The End of Polarization? Technological Change and Employment in the U.S. Labor Market

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Job Market Paper

January 18, 2015

Abstract

A key feature of the U.S. labor market since 1980 is the substantial growth of the employment in high skill occupations and low skill manual-service occupations at the expense of the middle-skill occupations, and there is a substantial literature attributing this change to technological change. However, since 1999, the employment growth of workers in high skill occupations has decelerated markedly despite continued rapid growth in technology. This paper documents this novel trend in the U.S. labor market and examines the role of technological change in explaining this phenomenon. I hypothesize that technological advancements have expanded what computers can do and, as a result, changed the relationship between technology adoption and labor demand. In this new paradigm, workers in high skill occupations face a double-edged sword of new technology adoption – as in earlier periods, some of the tasks performed primarily by workers remain as complements to computerization, while others are now substitutes as a result of the increasing capabilities of technology. This change has depressed the labor demand growth for high skill jobs. I test this hypothesis using the task-based framework developed by Autor, Levy and Murnane (2003) and later enriched by Acemoglu and Autor (2011), combined with data from the Current Population Survey and the Online Occupational Network Survey (O*NET). I find evidence for this changed relationship between technology adoption and demand for labor in highly skilled occupations; these changes in labor demand for tasks driven by technological adoption can explain a substantial portion of the stagnancy in labor demand growth for high skill occupation in the 2000s.

* I would like to thank Jason Abrevaya, Marika Cabral, Sandra Black, Mary C. Daly, Carolyn Heinrich, Bart Hobijn, Gerald Oettinger, Steve Trejo, Robert Valletta, participants at the University of Texas at Austin research seminar, and participants at the Federal Reserve Bank of San Francisco brown bag seminar for their helpful comments on this research. All remaining errors are my own.

1. Introduction

A key feature of the U.S. labor market in the 1990s was the substantial growth of the employment for both high skilled occupations and low skill manual-service occupations, all at the expense of the middle-skill occupations. This period is often described as a period of job polarization, and the pattern is attributed to the dramatic increase in the use of computer-based technologies at work since the 1980s (Goos and Manning, 2007; Autor, et al., 2006, 2008, among many others).

The first goal of this paper is to document that since 2000, the polarized pattern of growth of the occupational distribution has undergone important changes. While the employment share of low-skill manual service occupations has continued to grow and that of middle-skill sales, administrative, production occupations continued to decline, the growth of high-skill professional, managerial and technical occupations has decelerated markedly. In addition, during this time period, the share of college educated workers has been continuously increasing and the wage growth of high skill occupations has flattened. Together, these trends suggest that the demand growth for high skill occupations has significantly slowed down in the post-2000 period.

At the same time, technological progress that traditionally boosted the demand for high skill workers has been advancing at an even faster pace since the late 1990s. In addition to the accelerating growth of computer processor power, the post 2000 period has witnessed the onset and rapid adoption of new types of technologies, such as the Internet. The puzzle, then, is why the growth of high skill occupations has plateaued while the technological change has continued. The second goal of this paper is to examine how technological change is related to the deceleration. Starting from the observation that new and advanced technologies have expanded what computers can do at work, I hypothesize that while previous computerization mainly substituted for middle skilled jobs, technological change today is substituting for high skill jobs. To test this hypothesis, I use the task-based framework developed by Autor, Levy and Murnane (2003) (hereafter ALM2003) and later enriched by Acemoglu and Autor (2011) (hereafter AA2011), which conceptualizes what workers do at jobs as a set of job tasks and predicts how technological adoption affects the tasks performed by workers at their jobs and ultimately the demand for jobs. I show that, in contrast to earlier periods, technological change in the post-2000 period substitutes for some of the tasks that were previously performed by workers in high skill jobs as a result of the increasing capabilities of technology, such as information acquisition and interpretation. Meanwhile, as in earlier periods, new technology adoption continues to complement workers for tasks that require critical thinking, creativity and interpersonal relationship management. This double-edged effect of technological change leads to a smaller increase in the demand for high skill occupations relative to computer-technology introduced in the 1980s and 1990s that primarily complemented the job tasks used in high skill occupations. This change in the relationship between technological change and high-skilled labor demand can explain a substantial portion of the stagnancy in high skill occupation growth in the 2000s.

I consider a number of alternative explanations for the employment change in the 2000s. Two demand side factors that I examine are offshoring and import competition. Both factors could potentially cause shifts in job task composition independent of new technology adoption. As I show below, both offshoring and import competition are associated with declining labor demand for tasks used in middle skill occupations but have little effect on tasks used in high skill occupations, indicating that they are not likely the main driving forces for high skill employment growth deceleration. The results are also pervasive within gender, education and cohort groups, suggesting that compositional changes in the labor force are not likely to drive my results.

The contributions of this paper are twofold. First, I document the novel trend of employment in the U.S. after 2000. The trend suggests the polarized employment growth that has been prevailing the U.S. for two decades has changed, due to a significant deceleration in the growth of high skill employment. The second contribution of the paper is to propose a new hypothesis to explain this trend with technology and test this hypothesis by extending the task-based framework in ALM2003. By allowing new technologies to have different effect on task demand from earlier technologies, this paper provides a unified explanation of technological adoption for both the pre- and post-2000 trend.

The remaining sections of the paper are organized as follows. Section 2 documents the trends of employment and accompanying changes in the U.S. labor market between 1980 and 2007. Section 3 discusses the task-based framework. Section 4 describes the data sources and measures for job tasks and technological adoption at work. Section 5 discusses the empirical method and presents the results. Section 6 concludes.

2. Trends of Employment and Technological Progress in the U.S.

Prior studies have documented a strong growth in the employment for both high paying occupations involving a high degree of cognitive skills and low paying manual-service occupations at the expense of the middle-skill occupations in the 1980s and 1990s. This period is often described as a period of job polarization (Goos and Manning, 2007; Autor, et al., 2006, 2008, among many others). The pattern is shown in Figure 1, which uses Census IPUMS and American Community Survey and calculates the smoothed change in the employment share of all 318 US nonfarm occupations ranked by skill level, where skill level is approximated by the average occupational mean log wage in 1980.[1] During the period of 1979-1999, high skill occupations above the 80th percentile and low skill occupations below 10th percentile have disproportionally gained employment shares while at the same time occupations between the 10th and 60th percentiles have lost shares. As shown in Table 1b, along with the polarized growth of employment, wage growth is also strong for high and low skill occupations, while very little for occupations in the middle of the skill distribution, suggesting a strong increase in the demand for cognitive-intensive high-paying and manual-intensive low-paying occupations, and a reduction in the demand for routine-intensive middle paying occupations. There has been much work analyzing possible explanations for these patterns. One contributing force behind the polarized employment growth is the adoption of computer-based technologies beginning in the early 1980s that complement high skill workers while substitute for middle-skill workers (ALM2003; Autor and Dorn 2013; Goos and Manning, 2007; Dustman, et al. 2009). Another factor is offshoring, which decreased the demand for middle-skill workers by substituting them with cheaper labor in developing countries (Blinder, 2006, 2008; Crino, 2010; Feenstra and Hanson, 1996). Finally, globalization, especially the increase in import competition from China, led to reductions in the U.S. manufacturing employment, which also contributed to the hollowing out of the middle skill occupations (Autor, et al., 2013; Bernard et al., 2006; among others).

