules, have adopted computers to a greater extent than other industries. Skilled-labor endowment has been identified as another potential factor that encourages CBT adoption and use.[1] Evidence at the plant-level on computers flowing to high-wage and high-skilled jobs is presented by Doms, Dunne, and Troske (1997) and Dunne and Troske (1995); in a survey of 4,500 German firms, insufficient worker skills were identified as

[1] Bartel and Lichtenberg (1987), Greenwood and Yorukoglu (1998), Nelson and Phelps (1966), Schultz (1975), Welch (1970) and others argue that skilled labor conveys a comparative advantage in technology adoption.

the main obstacle to increased CBT use (Hempell, 2006).[2] The finding that skilled-labor endowment favors future CBT use suggests a substantial selection effect, and, if selection is related to the outcome of interest, as when explaining skills, a possible reverse causality.

CBT is adopted to make production cheaper and more efficient. The cost and benefits of CBT vary across firms (Bresnahan et al., 2002). ALM argue that as CBT executes routine tasks it both reduces the cost of production and makes it more efficient – less expensive and more productive. ALM argue further that workers freed of routine tasks can concentrate on complex tasks of the kind that computers cannot carry out (at this time) as effectively as workers.

We extend ALM's argument by differentiating between occupations in which there is scope for expansion of the complex tasks component of the job and occupations in which such scope is very limited or does not exist. CBT substitutes for workers in performing tasks that can be programmed, that is, *routine tasks*. This substitution effect eliminates jobs or frees workers to carry out other tasks, either simpler or more complex, that CBT cannot do as effectively. ALM argue that the latter possibility (shifting attention to complex tasks) prevails and refer to it as *skilling*. But even routine tasks require a certain amount of skill (e.g., recognizing different items in the check-out cashier's case) that CBT may displace, leaving the worker to do even simpler tasks that cannot be carried out economically by CBT (such as scanning items at the check-out counter). This amounts to *deskilling*.

In some cases, time freed up by computers that do routine tasks can be usefully and naturally expended on the execution of complex tasks. And, sometimes, information generated by CBT enables complex tasks such as innovation (Zuboff, 1988, Bresnahan and Trajtenberg, 1995), a complementarity effect. But in many occupations one or both of these possibilities are missing. Furthermore, even if the substitution or complementarity effects could be created by CBT,

[2] Why is CBT complementary to skills? One perspective argues that CBT is intrinsically complementary to skills (Berman, Bound, and Griliches, 1994; Griliches, 1969; Tinbergen, 1975; Goldin and Katz, 1998). Acemoglu (1998) argues that CBT and skills are not complementary by "nature" but by design. He argues that technological change is endogenous and dependent upon the supply of skills: the technology to be developed and adopted is the one that makes the most efficient use of existing factors. Because skill-biased CBT is more efficient at using skilled-labor, the presence of more skilled workers will favor the development and adoption of such technology. In a similar vein, Caselli and Coleman (2006) suggest that cross-country differences in technology are not merely a matter of some countries having an overall higher level of technical efficiency than others, but also a matter of having a higher level of skilled labor endowments.

employees in an occupation/firm that had required pre-CBT low skills may not be able to acquire the requisite skills associated with complex tasks post-CBT. Firms have an existing workforce and few regard it as completely and instantly replaceable, so managers' choices of technology are constrained by their current employees' abilities and the scope of the training they can receive. Hence the scope for job complexity expansion from the introduction of CBT and its extent are positively correlated with the pre-computer complexity of tasks in an existing occupation.

Obviously, computers are not of equal value for all occupations. For example, supermarket check-out cashiers have no scope in their jobs for complex tasks and therefore no scope for their extension or expansion. In contrast, there is scope for complex tasks expansion in architects' job who, freed of routine tasks, can dedicate themselves to perform more complex tasks such as innovation. Hence the architect will lose some skills of technical nature such as drafting but will gain skills required for innovation, improvisation and creativity or more broadly complex problem-solving skills in data analysis and relating to people. Similarly, whereas financial analysts have to complete a wide range of interrelated complex tasks (analyze financial data, recommend investments and present oral and written reports) that can be complemented and coordinated by computers, janitors' jobs consist of simpler tasks that computers cannot complement or substitute. The foregoing discussion can be summarized as follows.

> *H1*: Pre-computer task complexity of employees in key jobs in a firm influences positively the firm's subsequent adoption of CBT and the intensity of its use.

II.2. Does CBT complement or substitute for skills?

CBT is characterized by a fundamental duality: it automates activities *and* registers data about those automated activities, thus generating new streams of information (Zuboff, 1998). This is exemplified by the computerization of store check-out. Scanning devices not only identify the cost of the item but also generate data that can be used for inventory control, warehousing, scheduling of deliveries, and market analysis. In its automating function, the scanner substitutes for the worker and thus reduces the employee's duties; as data collector, the scanner plays the

role of an "enabling technology," opening up new opportunities (rather than providing solutions), and thus complementing the worker (Bresnahan and Trajtenberg, 1995).

Firms have access to a menu of feasible CBTs (Acemoglu, 1998). The task conditions of the key occupations and jobs held by incumbent workers influence firms' decisions about the type of CBT they select. Firms in which the core employees performed complex tasks prior to the computerization decision and thus were skilled-labor abundant firms would tend to adopt skill-biased CBT that complements employees' high skills, whereas firms where core employees' tasks were simple would tend to adopt non-skill-biased CBT that substitutes employees' low skills, or replaces these employees.

The ideas presented above can be represented in a simple model of individual skill accumulation similar to that of Lucas (1988).[3] The model relates the growth of skill, $ds(x)/dx$, to the level already attained, $s(x)$, and the effort devoted to acquiring more, such that:

$$\frac{ds(x)}{dx} = s(x)(\delta_0 \frac{1}{s(x)} + \delta_1) \qquad (1)$$

where x is CBT use, and $x, s(x) \geq 0$.

In equation (1), if this paper's contingency hypothesis is correct, we have $\delta_0 < 0$ and $\delta_1 > 0$. Given that $s(x) \geq 0$, there exists a level of skill, $s^*(x)$, such that $ds(x)/dx = 0$ and thus for $s(x) > s^*$ (that is, a "high" level of existing skill) the level of skill will increase as CBT rises, $ds(x)/dx > 0$, but for $s(x) < s^*$ (which we interpret as unskilled-labor) the level of skill will decrease as CBT rises, $ds(x)/dx < 0$.

We summarize the foregoing discussion as follows.

> *H2*: CBT has a positive effect on the level of skills required for occupations that, pre-CBT, were intensive in complex tasks, and a negative effect or no effect for other occupations.

[3] By "human capital" Lucas (1988) means general skill level, and his model focuses on the fact that the way an individual allocates time over various activities in the current period affects the skill level in future periods.

Solving the differential equation in (1), we obtain the relationship between skill levels and levels of CBT use,

$$s(x) = -\frac{\delta_0}{\delta_1} + Ce^{\delta_1 x} \qquad (2)$$

Figure 1 plots the curve in (2). Different values of the parameters δ_0, δ_1 account for three alternative hypotheses concerning the impact of CBT use on skills: $\delta_0, \delta_1 > 0$ represents the skilling hypothesis whereby the impact of CBT use on skills is always positive (Figure 1.a); $\delta_0, \delta_1 < 0$ represents the deskilling view that CBT use always has a negative impact on skills (Figure 1.b); and $\delta_0 < 0$ and $\delta_1 > 0$ represents our contingent view that the impact of CBT use on skills is positive for skilled-labor endowments but negative for unskilled-labor endowments (Figure 1.c). For each figure, 1.a, 1.b, and 1.c, the four different slopes refer to different initial pre-computer skill endowments, $s_j(0) = (-\delta_0/\delta_1) + C_j$, with j indicating occupation, but the same parameters, δ_0 and δ_1. Only Figure 1.c is consistent with both hypotheses H1 and H2.

{{Figure 1 here}}

In sum, both the decision whether to use CBT and its intensity, and the decision whether to invest in a skill-biased CBT or in a non-skill-biased CBT are influenced by the same variable: pre-CBT skill requirements. Unskilled-labor abundant firms performing simple tasks will tend to choose low-intensity CBT that substitutes for human skills, whereas skilled-labor abundant firms performing more complex tasks will tend to promote CBT use that complements human skills.

III. DATA DESCRIPTION

The empirical objectives of this paper, which have driven the collection of the data and the construction of the variables described in this section, are as follows. First, we seek to evaluate the relationship between pre-CBT skill level and subsequent introduction of CBT. Second, we wish to investigate the relationship between CBT and skill change. Third, we want to examine the relationship between CBT and the post-CBT task environment. Most of the variables come from our firm-level original survey, which was designed, in part, to provide information relevant

to the investigation of the relationships described above. Additional key variables at the level of occupations were derived from various public datasets that were used by ALM and other researchers who have studied the question of CBT and skill change.

III. 1. The dataset

The primary dataset used in this study comes from the "Minnesota Human Resource Management Practices Survey 2000" (MHRMPS-2000). We obtained additional information for our sample firms from Dunn & Bradstreet for sales and the Minnesota State Department of Economic Security for average wages. Information about tasks associated with sample occupations is derived from Fourth Edition 1977 DOT and other sources described briefly later (ALM describe these data sources in detail). Historical wages, educational attainment and employment for sample occupations are extracted from Integrated Public Use Microdata Series, Current Population Survey (IPUMS-CPS). The number of workers engaged in R&D activity for sample industries is drawn from 2001 Survey of Industrial Research and Development by the National Science Foundation.

MHRMPS-2000 was administered in late 1999 and in 2000 by mail, with a phone survey administered to firms that did not respond. The data comprise 819 privately-held and publicly-traded firms that employed 20 or more employees in diverse industries (NAICS 22-92) outside agriculture, forestry, fishing, hunting, and mineral industries, headquartered in Minnesota and with at least 50% of their employees working within that state. The choice of a single state offers several advantages. First, the workforce is likely to be more homogeneous than in firms operating in several states. Second, all firms are subject to the same state laws and regulations. Third, crucial firm-level data that are not in the public domain are available from state agencies. Fourth, survey response rates are much higher than in surveys with a broader geographical scope.

The survey was completed by a senior human resources manager for the firm and the overall response rate was 33.37%. MHRMPS-2000 was designed to explore a broad range of issues relating to firms and their employees. The sample was constructed to include a diverse group of firms that represent the variety of workplace programs and practices found in U.S. companies as well as a wide range of production technologies. One of the survey's aims was to shed light on

the relationship between use of CBT and employees' skills. The sampling strategy is described in detail in Appendix A. The survey is available upon request.

III. 2. Measures

Table 1 presents the description of the variables and their sources. The variables concern the sample firms' core employees in Minnesota, as well as firm, occupation and industry-level variables. Descriptive statistics are in Table 2.

{{Table 1 here}}

Change in core employees' skills. MHRMPS-2000 contains information about various aspects of core employees' skills and tasks. Core employees are non–supervisory, non–managerial employees at the firm who are directly involved in making the product or providing the service (Osterman, 1991). These employees represent a relatively homogeneous group. A group of survey items focused expressly on the relationship between CBT and skills, asking respondents to rate "to what extent does reliance on computer-based technology reduce or enhance the skill sets possessed by core employees." This question addresses separately changes in seven types of skills: *content*, *process*, *social*, *complex problem-solving*, *technical*, *system*, and *resources management* skills. The changes are on a 7-point scale, with -1, -2, -3 indicating that reliance on CBT reduces skill from "slightly" to "greatly," 0 indicating "no change," and 1, 2, 3 indicating that reliance on CBT enhances skill from "slightly" to "greatly." The question does not ask respondents to date the introduction of CBT, only to assess its effects on changes in the seven skills. In Table 2 all means of change indicators are positive but close to 0.[4]

Core employees' task attributes. MHRMPS-2000 provides information on the nature of core employees' tasks, *complexity* and *routine*, and about the degree of skill needed to execute these tasks, *skill requirement*, all rated on a 5-point scale, with 0 "not at all", 1 "slightly", 2 "moderately", 3 "very", and 4 "extremely." This information pertains to the year of the survey.

[4] There might be a concern with the fact that survey responses on skill changes are not accurate because CBT was introduced several years before the survey was conducted. The use of retrospective data may cause two kinds of recall errors: memory effects (forgetting the precise nature of some events) and telescoping effects (incorrectly timing an event). The problem here has to do with memory effects and may cause measurement errors in the dependent variable. However, the memory distortion process is likely to be random and not associated with firm CBT at the time of survey or the complexity of tasks of their core employees' occupation in the 1970s.