However, the patterns of polarized growth of the occupational distribution has undergone several important changes after 2000. As shown in Figure 1, while the employment share of low-

[1] The skill ranks of occupations are quite stable over time. Acemoglu and Autor (2011) use the average occupational wage in 1980 as a proxy for skill ranking and show similar patterns. The pattern is not sensitive to the choice of base year for skill ranking (here, average between 1980 and 2000). See Data Appendix for more details of the data source and construction of the graph.

skill manual service occupations has continued to grow in the 2000s at an even stronger pace and the share of middle-skill occupations continues to decline, the growth of high-skill occupations has decelerated markedly between 1999 and 2007. In addition, occupations that lose employment share in the 2000s have always moved upward to around 80th percentile, suggesting that the "hollowing out" of the middle skill occupations has moved up into higher skilled territory.[2] Figure 2 plots the change in employment share of high skill professional, managerial and technical occupations over time. Consistent with Figure 1, the employment share flattens out in the 2000s with a trend break at year 1999.[3] To better understand the changing pattern, in Table 1a, I explore changes within four broadly classified occupational groups over time. Managerial, professional and technical occupations are classified as high skilled, sales and administrative, and production and operators occupations are both as middle skilled, and service occupations as low skilled. The patterns in Table1a show that (1) the deceleration of high skill occupations prevails in most of the professional and managerial occupations; and (2) technicians, except software developers (programmers), did not experience employment losses until 2000, contributing to the hollowing out of more skilled occupations.[4] The share of technicians in science, engineering and health decreased by about 3 percent between 1999 and 2007. A key exception were the software technicians, whose employment share has increased by almost 8 percent between 1999 and 2007.

Along with the employment growth deceleration of high skill occupations, the wage growth of high skill occupations shows a contemporaneous slowdown. Figure 3 plots the wage patterns of high skill occupations using two different measures. The first measure is the average log hourly wage of high skill occupations, which shows an increase in the wage rate until the beginning of the 2000s and a flattening trend afterwards. However, part of the increase in wage could be due to compositional changes - the quality of workers in high skilled occupations could be changing over time. For example, the increase in the wage rate may be driven by more workers with advanced degrees (masters, PhDs, etc.) working in the high skill occupations. Therefore, I calculate the average wage in each occupation while holding the composition of

[2] A concurrent paper by Autor (2014) shows similar trends of employment in the U.S. after 2000.
[3] The Zivot-Andrews (JBES 1992) unit-root test allowing for one structural break in the series of high skill occupation employment share over the period 1983 and 2007 suggests the break point is year 1999.
[4] Exceptions are health/medical professionals and primary to postsecondary instructors. These two groups of occupations have been continuously increasing in the 1990s and 2000s.

education, age, gender and race constant at their 1980 levels.[5] As shown in Figure 3, the change of the composition-adjusted wage rate is similar to that of the observed wage rate, suggesting that compositional change is not the main driving force for the change in high skill occupational wage. Both measures show much smaller increase between 2000 and 2007 than in the 90s. The relative wage growth of high skill occupations to the middle is also much smaller in the 2000s than previous decades, as shown in Figure 4. The correspondence in employment and wage change suggests an important role for demand side factors.

In the 2000s, the relative supply of skilled workers continues to increase. Figure 5 plots the relative employment share of college educated workers to non-college educated workers. It shows that the growth rate of skill supply in the 2000s is similar to what it was in the 1990s, suggesting that the high skill employment deceleration is not likely mainly due to changing supply. Furthermore, the shift in high skill employment share prevails within education and cohort groups. Figure 7 plots the share of five educational groups employed in the high, middle and low skilled occupations. It shows that an increasing share of college educated workers, especially those with only four-year college degrees has been pushed out of high skill occupations and into middle or low skill occupations. This corresponds to the "de-skilling" process discussed in Beaudry et al. (2013). Figure 8 then shows the employment share in high skill occupations by education for three experience groups (0-9, 10-19 and 20-29 years of potential work experience). It shows that this de-skilling process is happening for all three experience groups, suggesting that it is not mainly driven by cohort-related effects. Taken together, the patterns of wage growth and supply growth together suggest that the deceleration is mostly likely driven by a deceleration in the demand growth for high skill jobs in the post-2000 period.

[5] I choose the base year as 1983 and pool the base year with each year in my May/ORG data series to construct a dummy variable equal to one if an individual is observed in 1983. Then I run a logit regression, in which the dependent variable is this dummy variable, and the right hand side variables include education (five categories), age(in two-year bins), indicators for gender and non-white ethnicity, and the interactions of education and gender with every variable. I use the predicted values from the logit regression *yhat* to calculate the probability of being in the 1983 sample as *yhat/(1-yhat)* for each observation in the years 1984-2007. The compositional-adjusted wage series is constructed using the labor supply weight multiplied by *yhat/(1-yhat)* as the weight for the years between 1984 and 2007. Since this correction only accounts for changes in the observable characteristics, it likely underestimates the effect of selection on the wage series, if selection on unobservables goes in the same direction as that on observables.

The puzzle now is why the growth of high skill occupations plateaus despite the continued increases in technological change. So far there has been little work examining the effect of new technologies on the demand for high skill jobs in the 2000s.[6] In this paper, I hypothesize that technological advancements have expanded what computers can do and, as a result, changed the relationship between technology adoption and labor demand. Figure 9 plots the real investment in Information Technology equipment and software, both in level terms and as a percentage of real GDP, along with a time line of key breakthroughs of computer-based technology since the late 1990s. It shows that except for a bump around 2000, when the tech bust occurred, the investment in information technology has been continuously increasing during the 1990s and 2000s. More importantly, the late 1990s and early 2000s has witnessed the onset and rapid adoption of new and more advanced technologies. One leading example is the onset of Internet in the late 1990s. The percentage of Americans who have access to broadband Internet has increased from 4% in 2000 to 55% in 2007 (Bureau of Labor Statistics, 2011). The Internet has significantly improved the cost and quality of communication, served as a pool of free or low-cost resources, changed the traditional way of sales and marketing, and catalyzed the research and development of innovative artificial intelligence and machine learning (MGI, 2011). Since its rapid adoption in the late 1990s, the Internet has fundamentally changed the functions of computers and how computer-based technology interacts with workers at work. For example, the software Turbotax can now substitute for accountants and prepare the tax returns for users. Google.com and Wikipedia.com have become the go-to choice for consulting problems due to their low-cost large pool of online tutorials, and thus reduce the need for in-personal technicians. These motivating observations suggest that internet may have a different effect on high skill jobs from earlier computer-based technologies. Because internet expands the capabilities of what computers can do, the adoption of new technology may become a double-edged sword for workers in high skill jobs – as in earlier periods, some of the job tasks performed primarily by workers remain as complements to computerization, while others are now substitutes as a result of the increasing capabilities of technology. To test this hypothesis, I use the task-based

[6] Beaudry, et al.(2013) argue that the demand for cognitive tasks has reversed to decline after 2000 and develop a theoretical model with a boom and bust of demand for cognitive skills induced by technological adoption. However, there is little empirical evidence for the model.

framework developed by ALM2003 and augmented by AA2011 to examine how this technological change affects the demand for occupational job tasks.

3. Task framework

To examine the effect of technology on job skill demand, the task framework conceptualizes work from “a machine’s eye” view as a set of job tasks, such as resolving a conflict, analyzing information, performing a calculation and moving an object. The effect of computer-based technologies on workers in a given occupation may be multi-dimensional, because they can be used to accomplish one or more job tasks independently and thus substitute workers who perform these tasks, such as performing a calculation, and meanwhile complementing workers who perform job tasks such as analyzing a piece of information. Therefore, by looking at how technological adoption is associated with the labor inputs for different tasks rather than for different occupations, the task framework provides a more nuanced explanation for how technology affects the labor demand.

The task framework used in this paper builds on ALM2003 and AA2011.[7] Based on the observation that the main functions of computers in the 80s and 90s are rapidly and accurately performing tasks that repeat pre-specified instructions, which are defined as routine tasks, ALM2003 classifies tasks into routine tasks, non-routine analytical and interpersonal tasks and non-routine manual tasks. Computers substitute for workers who perform routine tasks, while complement workers who perform non-routine analytical and interpersonal tasks. Manual tasks are little affected. As the price of computer-based technologies fell significantly and plausibly exogenously at the beginning of the 1980s, large increase in computer capital was used to substitute for labor that used to perform routine tasks, thus depressed the demand for middle skill occupations that used routine tasks most intensively and increased the demand for high skill occupations that used the non-routine analytical and interpersonal tasks most intensively. This "routinization" hypothesis explains the job polarization of the labor market up till 2000. This task framework can also be used to examine the effect of offshoring, since technological advances

[7] See Theoretical Appendix for a detailed description of the model and the analysis of an extension proposed by this paper.

have made tasks that are information/data related and do not require face-to-face communication easier to be performed by cheaper labor in other countries.

I extend this framework, looking at the effect of technological advances on job task demands in the 2000s, based on the observation that technical progress has expanded the range of tasks that computers can do. As a result of this, some of the complex non-routine tasks that previously could not accomplished by computers can now be done by computers. One leading example of the technological advancement is the rapid diffusion of Internet use at work since the late 1990s, as discussed in the previous section. The main function of the Internet is the fast and inexpensive transfer of information and data. This then in return enables the development of software and artificial intelligence that perform complicated computations and analyses, along with the fast improvement in data storage and processor power of computers. For example, traditional accountants who help customers with tax preparation can now be replaced by the software Turbotax, and entry-level financial analysts now need to compete with cheap personal financial software. As a result, job tasks that are intensively used in high skill occupations and involve searching information, detecting pattern and computing are all gradually being taken over by computers, whereas in the 1980s and 1990s these tasks were complements to computer technology. At the same time, job tasks that involve managing interpersonal relationships and complex problem solving are still complemented by the adoption of internet technology. As the price of the internet, especially broadband internet technology, fell significantly and plausibly exogenously in the late 1990s, internet technology use has been increasingly adopted at work. The increase in internet use depresses the demand for the job tasks that are easily done on the internet, such as those that are involve cognitive reasoning and information transfer, and increases the demand for managerial and analytical tasks. Since both sets of tasks are intensively used in high skill occupations, the double-edged effect of internet adoption leads to a smaller increase in the demand for high skill occupations, compared to earlier computer-technology which mainly complemented the job tasks used in high skill occupations.

As a consequence of technologies now replacing cognitive reasoning and information transfer tasks that previously performed by high skill workers, there will be a reallocation of tasks in the economy. In particular, high skill workers will now start to perform some of the tasks previously performed by middle or low skill workers, leading to a growth deceleration in the labor inputs for cognitive reasoning and information transfer tasks.[8] The changes in task allocation happen both within occupations (i.e. the intensive margin) and between occupations that have difference task-contents (i.e. the extensive margin). The intensive margin measures the changes in task content within occupations, while the extensive margin measures changes over time in the occupational distribution of employment, holding task content constant within occupations. ALM2003 show that starting in the 1970s, the task-content of occupations become gradually more non-routine and less routine intensive. They also find that this shift is a combination of changes in both the intensive and extensive margins and thus pervasive at both occupational and industrial level.[9] Due to data limitations, in this paper I will empirically test the "doubled-edged effect" hypothesis by exploring changes at the extensive margin, i.e. changes in the employment shares of occupations that have different task intensity at industrial level. Since the changes at intensive margins tend to go the same direction as changes at the extensive margin, only using the changes at extensive margin would likely underestimate the actual changes in task-contents and thus bias against finding any effect of technological adoption. Bearing this caveat in mind, I expect industries that have greater increases in internet adoption to experience greater decreases in the employment shares (or labor inputs) for tasks that are substituted by new technologies, such as detecting a problem or pattern, computing and transferring information, and greater increases in the employment shares for tasks that are complemented by new technologies, such as managing interpersonal relationships and complex problem during the post-2000 period.[10] I also expect the link between technological adoption and the labor inputs for routine and manual tasks to remain the same as pre-2000 period. In the next section, I describe the two key measures for the empirical analyses – change in technological adoption and change in the labor inputs for job tasks.

[8] Suppose the induced changes in wage rates of tasks by technology also affect supplies in the short run, workers may also change the types of skills they supply to the market. When advanced technologies replace high skill workers in a set of tasks, this will workers that previously supplying high skills now to supply either medium or low skills. Thus, this complements the changes of skills across tasks.

[9] ALM2003 use the 1977 and 1991 versions of the Dictionary of Occupational Titles to exploit the over-time variation in task variables and measure changes along the intensive margin. However, since the 1991 version of DOT only select a few occupations to update the task measures, the measured changes at intensive margin may be subject to measurement errors and biases. Since the task data set used in this paper, O*NET, suffers from the same problem, I choose to only look at the changes along the extensive margin.

[10] The terms employment shares and labor inputs of tasks are used interchangeably here. They both refer to the changes in task content at extensive margin.

4. Data Sources and Measurement

4.1. Measuring Technological Change at Work

Prior work in the literature uses the change in computer use at work to approximate for the adoption of computer-based technologies in the 1980s and 1990s (ALM2003, among others). I construct this same measure to approximate technological adoption before and after 2000. Using data from the October 1984, 1997 and 2003 Computer and Internet Use Supplements to the Current Population Survey (CPS), I calculate the percentage of workers using a computer at work at the industry level in each year. The annual change in computer use between 1984 and 1997 is used to proxy for the change in technological adoption for the pre-2000 period, and the annual change between 1997 and 2003 to proxy for the post-2000 period. On average, the percent of workers using computer at work increases from 24.7 in 1984 to 52 in 1997 and 56.5 in 2003, as shown in the upper panel of Table 2. Similarly, I calculate the percentage of workers using Internet at work in 1997 and 2003 and show in the upper panel of Table 2 that it has increased substantially during this period, from 17.5 in 1997 to 42.8 in 2003. This suggests that computers adopted at work have been used for different purposes since the late 1990s. To support this argument, I examine the survey questions on the purposes of using computer at work in 1997 and 2003 and calculate the percentage of workers using computers at work for word processing, scheduling, Internet, spreadsheet, graph design and programming. The lower panel of Table 2 shows that in 1997, computers are most used for word processing (57.3%), while in 2003 it is most used for Internet (75.8%). The largest increase among these applications of computer use between 1984 and 1997 is word processing; between 1997 and 2003 it is Internet use. All together the lower panel suggests that the purpose of using computer-based technologies at work has changed from traditional word processing in the 1990s to Internet-based applications in the 2000s. While the main specification uses the changes in computer use since the late 1990s as a proxy for the technological progress in the 2000s, I also use the change in Internet use between 1997 and 2003, as well as between 1997 and 2011 to approximate the post-2000 technological change to test the robustness of my results to the choice of technology measures. The results are shown in an appendix and similar to the main specification.