CBT and core employees. The extent of reliance on CBT is captured by a 5-point scale question: "Are the tasks of core employees affected by computer based technology?" This measure of CBT use captures exactly the concept in which we are interested (unlike the common measures of the percentage of workers using computers and investment in IT, which are weak proxies for the extent of influence that technology exercises on the tasks of employees).

Occupational titles of core employees. MHRMPS-2000 contains information on core employees' job titles, such as software engineer, waiter, check-out cashier, and assembly worker. We have coded this information using the Occupational Information Network (O*NET) database system, the US Department of Labor' recent successor to the DOT. As a result, 221 distinct 8-digit O*NET-SOC 2000 codes were identified (out of a total of 1167).[5] Thus each sample firm is represented by one occupational title, that of its core employees. To test whether computer use represents a selection effect, we examine whether pre-computer skill endowment explains computer use. Many consider the introduction of the IBM-PC in 1981 as the beginning of the "computer revolution" (Card and DiNardo, 2002), and microprocessors were first introduced on a wide scale in manufacturing machinery in the 1970s (Autor, Katz, and Krueger, 1998). In a survey that we conducted in the middle of the 1990s with similar sampling frame as MHRMPS-2000 we also asked about the year in which firms implemented their CBT. The results are plotted in Appendix C Figure C1; they portray a similar picture to that presented by others on the basis of less direct data (e.g., the percentage of workers using computers, as in ALM, or the widely-used expenditure on computers), that is, a surge in CBT adoption occurred in the early 1980s. We consider specifically the year 1971 as the pre-CBT date for practical reasons. The data about the complexity associated with occupations were collected in 1971. Historical (pre-CBT) data on task complexity of an occupation from the Fourth Edition of DOT (1977) are used as proxy for pre-computer skill endowment. Task complexity reflects the demands that jobs make on workers, hence it requires greater skill (Campbell, 1988).

Pre-CBT occupational complexity in relation to data, people and things. We used sample SOC 2000 codes to append variables from the pre-computer era to the MHRMPS-2000 dataset. We obtained the levels of complexity at which workers in different occupation functioned during the

[5] O*NET-SOC is the current O*NET taxonomy, which represents the transition from the former Occupational Units (OUs) of O*NET 98 to the SOC (Levine, Nottingham, Paige, and Lewis, 2000).

pre-CBT era in relation to *data*, *people*, and *things:*[6] $\text{Data}_{i,1971}$ (measured on a scale of 1 to 7), $\text{People}_{i,1971}$ (1 to 9) and $\text{Things}_{i,1971}$ (1 to 8). The scales were created from ordinal ranks of the tasks used to characterize the degree of complexity of work, described in Appendix B.

Pre-CBT education and wages. Educational attainment and annual wages from the pre-computer era are also appended to sample 1970 COC codes.[7] $\text{Education}_{i,1971}$ is measured on a scale of 1 to 9 and $\text{Wages}_{i,1971}$ indicates occupational pre-tax wage and salary income in thousands of dollars.

Control variables. Other variables are the number of core employees, percentage of unionized employees, average age, education, percentage of females, and wage for all employees in the firm, and firm sales, the last two variables lagged by one year. The number of full-time equivalent R&D scientists and engineers for 42 NAICS codes in the sample is included to reflect industry-level R&D intensity.

IV. EMPIRICAL ANALYSIS

Table 2 presents descriptive statistics. The number of observations varies across variables because of missing observations in the various datasets. The first seven variables concern change in various skills; about 20% of respondents failed to provide this information (mostly phone respondents, 131 out of 177 non-respondents to this question). Non-responses are inversely correlated with the degree of CBT, with heaviest concentration in occupations that have seen little CBT (waiters, food preparation workers). For job titles of core employees, discussed in the previous section, we have just one missing observation, and six for pre-computer complexity in relation to data, people, and things. However, several occupations could not be matched with data on average wage and education in 1971, which reduces the sample size for relevant estimations to 746 (in Table 4). A substantial number of missing observations occurs for the firm-level unionization rate and average wage, which are used as control variables in the analysis

[6] We first mapped sample SOC codes to 1970 Census Occupational Classification (COC) using crosswalks provided by the National Crosswalk Service Center, obtaining 152 1970 COC codes (26.5% of the total number of occupational categories of the 1970 Census, and 31.06% of ALM). Next, we appended weighted means (using weights to approximate U.S. civilian labor force) of 1977 DOT task measures to sample 1970 COC codes using the April 1971 CPS augmented with DOT characteristics data file.

[7] Weighted means for educational attainment and annual wages in 1971 extracted from IPUMS-CPS are appended to sample 1970 COC codes.

of the relationship between CBT and task environment (Table 6). We ran the analysis without these variables and obtained similar results to those reported in the text.

{{Table 2 here}}

Table 3 presents Pearson's correlations for the variables included in the analysis. The intensity of CBT use is positively associated with skilling across all seven skills. Computerization is positively correlated with *contemporary* (survey year) task complexity and with task skill requirement (complementarity effect) but negatively correlated with task routine (substitution effect), consistent with ALM's framework. CBT use is positively correlated with average employees' wage (a standard finding), education and age, as well as with productivity (sales per core employee) and R&D intensity. These cross-sectional correlations are interesting but, as DiNardo and Pischke (1997) caution, they do not inform about causality. More suggestive about causality is the positive correlation between pre-computer (1971) task complexity in working with data, people, and things, and subsequent CBT use, as well as between pre-computer employees' education and wages and subsequent CBT use.

{{Table 3 here}}

In the remainder of this section we examine these relationships in detail. First, we estimate in Table 4 the relationship between pre-CBT task complexity and subsequent CBT adoption and use. We test whether a firm whose core employees' tasks were complex before computerization and were run by skilled workers will tend to choose a more intensive use of CBT than a firm whose core employees' tasks prior to computerization were simple and run by unskilled workers. Second, in Table 5 we present firm-level estimations of the probability that a positive change in skills is associated with the use of CBT, conditional on historical values of task complexity. We test the hypothesis that, in addition to influencing the intensity of use of CBT, pre-CBT task complexity determines whether CBT is a skill-biased technology.[8] Finally, in Table 6 we

[8] Of the 810 sample firms, 165 do not use CBT, and for them, obviously, there is no CBT skill variation. The fact that CBT skill effects are observed only for CBT users, which is a nonrandom sample, may cause a sample selection bias when explaining the effect of CBT on skills. To deal with this issue we estimate first-differenced regressions. Furthermore, we are dealing with the direction of causality by using pre-CBT explanatory variables and a dependent variable that, as the survey question states explicitly, is caused by CBT.

examine the relationship between the intensity of CBT use and the task environment (complexity, routine, and skill requirements).

IV.1. Pre-computer task complexity favoring adoption and use of CBT

ALM (2003) estimate industry-level CBT adoption (the percentile rank of an industry in computer use in 1997) as a function of industry-level routine task intensity in 1960. As noted, they find that CBT is positively related to historically routine task intensity. We expand on their model by developing a richer and more detailed description of the nature of pre-CBT work: instead of routine, we characterize tasks in terms of three dimensions of complexity, in relation to data, people, and things. These three dimensions require different skills and can capture greater diversity among different occupations than the single dimension of routine, as shown by the relatively low correlations among them in Table 3. Figure 2 shows mean values of firm-level CBT by quartile categories of pre-CBT complexity in our sample core employees' occupations. CBT intensity increases with pre-computer task complexity, with the strongest pattern revealed for complexity in working with data.

{{Figure 2 here}}

We test further how this multidimensional complexity influences subsequent CBT use by estimating the following equation:

$$x_{i,2000} = f(Data_{i,1971}, People_{i,1971}, Things_{i,1971}) \quad (3)$$

where x measures CBT (adoption or intensity of use) for each firm's core employee group, *i*, $t = 1971$ refers to the pre-CBT era (with $x_{i,1971} = 0 \ \forall i$) and $t = 2000$ to the survey reference year. We implemented equation (3) to include a linear combination of complexity with respect to data, people, and things and also interactions among them to capture multidimensionality or task variety as an additional source of task complexity. Results for three alternative specifications of equation (3) are displayed in Table 4. In the first specification the dependent variable is whether a firm uses CBT, and logit estimates are reported. In the second specification the dependent variable is the intensity of CBT use on a 4-point scale, from "slightly" to "extremely" so that non-users are excluded; ordered logit estimates are presented. In the third specification the

dependent variable is the intensity of CBT use on a 5-point scale ("not at all" to "extremely") so that non-users are included in the Poisson estimation. For each specification, we first show a control model (columns 1.a, 2.a, and 3.a) with pre-CBT occupation average wages and educational levels as the explanatory variables that capture pre-CBT skill at the firm level. The second, third, and fourth models (columns b, c, and d in each specification) focus on the subsample of firms with occupations for which one of the three dimensions – data, people, or things – is not relevant (its value is less than or equal to the 15th percentile). For example, there are 121 sample firms where core employees' occupations concern data and people but not things, represented in column 1.b. The fifth model (columns e) includes all three types of task complexity and interactions among them. No survey-year control variables are included (their inclusion does not change the results).

{{Table 4 here}}

There are four principal findings. (1) Pre-CBT educational attainment and wages at the occupation/firm level affect positively both CBT adoption and intensity of use; this finding supports the conjecture that intensive CBT users possess skills which have to do with education and are in higher-paying occupations. (2) Pre-CBT complexity with respect to data stands out as the most significant dimension affecting CBT adoption and intensity of use. Furthermore, complexity with respect to data and people exhibit multiplicative effects when explaining CBT adoption (column 1.e.); complexity with respect to data, people, and things exhibit multiplicative effects regarding both CBT adoption and intensity of use (columns 1.e., 2.e., and 3.e.). (3) Pre-CBT complexity with respect to things also matters: it positively impacts CBT adoption and use in the presence of data and people complexity (columns 1.e. and 3.e.) and CBT use in the presence of people-complexity (column 2.d.), and negatively impacts CBT use in the presence of data-complexity (column 2.c.). The interactive effect of complexity with respect to data and things shows a declining effect on both CBT adoption and the intensity of its use (columns 1.e., 2.c., 2.e., 3.c., and 3.e.). (4) Pre-CBT people-complexity exhibits little relevance for the adoption of CBT. Pre-CBT complexity with respect to people positively influences CBT adoption and intensity of use interactively with data or with things (see columns 1.e. and 2.d.) but has no effect on its own.

In sum, we find broad evidence that pre-computer task complexity has a significant effect on CBT adoption and intensity of use. The distinction among data, people, and things related tasks has proven to be valuable in explaining CBT; the impacts are positive for pre-computer task complexity in relation to data and things acting on their own as well as in relation to people when interacting with any of the other complexity dimensions. These results support hypothesis H1.

IV.2. CBT and skills

In order to shed light on the impact of CBT on skills, we next estimate the relationship between change in skills, $ds(x)$, and change in CBT, dx, as represented in equation (1). We estimate this relationship at the firm-level, with *i* indicating the firm. In the pre-CBT era (at $t = 1971$ such that $x_{i,1971} = 0 \quad \forall i$) we assume that firms differ in their skill endowments depending on their core occupation, denoted by *j*: $s_{\bullet j}(0) = (-\delta_0/\delta_1) + C_{\bullet j}$ for all firms with the same core occupation, according to equation (2). We proxy marginal changes in (1) by the following discrete changes: $\Delta s(x_i) = s(x_{i,2000}) - s(x_{i,1971})$ for $ds(x)$, and $\Delta x_i = x_{i,2000} - x_{i,1971}$ for dx, where $t = 2000$ refers to the survey reference year. Substituting $x_{i,1971} = 0 \ \forall i$ and the discrete changes in equation (1), we obtain the following equation to estimate:

$$\Delta s_i = \tilde{\delta}_0 \, x_{i,2000} + \tilde{\delta}_1 \, s_{\bullet j}(0) \, x_{i,2000} + \varepsilon_i \qquad (4)$$

where ε_i is random error, and $s_{\bullet j}(0), x_{i,2000} \geq 0$. CBT interacts with pre-CBT skill endowment, $s_{\bullet j}(0)$, which we proxy by a linear combination of pre-CBT task complexity in working with data, people, and things from 1971 CPS augmented with DOT Fourth edition occupation-level data. We hypothesized in H2 that, in addition to influencing the intensity to which CBT is used, but not as a mere consequence of such influence, pre-CBT complexity determines whether or not CBT positively impacts skills. In particular, for high enough levels of pre-CBT complexity we expect a positive impact, but for low levels of pre-computer complexity we expect a negative or null impact, which in terms of equation (4) implies that $\tilde{\delta}_0 < 0$ and $\tilde{\delta}_1 > 0$.