One concern of looking at the effect of technological change in the post-2000 period is that overall trends may be mismeasured as a result of the tech-boom and bust that happened in the early 2000s. As shown in Figure 9, both the level and share of investment in Information technology kept increasing in the 2000s after a sharp dip in the year 2000, which suggests that technological progress has been roughly continuous and trending upward over time. To verify that that temporary shock is not driving my results, I check the sensitivity of the results to different starting point of the post-2000 period (i.e. 1999, 2000 and 2001) and the results are quite robust.[11]

4.2. Measuring Labor Inputs for Job Tasks

A key implication of the task framework is that the labor inputs for job tasks have changed over time. To measure different aspects of occupational skill content, I draw on information from the August 2000 version of the US Department of Labor's Occupational Information Network (ONET) database. ONET is the successor of the Dictionary of Occupational Titles (DOT), which has been used ALM2003. It provides a richer set of data on key attributes and characteristics of 812 occupations based on the 2000 Standard Occupational Code (SOC). Each task in ONET is measured on a scale of [1, 5], with 1 meaning not important at all and 5 extremely important. In order to append ONET tasks to CPS MORG and construct a panel of task inputs, I construct a consistent set of occupation codes by using a modified version of the crosswalk developed by Meyer and Osborne (2005) and later revised by Dorn (2009) and convert the 2000 SOC used in the ONET to the consistent occupation scheme. Then I assign each worker in the CPS MORG from 1983 to 2007 data set a set of task scores by appending the O*NET task measures on the basis of his or her occupation, and average these task scores across workers into industrial level, weighting workers by the usual hours worked multiplied by the sampling weight. The data appendix describes more details.

A key issue with the task-based analysis is the need to identify a subset of tasks that best characterize an occupation. To do so, I follow ALM2003, Firpo et al. (2010) and Goos et al. (2011) and select tasks that are representative of job tasks requiring analytical skills, interpersonal skill, cognitive reasoning skills, information delivering and searching skills, skills of repeating and being accurate, and skills of manual dexterity. Table 3 presents the list of tasks,

[11] Results using 2000 as the starting point are shown in the Appendix. Other results are available from author upon request.

their meanings and examples, along with their hypothesized relationship with computer and Internet technology. In brief, analytical and managerial tasks require a high level of managerial ability and independent thinking. They are used intensively in professional and managerial occupations, and are complemented by both computer and internet technologies. Cognitive reasoning tasks mainly involve identifying problems (e.g. problem sensitivity, deductive reasoning) or computing (e.g. data comparison) based on a set of pre-specified abstract rules, and information transfer tasks involve delivering information (e.g. guiding, instructing) and searching for information (e.g. recruiting staff, reviewing information). Prior to the use of Internet, these tasks were complements with technological change but became substitutes with the spread of the Internet. Tasks that follow well defined rules, including those that measure the importance of the job being structured for the workers (allowing little freedom for the workers to determine tasks or goals), following the pace of machines, controlling machines and operation monitoring, are substitutes for both types of technologies over time. Manual tasks, including using hands, preforming manual tasks with dexterity, maintaining equipment, providing services , assisting others and performing for people, are hypothesized to be unaffected by either type of technologies.

The O*NET data are updated on a rolling basis, with a substantial lag between updates for most occupations. Consequently, there is little variation in the task content within occupations. Due to the time-invariance of occupational task means, I use the constructed panel of task inputs and exploit the variation in the change of employment shares between occupations that have different task content, i.e. the extensive margin.

Table 4 shows the average changes of labor inputs for the 30 tasks over the periods 1983-1989, 1989-1999 and 1999-2007. For each task category, two composite measures, the average of individual task means and the principle component of five tasks, are used to capture the average trend of tasks in the category. For each task, the change for each period is calculated as 100 times the log difference between the task means divided by the number of years in between, measuring the annualized percent change in the labor inputs for the task. Consistent with previous findings (ALM2003, Spitz-Oener 2006, Goos et al., 2008), analytical, managerial, cognitive reasoning and information transfer tasks have all increased substantially between 1983 and 1999, while routine tasks decreased over this period. In the period of 1999-2007, while analytical and managerial tasks have continued to increase at similar rates, cognitive reasoning and information transfer tasks have experienced little growth. For example, labor inputs for cognitive reasoning tasks measured by the average of problem sensitivity, deductive reasoning, data comparison, system analysis and judging quality increased by around 0.10% annually between in 1983-1999, but declined to 0.02% between 1999 and 2007. The labor inputs for information transfer tasks measured by the principal component of guiding, coaching, instructing, recruiting staff and reviewing information increased by 0.19% annually in the 1990s, but declined to 0.06% after 2000. Overall, the trends are consistent with the hypothesis that advanced technology adoption will lead to a continuous increase in the labor demand for analytical and managerial tasks while a decline in the labor demand for cognitive reasoning and information transfer tasks.

5. Empirical Strategy and Results

As discussed in Section 3, the task framework predicts that as advances in technology expand the set of tasks that can be accomplished with computer, computer adoption increasingly substitute for previously non-routine tasks. At the same time, analytical and managerial tasks continue to be complemented by the adoption of new technologies. Since both sets of tasks are intensively used in high skill occupations, the double-edged effect of technology adoption leads to a smaller increase in the demand for high skilled occupations, relative to earlier technological change that mainly complemented the job tasks used in high skill occupations.

5.1. Task demand and technological change: industrial level evidence

I next examine the relationship between technology adoption and the change in labor inputs for tasks over the period 1983 and 2007. I use the same empirical strategy as ALM2003 and estimate the following equation at the industry level:

(1) $\Delta T_{jt}=a_1+b_1\Delta PC_{jt} +b_2\Delta Tech_{jt} *1\{post\text{-}2000\} + b_3 1\{post\text{-}2000\}+ X'_{j0}\,\boldsymbol{\Theta}+\varepsilon_{jt}$

where ΔT_{jt} is the annual log difference in labor inputs for task T in industry j over time period t; ΔPC_{jt} is the annual log change in the proportion of workers using computer in industry j over period t; 1{ post-2000} is a dummy variable indicating the period 2000-2007; X_{j0} is a set of industry-specific start of period controls, including the initial level of technology adoption for the baseline specification and other control variables such as industrial sector dummies, share of female and black workers, etc.. ΔPC for the period 1983-1999 is measured by the change in computer use at the workplace between 1984 and 1997 and by the change in computer use at workplace between 1997 and 2003 for the period 2000-2007.[12] There are 203 consistent industries for each period. I fit this equation for stacked first differences covering the two periods 1983-1999 and 2000-2007, and focus on comparing the differential effect of technology adoption on task demand in the post-2000 period (captured by b_2).