Table 5 reports estimations of equation (4) assuming a logistic cumulative distribution function for the probability of increases in the level of skill (probit and complementary log-log analyses show similar results). We define Δs_i in (4) as a binary variable that equals 1 for cases of skilling ($\Delta s_i > 0$) and 0 for cases of deskilling or no change ($\Delta s_i \leq 0$).Being a parsimonious measure, such a binary variable captures perfectly our bifurcation hypothesis. As a robustness test, we estimated a Poisson regression for a 4-point scale variable, with 0 indicating negative or no skill change and 1, 2, 3 indicating that CBT enhances skill from "slightly" to "greatly;" the results (in Appendix C Table C1) are similar to those presented in Table 5.

Seven logit regressions are estimated, one for each skill: content, process, social, complex problem-solving, technical, system, and resources management skills. For each skill, estimates are shown first for CBT without interaction terms (columns a), second for CBT and the interaction between CBT and pre-CBT wages[9] (columns b), and third for CBT and the interaction between CBT and pre-CBT task complexity (columns c). In this last specification, we consider complexity with respect to data, people, and things not interacted but separately. Inclusion of interacted terms here would cause severe multicollinearity problems.

In the simplest specification of CBT affecting skills (columns a), CBT is significantly positive for content, process, complex problem-solving, technical, and system skills, insignificant for resources management skills, and significantly negative for social skills. When the interaction term of CBT with pre-computer wage is introduced (columns b), the CBT coefficients turn significantly negative for all skills but for process and system skills, which are negative but insignificant. Hence the positive effect of CBT is restricted to high pre-CBT wages.

{{Table 5 here}}

Similar results are obtained when interaction terms of CBT with pre-computer task complexity are introduced: significant negative CBT coefficients for social, complex problem-solving, technical, and resources management skills and negative but insignificant for content, process, and system skills, combined with significant positive coefficients for the interaction between

[9] Estimates for CBT and the interaction between CBT and pre-CBT educational level were also calculated, but not considered because of severe multicollinearity problems.

CBT and pre-CBT data complexity in the case of content and complex problem-solving skills; significant positive coefficients for the interaction between CBT and pre-CBT people complexity in the case of process, social, and resources management skills; and significant positive coefficient for the interaction between CBT and pre-CBT things-complexity in the case of technical and system skills. The positive values of the interaction terms are consistent with results found above as well as in other studies, and the model overall estimation exhibits higher significance. The only negative interaction between CBT and pre-CBT complexity is for data in the case of social skills.

In H2 we hypothesized a contingent approach regarding the change in skill levels resulting from the adoption of CBT, with pre-CBT task complexity mediating the CBT-skills relationship. Our results generally support the contingent approach, with distinctions made among different types of skill. The *bifurcation* is most evident for *complex problem-solving, technical* and *resources management skills* where occupations with high pre-CBT complexity gained in these skills but those with low pre-CBT complexity levels experienced declines or no change. The estimated effect is negative when pre-CBT data-complexity is lower than 2.3 over 7 for complex problem-solving skills, pre-CBT people-complexity is lower than 2.9 over 9 for resources management skills and pre-CBT things-complexity is lower than 3.3 over 8 for technical skills. The positive effect of CBT on *content*, *process* and *system* skills seems to be stronger with pre-CBT complexity in relation to data, people, and things, respectively. *Social skills* decline when pre-CBT people-complexity is lower than 2 over 9 and increase otherwise, when there is no pre-CBT complexity in relation to data. Figure 3 illustrates these predictions for complex problem-solving skills.

{{Figure 3 here}}

IV.3. CBT and task environment

To provide additional evidence on the effect of CBT on skills, we estimate the effects of CBT on task complexity, task skill requirements, and task routine of core employees, that is, we estimate equation (2). Both CBT and task attributes are in levels rather than changes in them (as in equation (1) and its estimations in Table 5). We test first whether the empirical relationship

between CBT and each of the three task attributes is linear or exponential (as assumed in equation (2)). The Box-Tidwell test rejects the null hypothesis of CBT being a linear term (p-value < .10) for both task complexity and task skill requirements, suggesting that in these cases an exponential transformation of CBT offers a better fit than a linear one. In terms of equation (2), Box-Tidwell regression estimates are $\tilde{\delta}_1 = 0.4$ for task complexity and $\tilde{\delta}_1 = 0.29$ for task skill requirements. We use these estimates to present in Table 6 Poisson estimation exponentials on $\tilde{\delta}_1 \times CBT$ for task complexity and task skill requirements, and linear for task routine.

Since these equations are not in differences, there might be potential effects of core employees, firm and industry-specific features. We present first estimations without control variables (columns a) and then with control variables for the year of the survey: wage, education, percentage of females, and R&D intensity at the industry-level, which introduce many missing observations (columns b).[10] Providing confirmation of the contingent approach, positive and significant constant terms are obtained for the baseline models without control variables for both task complexity and task skill requirements and for the full model in the case of task complexity (in equation (2) if $\delta_1 > 0$ and $-\delta_0/\delta_1 > 0 \Rightarrow \delta_0 < 0$). The constant term for the full model is not statistically significant for task skill requirements. When we estimated skill changes in Table 5, the coefficient estimated on CBT, $\tilde{\delta}_0$, was negative for all skills except for content, process and system skills, which was not statistically significant (Table 5, columns c). The reason for obtaining an insignificant constant term here could be that task skill requirements are aggregate measures of different skills that exhibit different patterns and thus their aggregation may cause some effects to vanish.

{{Table 6 here}}

Finally, we focus on the initial conditions or pre-computer skill endowments, formalized by $s_{\bullet j}(0) = -\delta_0/\delta_1 + C_{\bullet j}$ for all the firms with the same occupation *j*, graphically represented by the intersection between the skill function and the y-axis in Figure 1. The exponential model in (2) exhibits different occupational slopes for different pre-computer skill values. Thus for the

[10] We also included unionization, employee age and firm age, but these turned out to be statistically insignificant as well as introduced more missing variables, and were dropped.

contingent model ($\delta_0 < 0, \delta_1 > 0$), an increase in $C_{\bullet j}$ implies an increase in the slope, turning from negative to positive once the initial skill endowment has surpassed a certain level. Separate interactions between the exponential term and pre-CBT task complexity in relation to data, people and things are introduced to capture differences in pre-computer skill endowments among occupations and to test whether increases in pre-CBT task complexity produce increases in $C_{\bullet j}$ and therefore in the slope.

Corroborating similar findings in the preceding section, in Table 6 pre-CBT task complexity in relation to data and things increases the exponential function's slope of CBT explaining future task complexity and task skill requirements. For low pre-CBT task complexity, CBT increases may produce negative changes in task complexity and in task skill requirements. On the other hand, pre-CBT task complexity in relation to people does not have any significant effect. For task routine, CBT has a linear positive effect for low pre-CBT task complexity in relation to data and a linear negative effect when such pre-CBT task complexities reach higher values.

In sum, these findings suggest that CBT is skill-biased only if the task was historically complex but not if the task was simple, which points to the robustness of our earlier findings concerning the role of pre-computer task complexity in the relationship between CBT and skills, that is, our bifurcation hypothesis.

V. COMPARISON OF OUR ANALYSES AND RESULTS WITH ALM

The results reported in the previous sections portray a different picture than that which emerges from ALM's analysis. ALM found evidence that CBT adoption was greater in industries historically intensive in routine tasks, whereas we demonstrated that CBT adoption is greater in occupations historically intensive in complex tasks. ALM found evidence that computerization raises demand for cognitive and interpersonal skills, reduces demand for repetitive skills and had little direct impact on the demand for nonroutine manual skills, these findings being pervasive within industries, occupations, and education groups. We found that computerization affects skills positively only for occupations historically intensive in complex tasks, but not for simple tasks, where computerization does not affect skills or affects them negatively. This section rationalizes these differences in findings.

Several factors can account for such differences. ALM distinguish between routine and nonroutine tasks, whereas we distinguish tasks by their complexity. ALM use task inputs as proxies for skills, whereas we use direct measures of skills. Furthermore, ALM use industry- and occupation-level samples from Current Population Survey (CPS) and Census of Populations that estimate U.S. labor force, whereas we use a sample of 819 firms from Minnesota. Beyond these differences in measures and data, we estimate a non-linear model to explain changes in skills by computerization, whereas ALM estimate a linear model. In the remainder of this section, we examine the most important differences. First, we explore the relationship between the characterization of tasks by ALM and the one we use. Second, we replicate ALM's estimation of computerization at the industry-level and add to it complexity variables. Third, we replicate ALM's analysis of the impact of CBT on skill change at the occupation level and augment it with interaction terms between CBT and ALM's characterization of tasks.[11]

V.1. Mapping routine variable onto complexity task variables

One critical element in the analysis of changes in skills is the way in which the task content of jobs is characterized. ALM focus on the degree of routine of tasks whereas we focus on complexity. ALM use five variables to characterize routine and nonroutine jobs. Two variables account for nonroutine cognitive skills: *math*, which measures complex problem-solving skills, and *dcp*, which captures communication and managerial skills. Routine cognitive skills are captured by *sts*, adaptability to work requiring set limits, tolerances, or standards. Routine manual skills are represented by *fingdex*, finger dexterity. Nonroutine manual skills are captured by *eyehand*, eye-hand-foot coordination (see ALM for a more detailed description). In contrast, we use three variables to characterize job complexity: *data* for tasks that have to do with knowledge and information, *people* for tasks that require people interaction and *things* for tasks that involve manipulation of tangible objects, such as machines (see our Appendix B).

To examine how routine and complexity map onto each other, we use a replication of ALM's industry-level dataset and explore simple correlations among the variables and interpret them in view of the specific definitions of the tasks. (Similar results were obtained for a replication of

[11] We thank ALM for making their dataset available. However, identical duplication of their data and measures was not possible because of the absence of some crosswalks.

ALM's occupation-level dataset). Table E1 in Appendix E indicates that measures for nonroutine cognitive tasks (*math* and *dcp*) are positively correlated with *data* (.89; .63) and *people* (.67; .43), whereas measures for routine, both manual (*finger*) and cognitive (*sts*) tasks are positively correlated with *things* (.52; .60). Therefore, ALM's routine task index (*rt)* exhibits negative correlations with *data* (-.23) and *people* (-.48) and a positive correlation with *things* (.48). The *data* variable includes only cognitive tasks, with 1, 2, 3 and 4 being routine (programmable) tasks and *data* 5, 6, and 7 being nonroutine (nonprogrammable) tasks; at the same time, tasks 1, 2, 3 and 4 are simple, or less complex tasks, whereas tasks 5, 6 and 7 are complex. So, almost by definition, routine is akin to simple and nonroutine to complex, in the domain of cognitive tasks that have to do with knowledge and information. ALM capture nonroutine cognitive tasks with *math*, which is quite similar to *data* (correlation .89). *People* includes mostly cognitive tasks (except for serving), but in this case simple is different from routine. Because different people have different needs, different styles of communication and so on, *people* tasks are generally nonroutine, with lower levels being simpler and higher levels more complex. The significant negative correlations of *people* with *sts* and ALM's routine index (-.54; -48) confirm the nonroutine nature of the *people* variable. Based on the correlation coefficients, *things* includes mostly routine tasks, with the simplest tasks (1, 2, 3, and 4) being clearly routine manual tasks, and the most complex tasks (6, 7, and 8) being both routine manual and routine cognitive tasks. Tasks 6, 7 and 8 can be considered routine on the basis of ALM's definition of *sts:* "adaptability to situations requiring the precise attainment of set limits, tolerances, or standards." Task 5, driving-operating, would be an exception as it is considered by ALM a nonroutine manual task. Apart from exhibiting different types of complexity, both *data* and *people* categorize a homogeneous range of tasks, cognitive analytic for data and nonroutine cognitive and interactive for people. *Things* exhibits broader task heterogeneity, ranging from simple routine manual tasks (1, 2, 3 and 4), nonroutine manual tasks (5), to routine cognitive tasks (6, 7 and 8), each level also increasing in complexity.

In sum, the two sets of variables capture different but related tasks attributes. *Data* overlaps substantially with ALM's measure of nonroutine cognitive tasks, whereas our *people* and *things* measures and ALM's variables overlap only to a limited extent. To check the robustness of the

simple correlation analysis, we conducted also a multiple correspondence analysis (MCA), which yielded similar results.[12]

V.2. Replication of ALM analyses

Predicting CBT

We replicate ALM's estimation of CBT adoption as a function of task routine, and then add into the equation task complexity. Task routine is measured with ALM's pre-CBT routine index and complexity with the *data* variable. (By construction, that routine index is positively correlated with *finger* and *sts* and negatively with *math*, *dcp*, and *eyehand*). Column 1 of Table 7 presents a replication of ALM's predictive test (their equation 12), where the dependent variable is the percentile rank of computer use in 1997 in 140 industries and the independent variable is routine task share in 1960. Column 2 adds complexity in 1960 defined analogously to task routine. Both independent variables were standardized. The inclusion of complexity increases R^2 substantially from 0.10 to 0.41. It also increases task routine's predictive power from a point estimate of 1.85 (standard error 0.48) to 13.27 (standard error 1.99). The point estimate of complexity is 17.43 (standard error 2.08).[13] These results attest to the importance of task complexity, whose effect on CBT is 31.27% stronger that the effect of task routine – although both clearly contribute to predicting which industries were more prone to adopt CBT.

{{Table 7 here}}

Estimating the effect of CBT on skills in our framework with ALM data

ALM estimate a linear regression of within-occupation change in task content on occupational computerization and a constant. They find that occupations that have undergone rapid computerization experienced a reduction in the labor input of routine cognitive skills and an

[12] MCA demonstrates that information contained in ALM's nonroutine-routine, manual and cognitive variables and in our complexity variables overlaps to a certain degree. The information these variables provide can be probably best captured through two different dimensions, one describing nonroutine complex tasks and the other describing routine tasks. MCA also shows that the nonroutine complexity dimension captures more variation in tasks – more information – than the routine dimension.

[13] Adding *People* in the equation further improves R^2 to .46, increases the estimate on the routine variable to 2.92 (s.e. .39), lowering the estimate on *data* to 16.60 (4.03), whereas the estimate on *people* is 11.06 (3.27). Adding also *things* increases R^2 to .47, changes estimate on routine to 2.84 (.39), increases that on *data* to 20.38 (4.50), reduces the estimate on *people* to 6.18 (4.19, p-value .14), and the estimate on *things* is negative, -4.71 (2.56).

increase in the labor input of nonroutine interactive skills. However, there was no increase in nonroutine analytic skills and no reduction in routine manual tasks. In contrast, we estimate a regression of firm-level change in employees' skills on firm-level CBT change, the interaction of firm-level CBT change and pre-CBT occupational complexity, and without a constant term. We obtain significant negative CBT coefficients and significant positive coefficients for the interaction for most skills, supporting the bifurcation hypothesis. ALM's model allows for just one type of results, either skilling or deskilling, whereas our framework allows also for contingent results, that is, skilling or deskilling depending on the degree of task complexity.

To assess the implications of the differences in the two models, we contrast the estimates derived from them in Table 8. The table replicates ALM's equation 16 and our equation 4, using ALM's dataset and measures. Column 1 of each panel presents ALM's original estimates from their Table VI. Column 2 eliminates the constant term and is equivalent to column (a) in our Table 5, whereas column (3) includes the interaction term. The interaction term results from multiplying computer use with $math_{1971}$ for nonroutine analytic skills, with dcp_{1971} for nonroutine interactive skills, with sts_{1971} for routine cognitive skills, and with $fingdex_{1971}$ for routine manual skills.

In column (2), computer use is insignificant for nonroutine analytic skills, significantly positive for nonroutine interactive skills and routine manual skills and significantly negative for routine cognitive skills. When the interaction term is introduced in column (3), R^2 increases and the computer-use coefficients turn significantly negative for nonroutine analytic skills, negative but insignificant for nonroutine interactive, and insignificant for routine manual skills, remaining negative for routine cognitive skills. These results are combined with significant positive interaction coefficients except for routine manual skills, for which the interaction is not significant. Thus except for routine manual skills, the contingent framework to explain CBT impacts on skills is broadly supported with ALM measures.

VI. DISCUSSION AND CONCLUSIONS

What is the effect of technological change on workers' skills? Thinking for the moment of an undifferentiated notion of skill, one can envision technological change that raises the skill level demanded of those who work with the new technology. For example, the introduction of the

typewriter required the acquisition of additional skills by secretaries, including coordination among 10 digits, reading and typing at the same time and performing some maintenance on the typewriter. This is a *skilling* technological change, and so might have been the introduction of computers for secretaries who had to learn functions embedded in word processing software and who almost universally have to carry out activities on computers that require more skills than before the introduction of computers. On the other hand, in the same way that tailors and other artisans experienced *deskilling* when technological change resulted in the introduction of mass production (James and Skinner, 1985; Cain and Paterson, 1986), cashiers in supermarkets and many other workers have likely seen some of their skill requirements lowered as a result of the introduction of computerized scanning and other CBT. In the sample of firms analyzed in this paper there are both skilling and deskilling cases. Waiters, bartenders, tellers and cashiers are examples of workers whose skills were lowered by CBT use, whereas truck repairers, salespeople and project engineers are examples of workers whose skills were enhanced by CBT; many others have seen little change.

In this paper we advanced two propositions. First, we argued that the intensity of CBT use is predicted in part by the historical (pre-CBT) complexity of the tasks carried out by core employees. Corroborating our expectations, we found that CBT is used more intensively in occupations that were high-complexity in 1971. We estimated our model with ALM's data at the industry level to include complexity and obtained very similar results. We found it useful to distinguish different types of complexity, in relation to data, people and things. Whereas data- and things-complexity affect positively CBT use on their own, people-complexity only affects CBT through interactions with the other two complexity dimensions. This result, as well as others, suggests that overall task complexity also contributes to CBT adoption and intensity of use.

Second, we argued that high pre-CBT task complexity leads to skilling in the wake of adoption of CBT but low pre-CBT task complexity does not, or leads to deskilling. In our sample firms, the bifurcation is most evident for *complex problem-solving, technical* and *resources management skills* where occupations with high pre-CBT complexity gained in these skills but those with low pre-CBT complexity levels experienced declines or no change. The positive

effect of CBT on *content*, *process* and *system* skills seems to be stronger with pre-CBT complexity in relation to data, people, and things, respectively. *Social skills* decline when pre-CBT people-complexity is low and increase when it is high, when there is no pre-CBT complexity in relation to data. In other words, there is no skilling effect for skills without pre-computer task complexity. We replicated our analysis on ALM's dataset for all the occupations in their sample and obtained similar bifurcation results with respect to nonroutine cognitive tasks and routine cognitive tasks. After combining our results with those of ALM's replication, we can conclude that the clearest and most consistent evidence of the bifurcation hypothesis is found in highly complex cognitive skills, such as complex problem-solving skills, resources management skills, and routine cognitive skills. However, this pattern dissipates slightly for arguably simpler and more basic skills, like content or process skills. For social skills, an overall deskilling trend is found. And finally, no effect was found for routine manual skills.

These findings resemble Autor, Levy and Murnane's (2002)'s findings in a case study of two different jobs in a large bank, deposit processing and exception processing of checks, jobs that were affected differentially by the introduction of the same technological change. In the case of deposit processing, greater access to information provided by introduction of new technology allowed managers to pursue a cost reduction strategy by exploiting economies of specialization, subdividing tasks that were not computerized into narrower, simpler jobs. In the case of exception processing, technology's *informating* capacity allowed to exploit interdependencies to improve customer service, combining tasks into broader, more complex jobs.

Are these findings particular to our sample firms? Our sample occupations, although not entirely random, concerns a substantial percentage (nearly 30) of occupations covered by the DOT classification. Replication of these results with ALM's dataset suggests that our findings are not specific to our sample, but are robust to an analysis of a much more representative sample of US workers and industries.

Furthermore, there are indications that these bifurcation trends are widespread and the process *is still continuing*. Figure D1 in Appendix D depicts the relative growth in employment and wages for occupations that were high in pre-CBT task complexity versus occupations that were low in task complexity, for the US workforce for the period 1970-1998, by task complexity in relation

to data, people, and things. Employment and wages of occupations that were pre-CBT complex in relation to data and people have been rising relative to employment and wages of simpler occupations. For complexity in relation to things, an opposite trend is observed: employment and wages have been rising for simpler occupations as compared with more complex occupations. Recall that neither ALM nor we have found change in simple routine manual skills due to computerization. Considering two broad categories of jobs, managerial and production jobs and focusing on recent years (2002-2008), we find a similar bifurcation in terms of complex problem-solving skill changes (see Figure D2 in Appendix D). Two main conclusions can be drawn from Figure D2, for the US labor force.[14] First, regarding computer use, high-skill (managerial) occupations use computers more intensely than low-skill (production) occupations. Second, regarding skill change, high-skill workers who use computers more intensely see higher increases in their complex problem-solving skills, whereas low-skill workers who use computers become even less skilled. An empirically similar picture is described for Britain by Goos and Manning (2007), who emphasize the growing polarization in wages and the quality of jobs as a consequence of recent technological changes.

Clearly, more research is required to understand the effects of technical change on skills, wages, employment and organization design and their effects on different groups of workers.[15] One important area that our paper highlights is a better understanding of the nature of tasks and their proper characterization in the context of different occupations. Another area is that of differentiation among different skills, how various skills are affected by computerization, how these skills are acquired, how they affect the employment of those who possess some but not other of these skills, and how these affect the distribution of incomes in the economy.

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[15] In a recent paper, Autor and Acemoglu (2010) develop a task-complexity based model and conclude in favor of a contingent effect of technical change on wages, akin to our findings on the bifurcated effect of CBT on skills. Ben-Ner, Kong and Lluis (2011) explore the role of task complexity and other attributes of the task environment in determining the organization design faced by core employees.

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Table 1. Description and sources of variables

	Variable name	Description	Source
	Core employee-level variables		
		Survey question: *To what extent does reliance on computer-based technology reduce or enhance the skill sets possessed by core employees?* [-3, -2, -1, 0, 1, 2, 3] scale	Minnesota Human Resource Management Practices Survey 2000 - MHRMPS-2000
1.	Change in content skills	Basic knowledge and skills that enable reading, computing, listening, writing, and speaking	
2.	Change in process skills	Skills needed to process information and facilitate procedures (e.g., critical thinking, monitoring, working with new information, etc.)	
3.	Change in social skills	Skills needed for working with people to achieve goals (e.g., social perceptiveness, coordination and negotiation skills, persuasion and instruction skills, and team-working skills)	
4.	Change in complex problem-solving skills	Skills needed for solving problems (e.g., idea generating and evaluation, implementation planning, and assessing outcomes, etc.)	
5.	Change in technical skills	Skills needed for designing, operating, and maintaining equipment (e.g., equipment selection, installation, programming, operating, testing, and repairing)	
6.	Change in system skills	Skills needed for understanding a system as a whole and acting upon it	
7.	Change in resources management skills	Skills needed for working with resources in creating products (e.g. time management, financial, materials, and personnel management)	
8.	Task complexity	Survey question: *Are the tasks performed by core employees complex?* [0, 4] scale	MHRMPS-2000
9.	Task skill requirement	Survey question: *Are the tasks performed by core employees highly skilled?* [0, 4] scale	MHRMPS-2000
10.	Task routine	Survey question: *Are the tasks performed by core employees routine?* [0, 4] scale	MHRMPS-2000
11.	Computer-based technologies (CBT)	Survey question: *Are the tasks of core employees affected by computer-based technology?* [0, 4] scale	MHRMPS-2000
12.	Number of core employees	Number of core employees	MHRMPS-2000
13.	Unionization	Percentage of core employees that are unionized	MHRMPS-2000
	Firm-level variables		
14.	Sales	Sales in 1999 (in millions of dollars)	Dunn & Bradstreet
15.	Wage	Average wage in 1998 (in thousands of dollars)	MN State Department of Economic Security
16.	Education	Average education (in years) of employees in Minnesota	MHRMPS-2000
17.	Employee age	Average age (in years) of employees in Minnesota	MHRMPS-2000
18.	Females	Proportion of females in workforce in Minnesota	MHRMPS-2000
19.	Firm age	Years in business	MHRMPS-2000
	Occupation-level variables		
20.	Complexity-Data$_{1971}$	Average level of complexity at which the worker performs in relation to data [1,7] scale	April 1971 CPS augmented with DOT Fourth Ed. 1977, for 1970 Census Occupation Codes
21.	Complexity-People$_{1971}$	Average level of complexity at which the worker performs in relation to people [1, 9] scale	April 1971 CPS augmented with DOT Fourth Ed. 1977, for 1970 Census Occupation Codes
22.	Complexity-Things$_{1971}$	Average level of complexity at which the worker performs in relation to things [1,8] scale	April 1971 CPS augmented with DOT Fourth Ed. 1977, for 1970 Census Occupation Codes
23.	Education$_{1971}$	Average educational attainment [1, 9] scale	IPUMS-CPS for 1970 Census Occupation Codes
24.	Wages$_{1971}$	Average annual wages (in thousands of dollars)	IPUMS-CPS for 1970 Census Occupation Codes
	Industry-level variables		
25.	R&D intensity	Number of full-time equivalent R&D scientists and engineers per 1,000 employees by industry in 2000	2001 Survey of Industrial Research and Development, National Science Foundation