A challenge for the analysis is that industries subject to greater technology adoption may also be exposed to other economic shocks that are correlated with technological change. I try to address this concern by adding extensive controls for potential confounding effects. The first set of controls includes industrial sector dummies and the employment share of female, black and college educated workers respectively, and the log of the average wage at the industry level for the initial years for both time periods and are used to account for cross-sector heterogeneity. Controlling for these factors, the regression identifies the industry-level impacts of technology using variation in technology adoption among industries with more similar labor attributes. Popular alternative explanations for the changes in demand for labor are offshoring and import competition. Due to advances in technology, job tasks that do not require face-to-face contact and easily transferable are increasingly likely to be offshored to developing countries. Therefore, industries that see greater increase in technology adoption are also more likely to offshore tasks. I try to control for the effect of offshoring by including the initial propensity to offshoring in the time period. To construct the propensity of offshoring, I use the offshorability index at industrial level constructed by AA2011, and append that by industry to CPS MORG in years 1983 and 2000 and calculate the employment weighted average of this offshoring score. The initial level of offshorability for each time period captures the extent to which industries are exposed to job task offshoring, with a higher index indicating a higher probability of transferring the tasks to other countries. Similarly, to control for the effect of import competition from countries such as China, I construct the initial level of trade exposure that are meant to capture the extent to which

[12] I also use the annual change in internet use between 1997 and 2003 a proxy for technology adoption in the 2000s as robustness checks. As shown in appendix table 3 and 4, the results are robust to a number of different specifications.

industries are exposed to import competition.[13] The effects of offshoring and import competition are discussed in more details in Section 6.

The results for all six groups of tasks are shown in Table 5. All the specifications include the industrial level controls discussed above.[14] For the five single measures of analytical tasks and managerial tasks as well as their composite measures in Table 5a, the estimates indicate a significant main effect as captured by the coefficient of ΔPC, and an insignificant interaction effect as captured by ΔPC *1{post-2000}. Consistent with the hypothesis, this suggests that technological adoption for the post-2000 period is associated with an increase in the labor demand for analytical and managerial tasks, which is not significantly different from the effect of technological adoption for the pre-2000 period. The point estimate of 0.046 in column 1 indicates that a one percent increase in computer use in the pre-2000 period was associated with a 0.046 percent increase in the labor input for analytical task. Given that the average annual increase in computer use between 1984 and 1997 was about 6 percent, the observed annual increase in analytical labor input (0.168 percent) is more than fully explained by the computer measure.

For each of the five cognitive reasoning tasks in Table 5b, there is a positive main effect and a negative interaction effect, which suggests that the relationship between computer adoption and labor demand for tasks has changed after 2000. Take the average measure of the five cognitive reasoning tasks as example. One percent increase in annual computer adoption before 2000 was associated with a 0.05 percent increase in the labor share employed in cognitive reasoning tasks. However, the effect has declined by 0.034 percent after 2000. Similar patterns are observed for information transfer tasks. One percent increase in annual computer adoption before 2000 is associated with 0.05% increase in the labor share employed in information transfer tasks, but decreased to almost zero after 2000.

The results for the routine tasks and manual tasks shown in Table 5c and 5d show that for routine tasks, technology adoption has been negatively correlated with the change in labor

[13] The trade data is downloaded from David Dorn's website. I thank David Autor and David Dorn for making their datasets public on their websites. Since the trade data is available for manufacturing industries, I assume that the initial level of trade exposure of other industries to be zero. I acknowledge that this restriction is strong and may lead to very noisy measure of trade exposure.

[14] Results only controlling for the initial level of computer adoption and industrial sector dummies are shows in the appendix table 2. They are very similar to results with controls.

demand throughout the two sub-periods, and there is no significant difference in the effect before and after 2000. The results for manual tasks need to be interpreted with caution, since the model does not have clear prediction about the link between computer-based technological adoption and the labor demand for manual tasks. Taken together, the results are consistent with the hypothesis and suggest a double-edged effect of internet adoption on the job tasks intensively used in high skill occupations.

5.2. Magnitude of the Effect of Task shifts

Since the units of tasks are not of familiar scale, it is not apparent how much we can contribute the shift in demand for high skill employment to task shifts. In this section, I use the fixed coefficients model discussed in ALM2003 to quantify the potential contribution of task shifts to the demand for high skill occupations, including professional, managerial and technical occupations, during 1983-1999 and 1999-2007 respectively.

To obtain an estimate of demand for high skill occupations as a function of industry task inputs as a first step, I estimate a fixed coefficients model of employment share of high skill occupations in industries as a function of their task inputs in the midpoints of the two periods respectively:

$$(2)\quad \mathrm{SkillShare}_j = \alpha + \sum_{k=1}^{5} \pi_k T_j^k + \varepsilon_j$$

where $\mathrm{SkillShare}_j$ is the high skill employment share in industry j in year 1990 for the period of 1983-1999 and in year 2003 for the period of 1999-2007, and the T_j^k's are the measures for task inputs in industry j. The coefficients $\widehat{\pi}_k$ are obtained and then used to predict changes in the demand shifts in high skill employment in each period using equation (3):

$$(3)\quad \Delta \widetilde{\mathrm{SkillShare}}_j = \alpha + \sum_{k=1}^{5} \widetilde{\pi_k}\, T_j^k + \varepsilon_j$$

I also use equation (1) to calculate the predicted task changes induced by computer adoption and calculate the contribution of technology-induced task shifts by substituting T_j^k in equation (3) with the predicted task shifts. The results are shown in Table 6. Panel A shows the results for the period before 2000 and Panel B shows the post-2000 period. Column 1 shows the observed log annual changes in task inputs during each period. Column 2 shows the predicted log annual changes in high skill employment share using equation (2) and (3). Column 3 calculates the predicted task shifts due to computer adoption and column 4 shows the predicted annual high skill employment share by technology-induced task shifts. The results suggest that shifts in reasoning and information tasks 1983-1999 induced by computer adoption predicts a 0.15 percent annual increase in high skill employment share, which accounts for about 44% of the actual annual growth 0.46%. During 1999-2007, shifts in reasoning and information tasks predicts a 0.081% annual decrease in high skill employment share, which accounts for a negative 38% of the actual annual growth 0.21%. Analytical and managerial tasks predict a 0.13% annual increase in 1983-1999, and 0.07% annual increase in 1999-2007. Overall, the shifts in labor inputs for tasks account for a substantial portion of the change in high skill employment share before and after 2000. In particular, the shifts in reasoning and information tasks explain a substantial portion of the employment deceleration in the 2000s.