Table 2. Descriptive statistics

Variable	Mean	SD	Min	Max	N
Core employee-level variables					
1. Change in content skills	.84	1.09	-2.00	3.00	642
2. Change in process skills	.95	1.14	-3.00	3.00	644
3. Change in social skills	.29	.91	-3.00	3.00	643
4. Change in complex problem-solving skills	.62	1.01	-3.00	3.00	642
5. Change in technical skills	.89	1.21	-3.00	3.00	642
6. Change in system skills	.71	1.06	-3.00	3.00	641
7. Change in resources management skills	.65	1.07	-3.00	3.00	640
8. Task complexity	1.86	.94	.00	4.00	802
9. Task skill requirement	1.82	1.07	.00	4.00	805
10. Task routine	2.23	.94	.00	4.00	807
11. Computer-based technologies (CBT)	1.82	1.30	.00	4.00	810
12. Number of core employees	88.30	234.83	1.50	330.00	805
13. Unionization	18.03	37.34	.00	100.00	638
Firm-level variables					
14. Sales	46.78	229.81	.01	3357.76	759
15. Wage	35.00	21.03	.56	177.29	634
16. Education	13.13	1.50	8.00	18.00	704
17. Employee age	34.26	7.14	10.00	55.00	745
18. Females (%)	45.68	25.75	.00	100.00	794
19. Firm age	34.57	27.64	.00	153.00	773
Occupation-level variables					
20. Complexity-Data$_{1971}$	3.75	1.39	1.00	7.00	813
21. Complexity-People$_{1971}$	2.28	1.18	1.00	8.34	813
22. Complexity-Things$_{1971}$	3.63	2.24	1.00	7.82	813
23. Education$_{1971}$	6.07	.75	3.48	8.63	754
24. Wages$_{1971}$	5.93	3.21	1.63	24.44	754
25. R&D intensity	50.16	54.82	1.00	366.00	766

Table 3. Pearson correlations

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1. Change in content skills																							
2. Change in process skills	.63*																						
3. Change in social skills	.29*	.29*																					
4. Change in complex problem-solving skills	.49*	.51*	.33*																				
5. Change in technical skills	.45*	.49*	.19*	.55*																			
6. Change in system skills	.45*	.50*	.34*	.54*	.60*																		
7. Change in resources management skills	.38*	.44*	.27*	.46*	.48*	.52*																	
8. Task complexity	.29*	.34*	.05	.31*	.36*	.27*	.25*																
9. Task skill requirement	.29*	.29*	.08	.28*	.30*	.22*	.24*	.70*															
10. Task routine	-.17*	-.12*	.00	-.12*	-.10*	-.15*	-.08	-.23*	-.21*														
11. Computer-based technologies (CBT)	.53*	.53*	.16*	.43*	.51*	.48*	.38*	.36*	.31*	-.13*													
12. Unionization	.01	.01	.03	.05	.03	.06	.05	.11*	.08	.02	-.01												
13. Productivity	.14*	.15*	.05	.15*	.17*	.19*	.13*	.13*	.06	-.05	.12*	.10											
14. Wage	.25*	.22*	.04	.23*	.28*	.22*	.13*	.32*	.30*	-.22*	.27*	.17*	.23*										
15. Education	.28*	.32*	.00	.27*	.25*	.20*	.24*	.30*	.29*	-.20*	.32*	-.04	.05	.39*									
16. Employee age	.18*	.18*	.03	.23*	.21*	.19*	.14*	.24*	.16*	-.05	.23*	.23*	.16*	.38*	.16*								
17. Females	-.06	-.06	.00	-.10*	-.25*	-.13*	-.04	-.18*	-.23*	.09	-.07	-.27*	-.11*	-.34*	-.03	-.23*							
18. Firm age	.06	.10	.05	.07	.07	.08	.01	.02	-.02	.04	.09	.25*	.12*	.09	-.04	.31*	-.11*						
19. Complexity-Data$_{1971}$	.33*	.30*	.03	.24*	.19*	.22*	.21*	.33*	.34*	-.25*	.36*	-.10	.08	.26*	.35*	.07	-.01	.00					
20. Complexity-People$_{1971}$	.25*	.21*	.08	.12*	.05	.12*	.18*	.14*	.10*	-.14*	.20*	-.10	.01	.07	.26*	-.04	.25*	.00	.59*				
21. Complexity-Things$_{1971}$	.03	.10	.01	.08	.20*	.13*	.02	.26*	.25*	-.03	.13*	.18*	.00	.24*	.05	.25*	-.33*	.14*	.12*	-.29*			
22. Education$_{1971}$	.34*	.30*	.12*	.21*	.12*	.18*	.20*	.13*	.10*	-.13*	.36*	-.10*	.05	.08	.27*	.01	.25*	.06	.63*	.70*	-.27*		
23. Wages$_{1971}$	.31*	.31*	.08	.29*	.31*	.25*	.24*	.30*	.29*	-.18*	.35*	.16*	.20*	.42*	.25*	.37*	-.31*	.21*	.58*	.28*	.15*	.43*	
24. R&D intensity	.27*	.28*	.00	.27*	.28*	.31*	.17*	.19*	.15*	-.19*	.34*	-.10	.08	.24*	.31*	.15*	-.13*	-.06	.27*	.12*	.04	.23*	.15*

*p<.01

Table 4. Estimates of CBT adoption and intensity of CBT use

	1. Adoption of CBT Logit					2. Intensity of CBT use Ordered logit; Non-users excluded					3. Intensity of CBT use Poisson; Non-users included				
	(1a)	(1b)	(1c)	(1d)	(1e)	(2a)	(2b)	(2c)	(2d)	(2e)	(3a)	(3b)	(3c)	(3d)	(3e)
Pre-CBT complexity variables															
Data	-	.69 (.51)	.10 (.92)	-	.70*** (.15)	-	1.58** (.55)	2.11* (.98)	-	.68*** (.10)	-	.54*** (.13)	.56+ (.29)	-	.26*** (.03)
People	-	.16 (.50)	-	-1.01 (.65)	-.18 (.17)	-	.06 (.45)	-	.02 (.92)	.09 (.13)	-	.17 (.17)	-	-.24 (.32)	.00 (.04)
Things	-	-	.26 (.94)	-.52 (1.11)	.38** (.12)	-	-	-1.9+ (1.09)	3.07* (1.35)	.12 (.10)	-	-	-.41 (.32)	.47 (.56)	.12*** (.03)
Data×People	-	-.02 (.29)	-	-	.41** (.13)	-	-.34 (.34)	-	-	.08 (.10)	-	-.17 (.13)	-	-	.05 (.03)
Data×Things	-	-	-.54 (.58)	-	-.32* (.16)	-	-	-.96+ (.57)	-	-.22* (.11)	-	-	-.35+ (.19)	-	-.15*** (.03)
People×Things	-	-	-	-.37 (.29)	.06 (.17)	-	-	-	3.42* (1.69)	-.02 (.14)	-	-	-	.24 (.67)	-.02 (.05)
Data×People×Things	-	-	-	-	.27+ (.16)	-	-	-	-	.28* (.12)	-	-	-	-	.11* (.04)
Pre-CBT skills variables															
Education	.56** (.18)	-	-	-	-	.75*** (.12)	-	-	-	-	.22*** (.04)	-	-	-	-
Wages	.26*** (.04)	-	-	-	-	.06* (.02)	-	-	-	-	.04*** (.01)	-	-	-	-
N	746	121	124	121	804	585	79	99	89	639	746	121	124	121	804
Wald	46.87***	7.89+	4.31	7.50*	52.86***	78.10***	11.11*	5.38	8.15*	79.49***	179.9***	28.2***	5.78	2.69	167***

Notes: (a) Robust standard errors of estimated coefficients are in parentheses. (b) A constant term was included in the logit and Poisson estimations, and three cut points were included in the ordered logit estimation (omitted here for space reasons). (c) Pre-CBT complexity variables are centered to control for multicollinearity. (d) +: p<.10; *: p<.05; **: p<.01; ***: p<.001

***Table 5*. Logit regressions for CBT and change in skills**

	Change in											
	1. Content skills			**2. Process skills**			**3. Social skills**			**4. Complex problem-solving skills**		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)	(3a)	(3b)	(3c)	(4a)	(4b)	(4c)
CBT	.25***	-.26*	-.16	.35***	-.12	-.14	-.33***	-.45***	-.44**	.08*	-.35**	-.25+
	(.04)	(.11)	(.15)	(.04)	(.11)	(.16)	(.04)	(.11)	(.17)	(.03)	(.10)	(.15)
CBT×Wages	-	.06***	-	-	.05***	-	-	.01	-	-	.05***	-
		(.01)			(.01)			(.01)			(.01)	
CBT×Data	-	-	.12**	-	-	.02	-	-	-.16***	-	-	.11**
			(.04)			(.04)			(.04)			(.03)
CBT×People	-	-	.01	-	-	.15**	-	-	.22***	-	-	-.01
			(05)			(06)			(.05)			(.04)
CBT×Things			-.02			.01			.03			-.02
			(.02)			(.02)			(.02)			(.02)
N	642	575	622	644	575	623	643	581	629	642	575	625
Wald χ^2	46.33***	47.88****	68.31***	75.77***	69.02***	87.48***	62.20***	53.83***	75.03***	5.14*	22.18***	21.31***

	Change in								
	5. Technical skills			**6. System skills**			**7. Resources management skills**		
	(5a)	(5b)	(5c)	(6a)	(6b)	(6c)	(7a)	(7b)	(7c)
CBT	.26***	-.40**	-.26+	.18***	-.05	-.11	.04	-.44***	-.33*
	(.04)	(.12)	(.15)	(.03)	(.10)	(.14)	(.03)	(.11)	(.15)
CBT×Wages	-	.08***	-	-	.02*	-	-	.05***	-
		(.01)			(.01)			(.01)	
CBT×Data	-	-	.00	-	-	.00	-	-	.03
			(.04)			(.03)			(.03)
CBT×People			.08			.05			.10*
			(.05)			(.05)			(.05)
CBT×Things	-	-	.09***	-	-	.04*	-	-	-.01
			(.02)			(.02)			(.02)
N	642	571	624	641	574	626	640	569	626
Wald χ^2	47.07***	52.13***	58.59***	24.92***	23.15***	34.99***	1.64	20.69***	19.11***

Notes: (a) Robust standard errors of estimated coefficients are in parentheses. (b) Estimates include firms with CBT=0, which have no skill variation (results are identical if CBT non-users are excluded). (c) Regression equations have no constant. (d) With all Variance Inflation Factors (VIF) less than 10, multicollinearity is not a problem. (e) The number of observations differs among columns because missing values differ and because outliers have been removed from estimation to improve significance (however, this does not affect the estimates). (f) +: p<.10; *: p<.05; **: p<.01; ***: p<.001

Table 6. Poisson regressions for CBT and task environment

	Task environment					
	Task Complexity		**Task Skill Requirements**		**Task Routine**	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
Constant	.35***	.19***	.27**	-.30	.86***	.98***
	(.04)	(.05)	(.08)	(.27)	(.03)	(.04)
$e^{\delta_1 CBT}$	-.04	-	-.06	-	-	-
	(.03)		(.07)			
$e^{\delta_1 CBT}$ **× Data**	.02***	.02***	.05***	.03***	-	-
	(.01)	(.00)	(.01)	(.01)		
$e^{\delta_1 CBT}$ **× People**	.01	-	-.01	-	-	-
	(.01)		(.02)			
$e^{\delta_1 CBT}$ **× Things**	.02***	.03***	.02**	.02***	-	-
	(.01)	(.01)	(.01)	(.01)		
CBT	-	-	-	-	.09**	.10**
					(.03)	(.03)
CBT × Data	-	-	-	-	-.03***	-.03***
					(.01)	(.01)
CBT × People	-	-	-	-	.00	-
					(.01)	
CBT × Things	-	-	-	-	.00	-
					(.00)	
Number of core employees	-	-.03***	-	-.37*	.	.01*
		(.00)		(.16)		(.00)
Wage	-	.11***	-	.08**	-	-.08**
		(.03)		(.03)		(.03)
Education	-	-	-	.07*	-	-
				(.03)		
Females	-	-	-	-.08*	-	-
				(.04)		
R&D intensity	-	-	-	-.10*	-	-
				(.04)		
N	795	345	798	344	800	345
Wald χ^2	304.81***	351.01***	87.89***	193.87***	45.69***	47.89***
p-values	.005		.097		.571	
δ_1	.40		.29		-	

Notes: (a) Robust standard errors of estimated coefficients are in parentheses. (b) Exponential function for task complexity and task skill requirements, linear function for routine. (c) p-values are Box-Tidwell tests for linearity. (d) +: p<.10; *: p<.05; **: p<.01; ***: p<.001

***Table 7*. Replication of ALM's estimation of computer adoption (ALM's equation 12), and addition of complexity in relation to data**

	Computer adoption$_{j,\ 1960\text{-}1997}$	
	(1)	(2)
Constant	-24.56 (20.14)	42.20*** (2.08)
Routine Task Share$_{1960}$	1.85*** (.50)	13.27*** (1.99)
Complexity Data$_{1960}$	-	17.43*** (2.08)
N	140	138
R^2	.10	.41

Notes: (a) Industry-level data. (b) Sources: for column 1, Autor, Levy, and Murname (2003)'s dataset, and for column 2, replication of Autor, Levy, Murname (2003)'s dataset. (c) There are very slight differences in ALM's and our estimates of standard errors for their model in column 1; these differences stem from small differences in our replication of the Autor, Levy, and Murname (2003)'s variables. (d) 2 industries out of 140 are missing in column 2 because of our replication of Autor, Levy, and Murname (2003)'s dataset. (e) Independent variables in column 2 are standardized. (f) +: p<.10; *: p<.05; **: p<.01; ***: p<.001

***Table 8*. Replication of ALM equation (16), Table VI, using our specification in equation (4), Table 5**
Using ALM dataset and measures

	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 $_{1984\text{-}1997}$	2.94	-.66	-7.21+	5.70**	3.90***	-.45	-18.18***	-15.99***	-20.88***	1.74	3.37+	4.52
	(1.84)	(.99)	(3.00)	(1.88)	(1.01)	(1.38)	(3.29)	(1.77)	(2.30)	(2.89)	(1.55)	(4.05)
Δ Computer use × Skill endowment	-	-	1.41+	-	-	1.16***	-	-	1.63**	-	-	-.30
			(.61)			(.26)			(.50)			(.96)
Intercept	-.92	-	-	-.46	-	-	.56	-	-	.42	-	-
	(.40)			(.41)			(.71)			(.63)		
R^2	.01	.00	.01	.02	.03	.07	.06	.14	.17	.00	.01	.01

Notes: (a) Source: Autor, Levy and Murname (2003)'s dataset. (b) Occupation-level data. (c) N=470 occupations. (d) +: p<.10; *: p<.05; **: p<.01; ***: p<.001

Figure 1. Alternative hypotheses concerning the impact of CBT use on skills

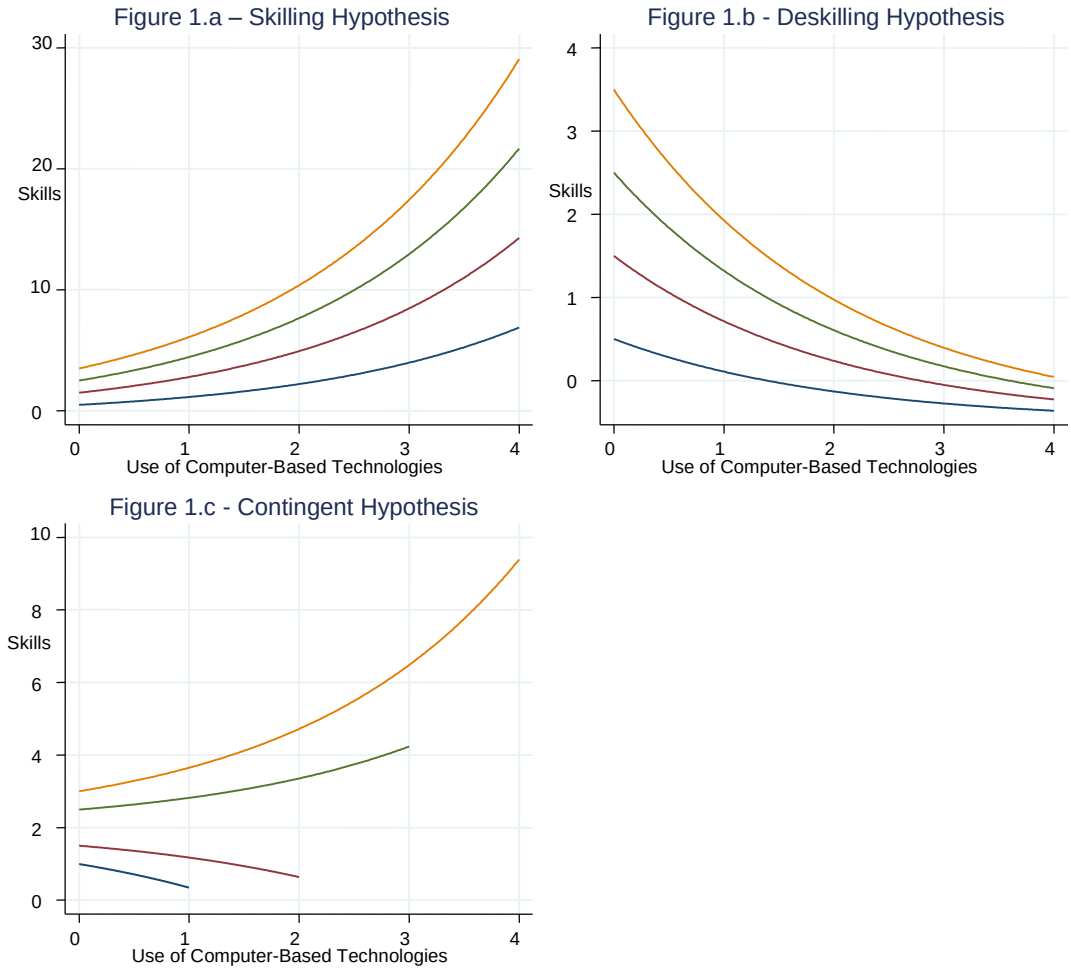
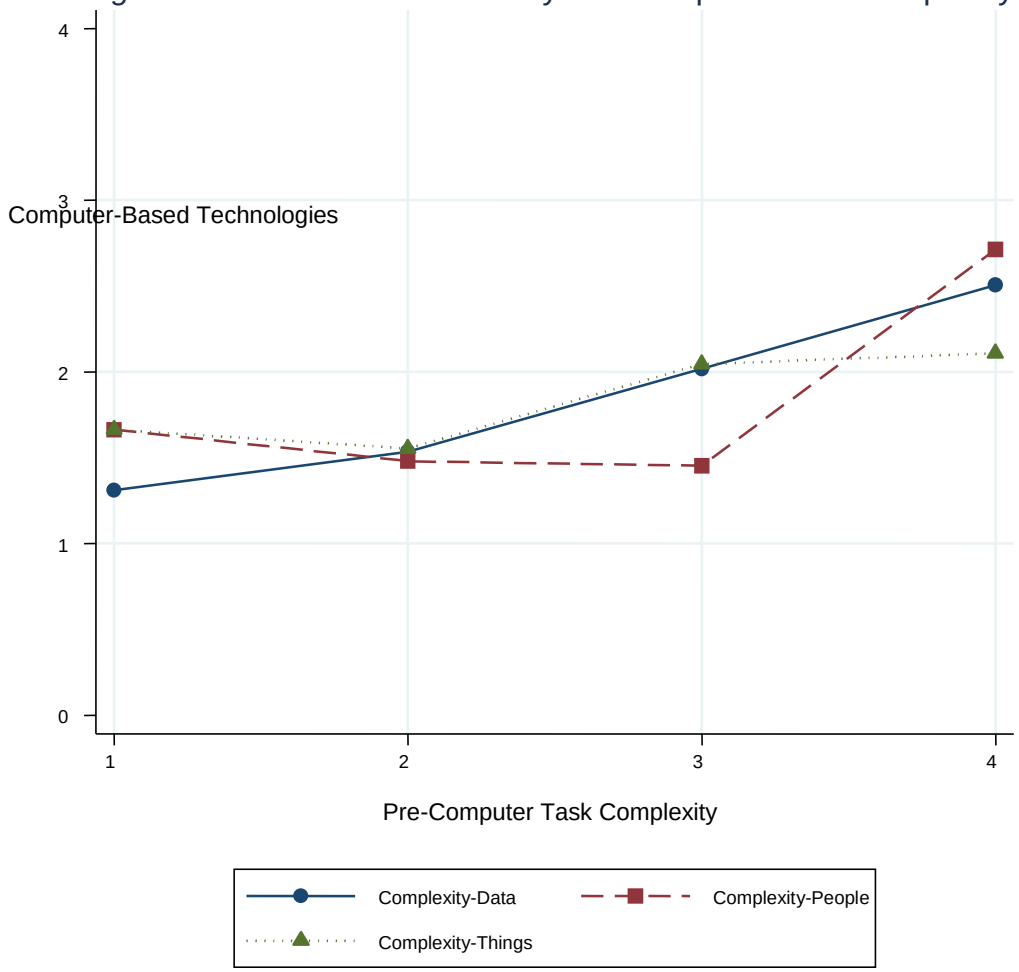


Figure 2. Mean Values of CBT by Pre-Computer Task Complexity

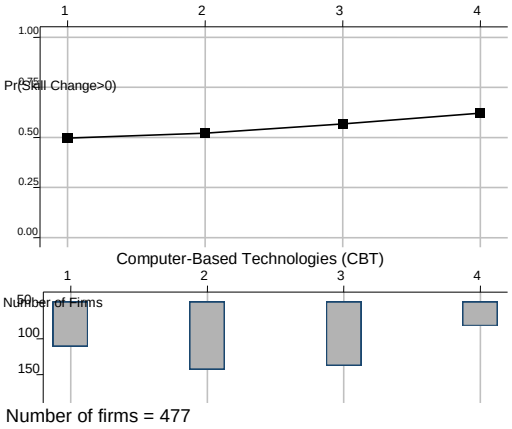


N=804

Sources: MHRMPS-2000; and April 1971 CPS augmented with DOT Fourth Ed. 1977, for 1970 Census Occupation Codes.

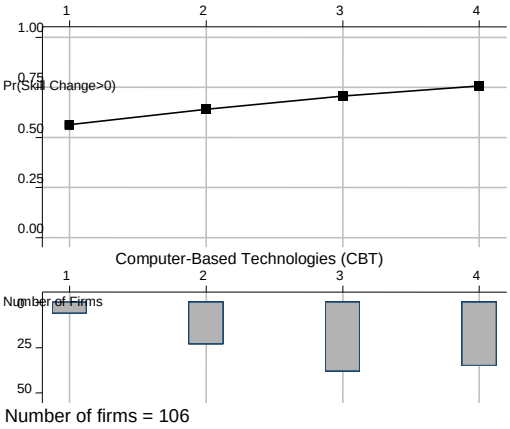
Figure 3. Estimated Probability of Positive Changes in Complex Problem-Solving Skills

Figure 3.a - Entire Sample



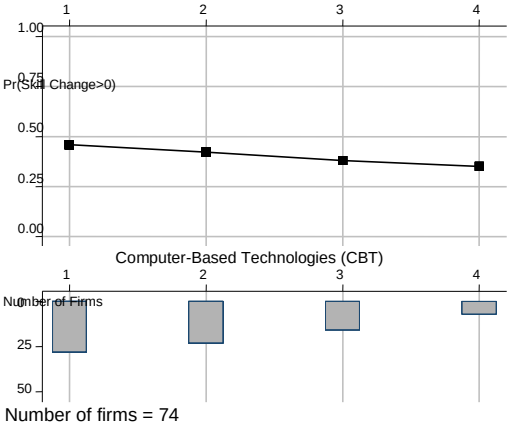
Number of firms = 477

Figure 3.b - Subsample-High Pre-CBT Task Complexity



Number of firms = 106

Figure 3.c - Subsample-Low Pre-CBT Task Complexity



Number of firms = 74

Notes: Firms with CBT=0 are excluded.

Sources: MHRMPS-2000; and April 1971 CPS augmented with DOT Fourth Ed. 1977, for 1970 Census Occupation Codes.

Appendix A. Data collection: Sampling Strategy and Returns

The data collection effort was generously funded by the Centers for Disease Control and Prevention-National Institute for Occupational Safety and Health, with additional funding from the University of Minnesota-Sloan Foundation Food Industry Center.