5.3. Alternative Explanations

In this section I consider a number of alternative explanations for the employment change in the 2000s. Two demand side factors that I examine are offshoring and import competition. Both factors could potentially cause shifts in job task composition independent of new technology adoption. As shown in table 7a and 7b, both offshoring and import competition are associated with declining labor demand for tasks used in routine tasks that are intensively used in middle skill occupations, but have little or positive effect on tasks used in high skill occupations. The results suggest that they are not likely the main driving forces for high skill employment growth deceleration.

Another concern is that the shifts in task inputs in the 2000s may be driven by compositional changes in labor supply rather than technology adoption. Since I am making the claim that the change in task inputs is driven by changes in demand for tasks induced by the adoption of advanced technologies, rather than a reflection of supplies changes, I examine the relationship between technology and task inputs within education and gender groups and expect the findings to hold across groups. The results by education and gender groups are shown in table 8 and 9. For both education groups, the main effect of computer adoption on analytical and managerial tasks is positive and the interaction effect is not significantly different from zero, suggesting that industry-level computerization in post-2000 period continues to be associated with shifts toward analytical and managerial tasks. For cognitive reasoning and information transfer tasks, the estimates reveal a significant decline in the association between industry-level computerization in post-2000 period and labor inputs for these tasks, as indicated by the negative interaction effect, and this prevails for both college educated and less than college educated workers. For gender groups, the substitution effect of technology adoption in the 2000s is stronger for female than for male, but in general the pattern is similar for both groups. Taken together, the results suggest that compositional changes in labor supply are not likely the main reason for the shifts in task inputs.

6. Conclusion

This paper documents a novel trend of employment in the U.S. after 2000 – the deceleration of high skill occupation growth, and aims to examine the role of technological progress in explaining it. I hypothesize that the increasing adoption in recent technologies at work depresses the demand for the job tasks that mainly involve cognitive reasoning and information transfer, and continues to increase the demand for managerial and analytical tasks. Since both sets of tasks are intensively used in high skill occupations, the double-edged effect of technology adoption leads to a smaller increase in the demand for high skill occupations, compared to earlier computer-based technology which mainly complemented the job tasks used in high skill occupations.

The results provide important implications for policy makers. Demand for skills has changed as technology becomes smarter. The question is how should we train the labor force and what skill sets are needed in the future? The answer is of much uncertainty, since technology is still advancing rapidly. Some skills, such as calculation and deductive reasoning, were valuable but not anymore. However, skills that are uniquely human, such as independent and critical thinking, and managerial abilities, will always be essential. Therefore, either for school education or on the job training, it is important to foster analytical and managerial abilities rather than skills used to solve specific problems.

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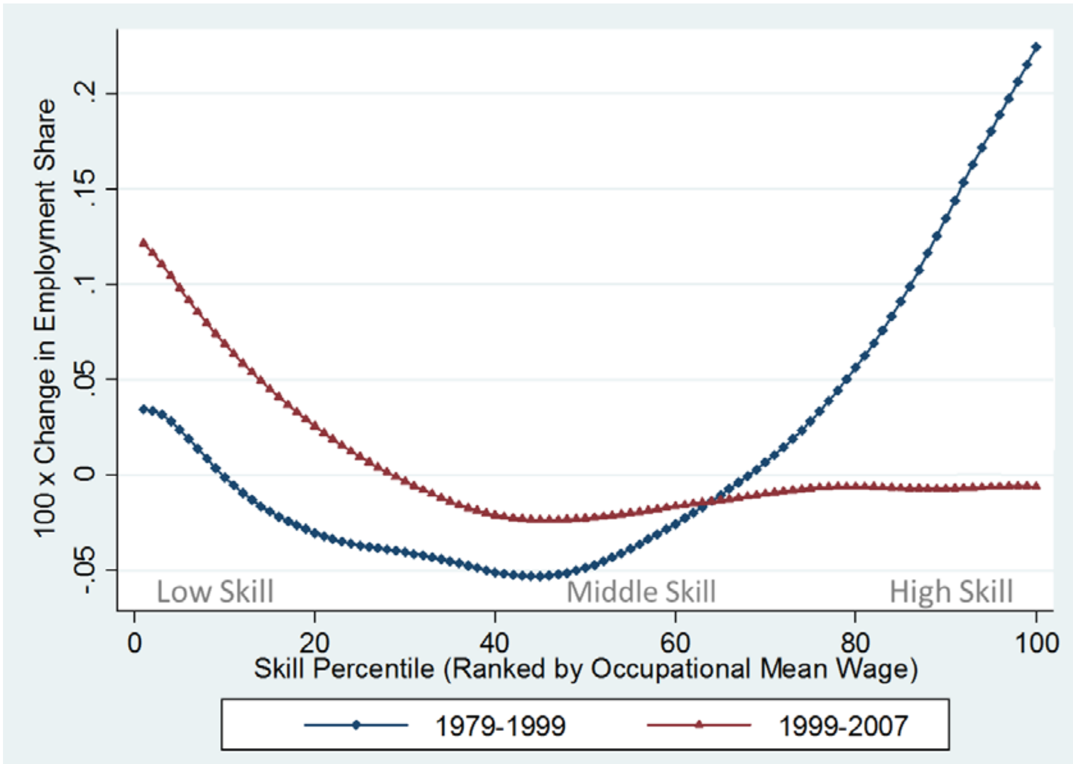
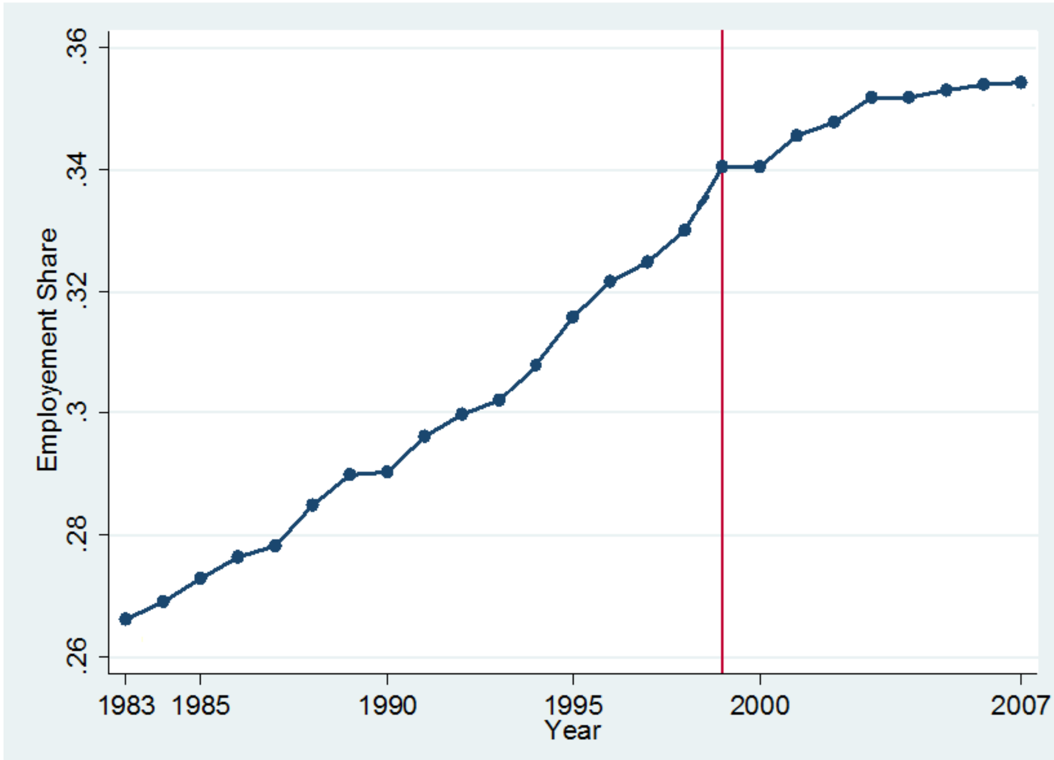
Figure 1. Smoothed Employment Changes by Skill Percentile, by Decade