The sampling strategy, closely emulating our previous survey efforts, was based on our desire to include large numbers of different types of for-profit firms from diverse industries. We also wanted to over-sample firms with employee-stock ownership plans (ESOP) and firms in the retail food industry, largely because our previous survey efforts had emphasized these firms and we wished to continue with the longitudinal aspects of the database. Our focus was on for-profit firms with at least 20 employees in diverse industries outside agriculture [SIC: 1000-8999], headquartered and operating (majority of employees) in Minnesota. The sample firms belonged to one five groups:

1. ESOP Firms: The names of these firms were retrieved from three independent sources: The National Center for Employee Ownership data set (1998), the Minnesota ESOP Association membership list (1998), and Form 5500 of 1997 (the federal tax form filed under ERISA). There were 246 such firms.

2. Public Firms: All publicly traded firms that appeared on the 1998 CompuStat database but were not already included above. There were 379 firms identified using this method.

3. Retail Food Firms: All firms in the retail and wholesale food industry [SIC: 5140-5149, 5400-5499, 5810-5813] with 20 or more employees, not already included above. These firms were identified in the 1999 Dunn and Bradstreet database. There were 1191 such firms.

4. Survivor firms from the earlier survey: All firms that were still operational who had previously responded to our 1994/1996 survey (MHRMPS-1996) not already included above. The number of firms in this category was 609.

5. Randomly Selected Firms: A random sample of private firms not already included above, identified in the 1999 Dunn and Bradstreet database. There were 268 firms identified in this manner.

Surveys were mailed to 2,693 firms in November 1999. Reminder postcards and a second mailing of surveys followed in early 2000. By June 2000 478 firms (19.5%) had responded with valid questionnaires. A telephone survey was conducted to increase the number of responding firms. Data collection efforts stopped in November 2000. Table 1 presents information about the number of firms that were mailed the survey, the number of valid candidates (firms that could have responded - i.e., the post office did not return the survey indicating that it could not be delivered - excluding firms that responded but did not meet the criteria for inclusion in the sample), and the number of returned surveys. The total number of valid survey returns was 819, which represents a response rate of 33.37%. The distribution of the sample across industries is shown in Table A1, below:

***Table A1*. Firms Surveyed and Response Rates**

Sampling Group	Number of firms surveyed	Valid candidates	Valid returns	Response rate
1. ESOP firms	246	226	76	33.63%
2. Public firms	379	336	81	24.11%
3. Food firms	1,191	1,100	296	26.91%
4. 1994-96 survey survivors	609	561	275	49.02%
5. Randomly selected firms	268	231	91	39.39%
Total	2,693	2,454	819	33.37%

***Table A2*. Distribution of Sample Firms and Response Rates by Industry**

Industry	Frequency: Entire sample[a]	Frequency: Respondents [b]	Response rate (%)
Construction	76 (3.10%)	35 (4.27%)	46.05
Manufacturing	467 (19.03%)	220 (26.86%)	47.11
Transportation and Public Utilities	55 (2.24%)	22 (2.69%)	40.00
Wholesale Trade	212 (8.64%)	80 (9.77%)	37.74
Retail Trade	1,113 (45.35%)	294 (35.90%)	26.42
Finance, Insurance, and Real Estate	104 (4.24%)	46 (5.62%)	44.23
Services	240 (9.78%)	122 (14.90%)	50.83
Firms with SIC codes Missing	187 (7.64%)	0 (0.00%)	0.00
Total	2,454 (100.0%)	819 (100.0%)	33.37

Notes: (a) Figures in parentheses represent proportion of the entire sample. (b) Figures in parentheses represent proportion of all respondents

Appendix B. Characterization of Occupational Complexity in Terms of Tasks Related to Data, People and Things

Table B1. List of Tasks Related to Data, People and Things, Ordered by the Degree of their Complexity
(Detailed description of the tasks is presented in Table B2)

Data	People	Things
1 Comparing	1 Taking instructions - Helping	1 Handling
2 Copying	2 Serving	2 Feeding-Offbearing
3 Computing	3 Speaking-Signaling	3 Tending
4 Compiling	4 Persuading	4 Manipulating
5 Analyzing	5 Diverting	5 Driving-Operating
6 Coordinating	6 Supervising	6 Operating-Controlling
7 Synthesizing	7 Instructing	7 Precision Working
	8 Negotiating	8 Setting-Up
	9 Mentoring	

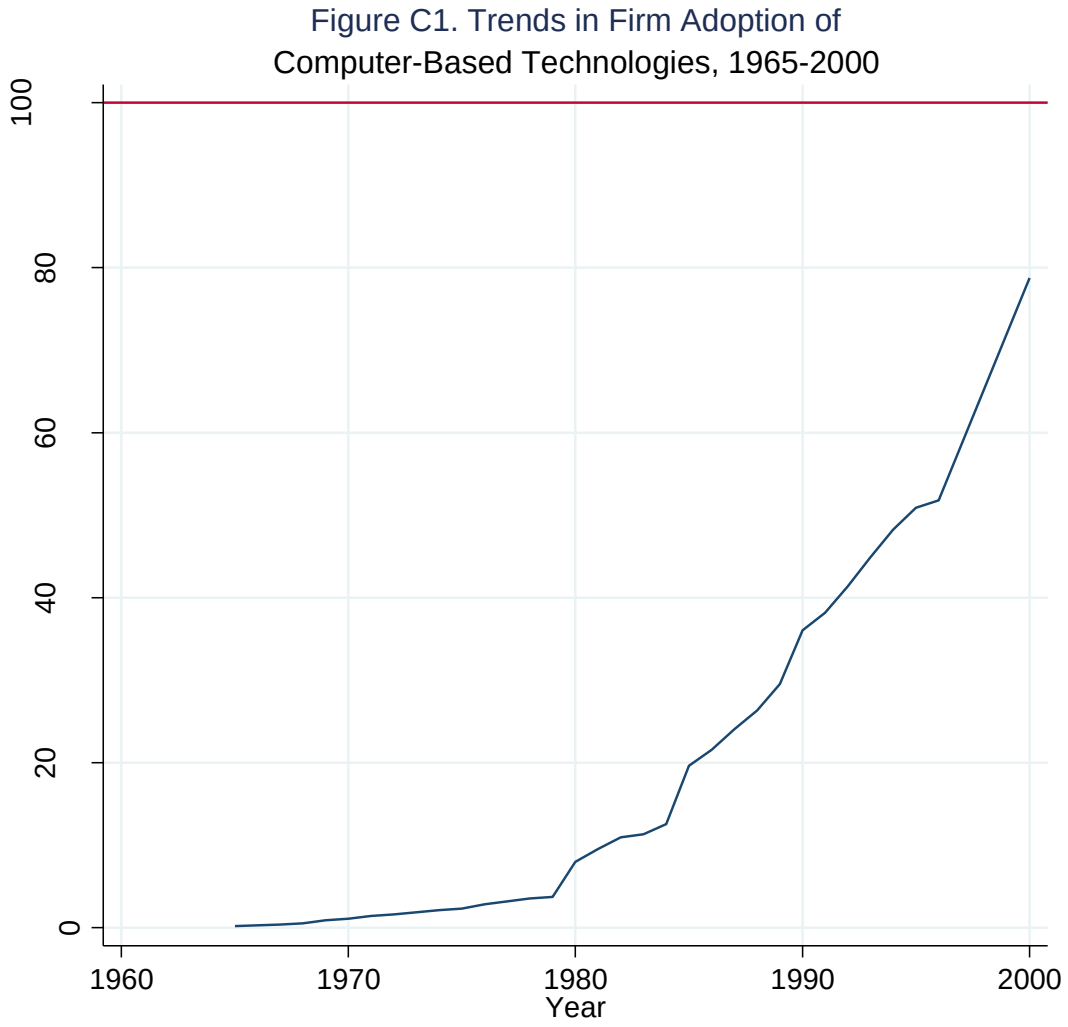
Source: U.S. Department of Labor (1977). *Dictionary of Occupational Titles.* Fourth Ed. Washington, D.C.: U.S. Government Printing Office

Table B2. Detailed description of Tasks Related to Data, People and Things

Data: Information, knowledge, and conceptions, related to data, people, or things, obtained by observation, investigation, interpretation, visualization, mental creation. Data are intangible and include numbers, words, symbols, ideas, concepts, and oral verbalization. 1 *Comparing*: Judging the readily observable functional, structural, or compositional characteristics (whether similar to or divergent from obvious standards) of data, people, or things. 2 *Copying*: Transcribing, entering, or posting data. 3 *Computing*: Performing arithmetic operations and reporting and/or carrying out a prescribed action in relation to them. Does not include counting. 4 *Compiling*: Gathering, collating, or classifying information about data, people, or things. Reporting and/or carrying out a prescribed action in relation to the information is frequently involved. 5 *Analyzing*: Examining and evaluating data. Presenting alternative actions in relation to the evaluation is frequently involved. 6 *Coordinating*: Determining time, place, and sequence of operations or action to be taken on the basis of analysis of data; executing determinations and/or reporting events. 7 *Synthesizing*: Integrating analyses of data to discover facts and/or develop knowledge concepts or interpretations.	**People**: Human beings; also animals dealt with on an individual basis as if they were human. 1 Taking instructions-Helping: Helping applies to "non-learning" helpers. No variety of responsibility is involved in this function. 2 *Serving*: Attending to the needs or requests of people or animals or the expressed or implicit wishes of people. Immediate response is involved. 3 *Speaking-Signaling*: Talking with and/or signaling people to convey or exchange information. Includes giving assignments and/or directions to helpers or assistants. 4 *Persuading*: Influencing others in favor of a product, service, or point of view. 5 *Diverting*: Amusing others (usually accomplished through the medium of stage, screen, television, or radio). 6 *Supervising*: Determining or interpreting work procedures for a group of workers, assigning specific duties to them, maintaining harmonious relations among them, and promoting efficiently. A variety of responsibilities is involved in this function. 7 *Instructing*: Teaching subject matter to others, or training others (including animals) through explanation, demonstration, and supervised practice; or making recommendations on the basis of technical disciplines. 8 *Negotiating*: Exchanging ideas, information, and opinions with others to formulate policies and programs and/or arrive jointly at decisions, conclusions, or solutions. 9 *Mentoring*: Dealing with individuals in terms of their total personality in order advise, counsel, and/or guide them with regard to problems that may be resolved by legal, scientific, clinical, spiritual, and/or other professional principles.	**Things**: Inanimate objects as distinguished from human beings; substances or materials; machines, tools, equipment, and products. A thing is tangible and has shape, form, and other physical characteristics. 1 *Handling*: Using body members, handtools, and/or special devices to work, move, or carry objects or materials. Involves little or no latitude for judgment with regard to attainment of standards or in selecting appropriate tool, object, or material. 2 *Feeding-Offbearing*: Inserting, throwing, dumping, or placing materials in or removing them from machines or equipment which are automatic or tended or operated by other workers. 3 *Tending*: Staring, stopping, and observing the functioning of machines and equipment. Involves adjusting materials or controls of the machine, such as changing guides, adjusting timers and temperature gages, turning valves to allow flow of materials, and flipping switches in response to lights. Little judgment is involved in making these adjustments. 4 *Manipulating*: Using body members, tools, or special devices to work, move, guide, or place objects or materials. Involves some latitude for judgment with regard to precision attained and selecting appropriate tool, object, or material, although this is readily manifest. 5 *Driving-Operating*: Starting, stopping, and controlling the actions of machines or equipment for which a course must be steered, or which must be guided, in order to fabricate, process, and/or move things or people. Involves such activities as observing gages and dials; estimating distances and determining speed and direction of other objects; turning cranks and wheels; pushing clutches or brakes; and pushing or pulling gear lifts or levers. Includes such machines as cranes, conveyor systems, tractors, furnace charging machines, paving machines, and hoisting machines. Excludes manually powered machines, such as handtrucks and dollies, and power assisted machines, such as electric wheelbarrows and handtrucks. 6 *Operating-Controlling*: Starting, stopping, controlling, and adjusting the progress of machines or equipment. Operating machines involves setting up and adjusting the machine or material(s) as the work progresses. Controlling involves observing gages, dials, etc., and turning valves and other devices to regulate factors such as temperature, pressure, flow of liquids, speed of pumps, and reactions of materials. 7 *Precision Working*: Using body members and/or tools or work aids to work, move, guide, or place objects or materials in situations where ultimate responsibility for the attainment of standards occurs and selection of appropriate tools, objects, or materials, and the adjustment of the tool to the task require exercise of considerable judgment. 8. *Setting-up*: Adjusting machines or equipment by replacing or altering tools, jigs, fixtures, and attachments to prepare them to perform their functions, change their performance, or restore their proper functioning if they break down. Workers who set up one or a number of machines for other workers or who set up and personally operate a variety of machines are included here.