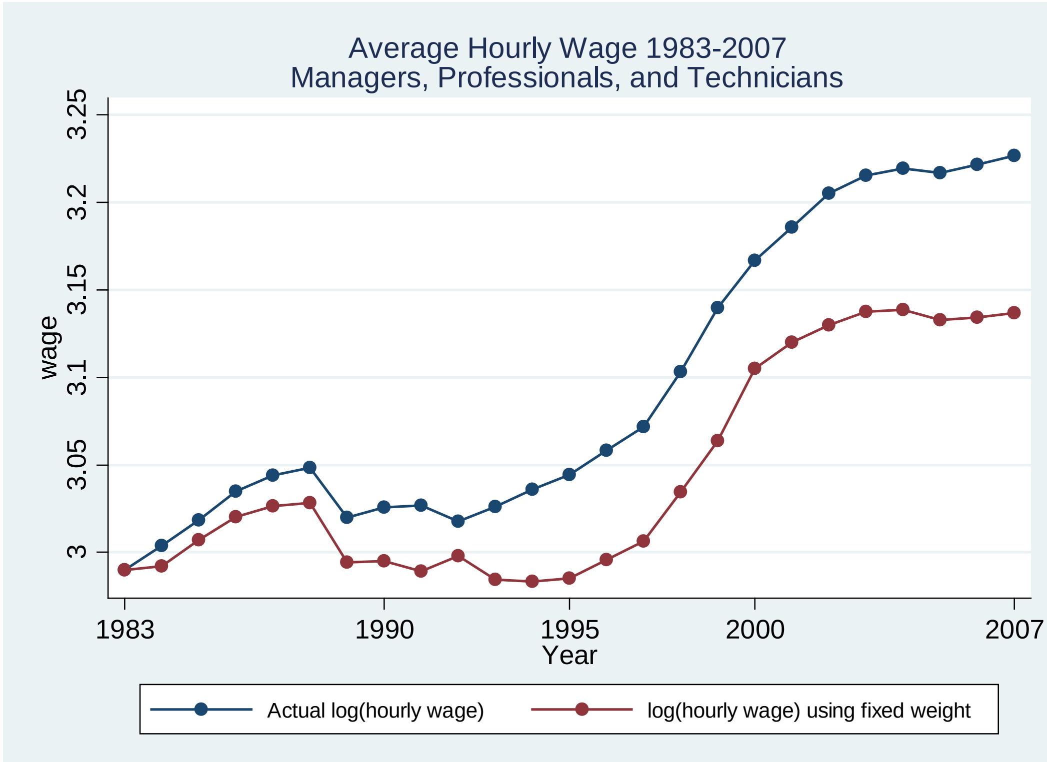
Source: Following Acemoglu and Autor (2011), this figure plots log changes in employment shares by 1980 occupational skill percentile rank using a locally weighted smoothing regression (bandwidth 0.8 with 100 observations), using data from Census IPUMS 5 percent samples for years 1980 and 2000, and Census American Community Survey for 2008. The skill percentiles are measured as the employment weighted percentile rank of an occupation's mean log wage in the Census IPUMS 1980 5 percent extract.

Figure 2. Employment Share of Professional, Managerial and Technical Occupations, 1983-2007



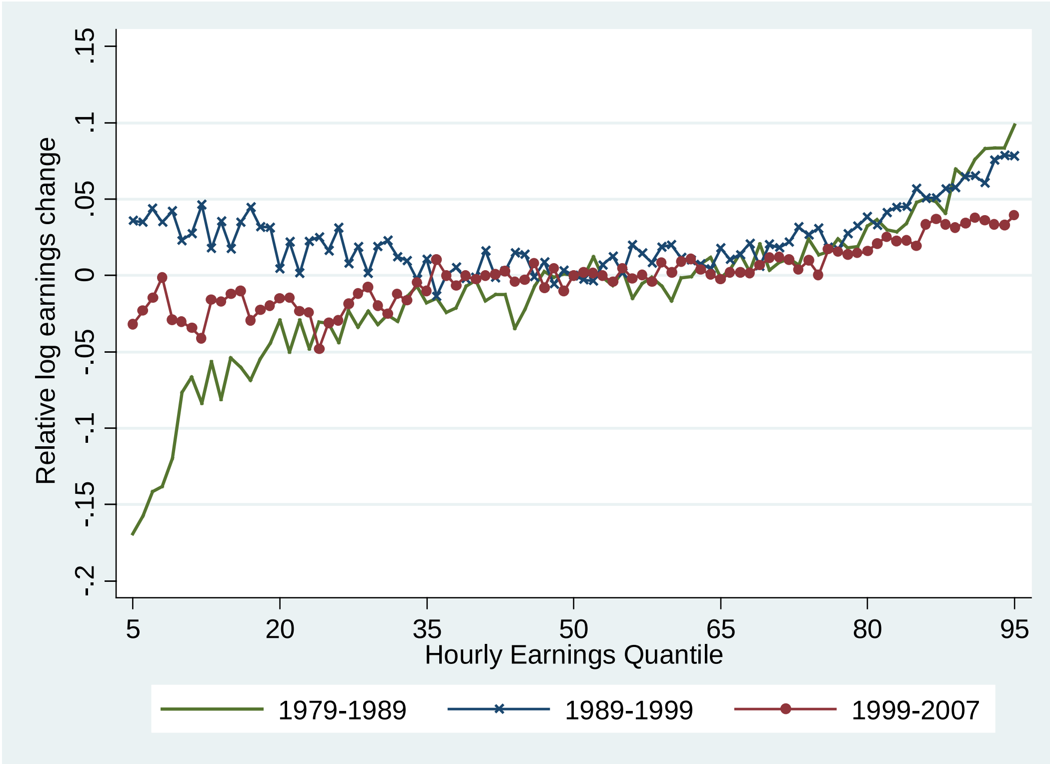
Source: CPS May/ORG data for years 1983-2007. The employment share is calculated as the ratio of total number of workers weighted by hour worked in professional, managerial and technical occupations to the total number of workers employed weighted by hour worked for each year.