Source: U.S. Department of Labor (1977). *Dictionary of Occupational Titles.* Fourth Ed., pp. 1369-1371. Washington, D.C.: U.S. Government Printing Office

Appendix C. Robustness tests



Note: This figure was constructed using MHRMPS-1996, which asked about the year of introduction of CBT. MHRMPS-1996 was administered from mid-1994 to early 1996 to a sample of firms similar to those surveyed in MHRMPS-2000, and with similar response rates and sample size (see Ben-Ner and Lluis 2011 for details of MHRMPS-1996). The data point for 2000 is derived from MHRMPS-2000 and reflects the use of at least some CBT. The segment between 1996 and 2000 reflects linear interpolation.

Source: MHRMPS-1996 and MHRMPS-2000.

***Table C1*. Poisson regressions for CBT and change in skills**

Replication of Table 5 with skill change as a 4-point scale variable, with 0 indicating negative or no change, and 1, 2, and 3 CBT increases in skills

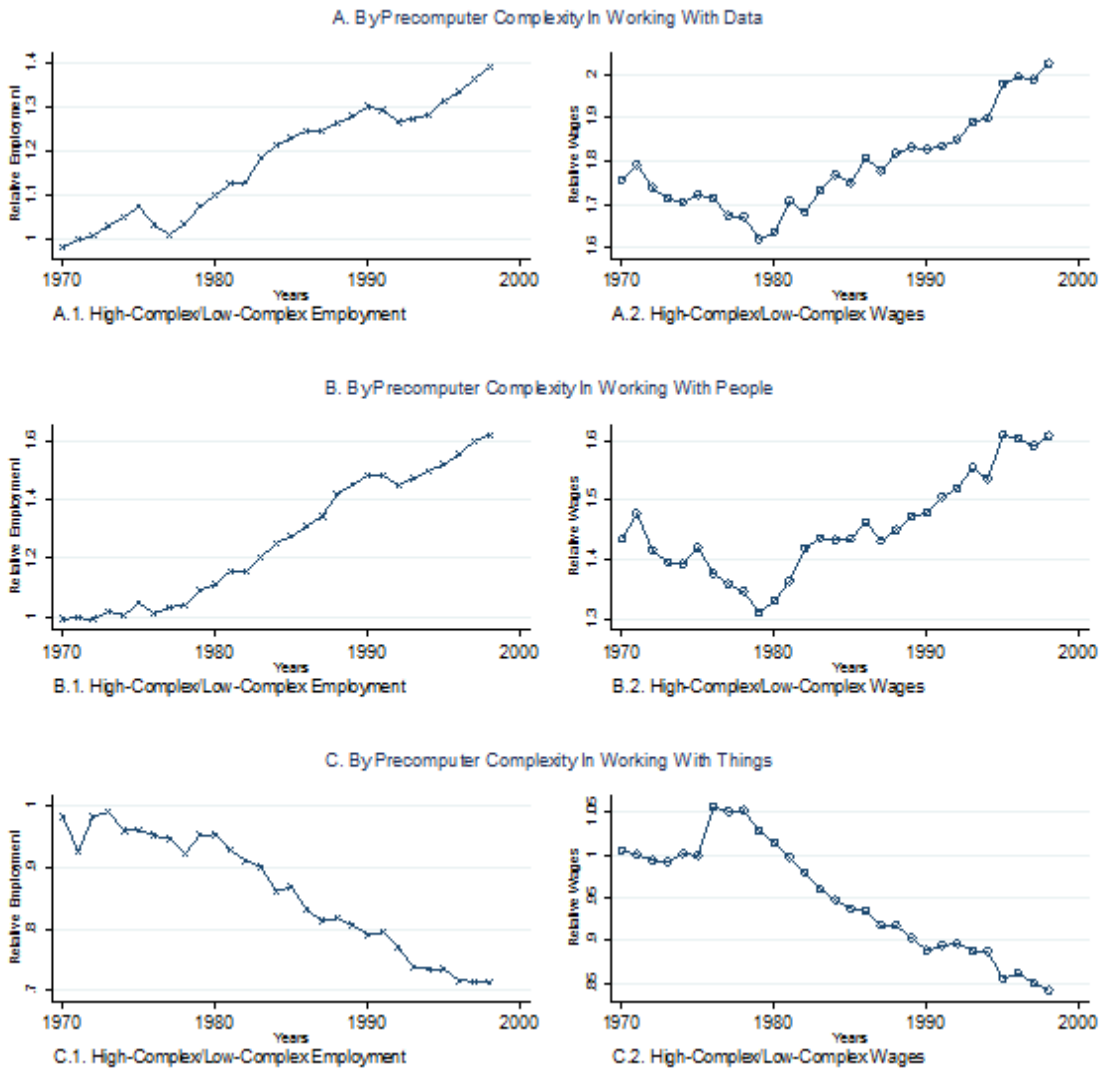
	Change in											
	1. Content skills			**2. Process skills**			**3. Social skills**			**4. Complex problem-solving skills**		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)	(3a)	(3b)	(3c)	(4a)	(4b)	(4c)
CBT	.09***	-.07	-.13*	.13***	.01	-.06	-.24***	-.33***	-.46**	.00	-.20***	-.24**
	(.01)	(.04)	(.06)	(.01)	(.04)	(.05)	(.04)	(.09)	(.12)	(.02)	(.05)	(.08)
CBT×Wages	-	.01***	-	-	.01**	-	-	.01	-	-	.02***	-
		(.00)			(.00)			(.01)			(.00)	
CBT×Data	-	-	.03*	-	-	.02	-	-	-.05	-	-	.05**
			(.01)			(.01)			(.03)			(.02)
CBT×People	-	-	.04*	-	-	.03*	-	-	.13***	-	-	-.00
			(01)			(01)			(.03)			(.02)
CBT×Things			-.00			.01			.02			.00
			(.01)			(.01)			(.02)			(.01)
N	642	585	638	644	587	640	643	586	639	642	585	638
Wald χ^2	39.86***	41.22****	68.31***	104.14***	86.53***	147.76***	47.92***	39.36***	60.49***	0.00	19.72***	18.21**

	5. Technical skills			**6. System skills**			**7. Resources management skills**		
	(5a)	(5b)	(5c)	(6a)	(6b)	(6c)	(7a)	(7b)	(7c)
CBT	.12***	-.03	-.03	.05**	-.06	-.15*	.01	-.15**	-.19+
	(.01)	(.04)	(.06)	(.02)	(.04)	(.07)	(.02)	(.05)	(.08)
CBT×Wages	-	.01***	-	-	.01*	-	-	.01**	-
		(.00)			(.00)			(.00)	
CBT×Data	-	-	.02+	-	-	.01	-	-	.03+
			(.01)			(.01)			(.02)
CBT×People			-.01			.02			.03
			(.02)			(.02)			(.02)
CBT×Things	-	-	.02**	-	-	.02*	-	-	-.00
			(.01)			(.01)			(.01)
N	642	586	638	641	585	637	640	583	636
Wald χ^2	77.94***	72.15***	137.37***	8.61**	8.23*	21.76***	0.25	9.78**	16.27**

+: p<.10; *: p<.05; **: p<.01; ***: p<.001

Appendix D. Aggregate Data – National Samples

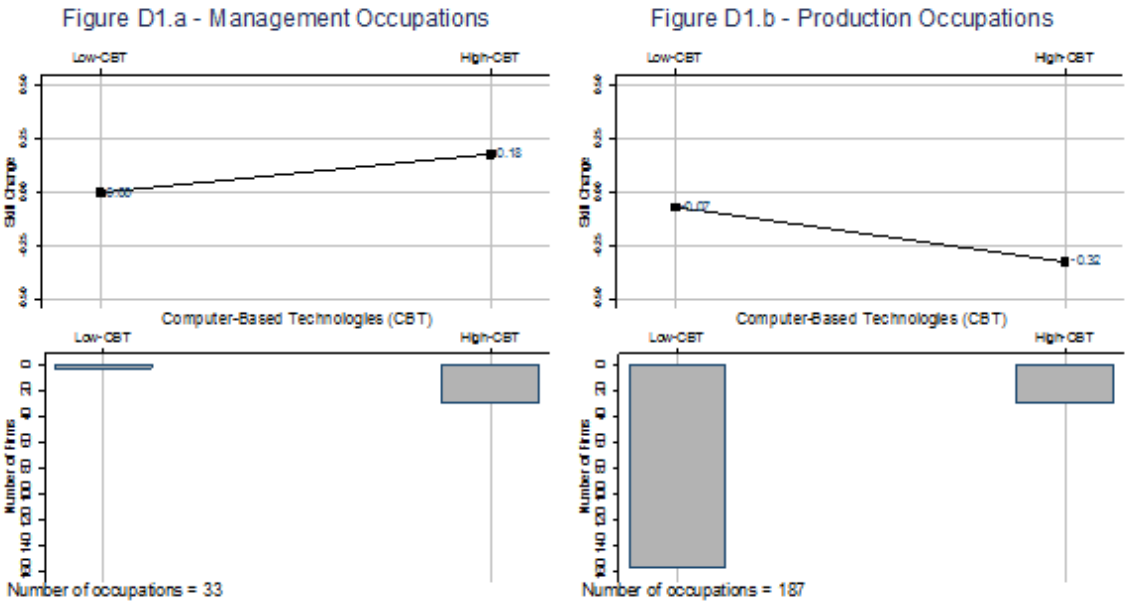
Figure D1. Relative Employment and Wage Trends, 1970-1999, by high (above-mean) and low (below-mean) pre-CBT task complexity



Note: Figures are for US employees in private industry that work for wages or salary from 1970 to 1998. IPUMS-CPS person-level weights have been used.

Sources: April 1971 CPS augmented with DOT Fourth Ed. 1977, for 1970 Census Occupation Codes; and IPUMS-CPS for 1950 Census Occupation Codes (individual-level data).

Figure D2. Changes in Complex Problem-Solving Skills by CBT use, 2002-2008



Note: The upper graphs show mean differences between complex problem-solving skills in 2009 (from O*NET 13.0 Database, mostly collected by incumbents) and in 2002 (from O*NET 4.0 Database, collected by analysts) for both low-CBT use and high-CBT use (being the median the cutpoint) and separately for managerial occupations and production occupations. Low and high-CBT use Tsacoumis and Iddekinge (2006) show that incumbents seem to inflate their ratings in relation to the analyst ratings (about 2/3 a standard deviation *higher*, which represents between a medium to large effect), being this inflation particularly large for production occupations. Therefore, corrections, proposed by Tsacoumis and Iddekinge (2006), have been applied in the case of production occupations.

Sources: Skills from O*NET 4.0 Database (June 2002) and O*NET 13.0 Database (June 2008); Tsacoumis and Iddenking (2006) for standardized mean differences between incumbent and analysts ratings by SOC major groups; computer use form Current Population Survey (CPS), October 2003, School Enrolment and Computer Use Supplement File; and IPUMS-USA for person weights.

Appendix E. Comparison of our results with Autor, Levy and Murnane (2003) results

ALM's routine task variables:

i. Nonroutine cognitive tasks:
   - **dcp**: direction, control, and planning of activities
   - **math**: measures quantitative reasoning requirements

ii. Nonroutine manual tasks
   - **ehf**: eye-hand-foot coordination

iii. Routine cognitive tasks:
   - **sts**: measures adaptability to work requiring set limits, tolerances, or standards

iv. Routine manual tasks
   - **finger**: finger dexterity

v. Index of industry-level routine task intensity
   - **rt**: (sts+finger)/(sts+finger+dcp+math+ehf)

***Table E1*. Pearson correlations among routine and complexity task variables, industry-level in 1960**

Variable	1	2	3	4	5	6	7	8
1. Data								
2. People	.74***							
3. Things	-.14	-.46***						
4. Dcp	.62***	.43***	-.21*					
5. Math	.89***	.67***	-.19*	.69***				
6. Ehf	-.58***	-.38***	.33***	-.23**	-.48***			
7. Sts	-.19*	-.53***	.60***	-.25**	-.12	-.07		
8. Finger	.20*	-.11	.52***	-.14	.20*	-.35***	.63***	
9. Rt	-.23**	-.48***	.48***	-.51***	-.28***	-.30***	.84***	.77***

Notes: (a) Number of observations varies between 138 and 140. (b) +: p<.10; *: p<.05; **: p<.01; ***: p<.001