Figure 3. Actual and Composition-Adjusted Average Hourly Wage for High Skill Occupations



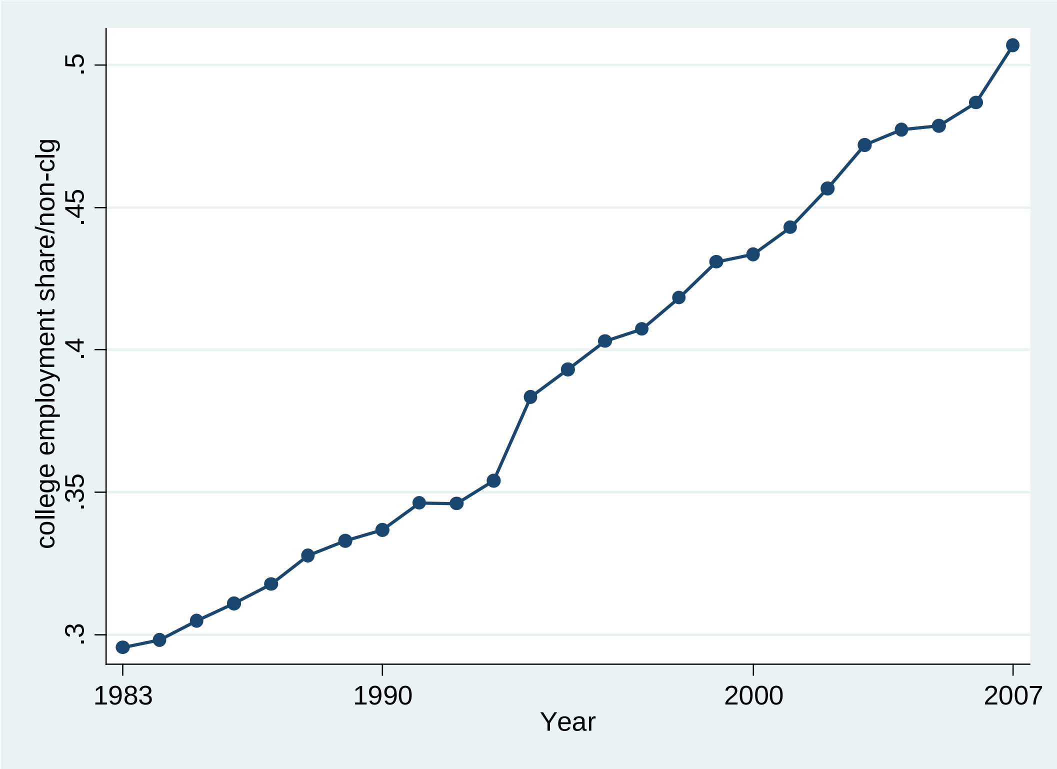
Source: CPS May/ORG data for years 1983-2007. To construct the log wage series using fixed weight, I choose the base year as 1983 and pool the base year with each year in my May/ORG data series to construct a dummy variable equal to one if an individual is observed in 1983. Then I run a logit regression, in which the dependent variable is this dummy variable, and the right hand side variables include education (five categories), age(in two-year bins), indicators for gender and non-white ethnicity, and the interactions of education and gender with every variable. I use the predicted values from the logit regression *yhat* to calculate the probability of being in the 1983 sample as *yhat/(1-yhat)* for each observation in the years 1984-2007. The compositional-adjusted wage series is constructed using the labor supply weight multiplied by *yhat/(1-yhat)* as the weight for the years between 1984 and 2007.

Figure 4. Changes in Log Hourly Wages by Percentile Relative to the Median



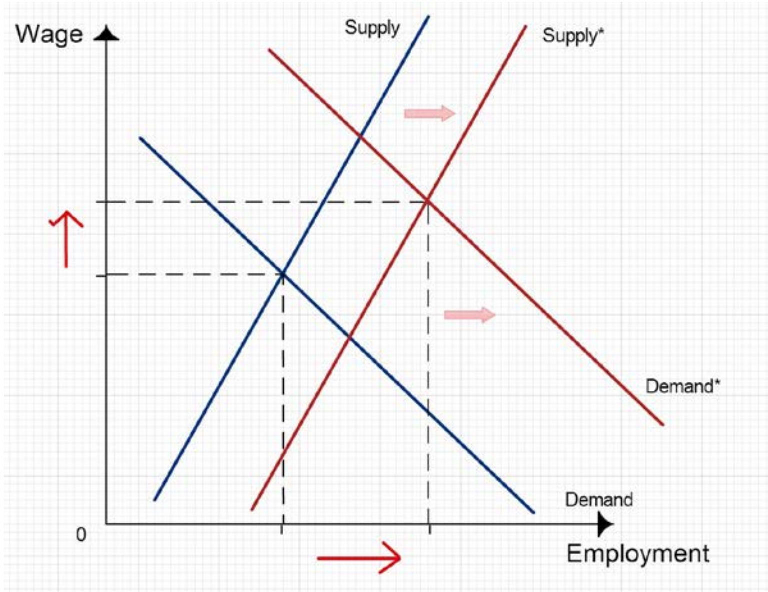
Source: CPS May/ORG data for years 1979-2007. For each year, the data are pooled using three year moving average (i.e. the year 1999 includes data from years 1998, 1999 and 2000). For each year, log hourly wages of all workers are ranked by percentile, and then for each percentile the difference from the 50th percentile is calculated. For each denoted period, the change in the 5th and the 95th percentile of relative log hourly wages is calculated.

Figure 5. Relative Supply of College Educated to Non-College Educated Workers, 1983-2007

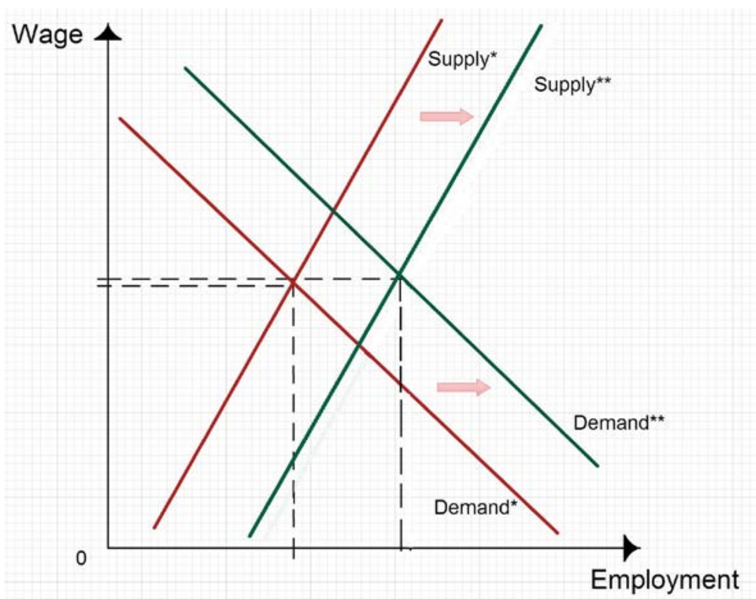


Source: CPS May/ORG data for years 1983-2007. The relative supply of college educated workers to , non-college educated in the labor force is calculated as the ratio of total hours worked by workers with a four-year college or more advanced degree to those by workers without a four-year college degree, using all persons aged between 16 and 64 who are in the labor force, excluding those in the military.

Figure 6. High Skill Market, Before and After 2000

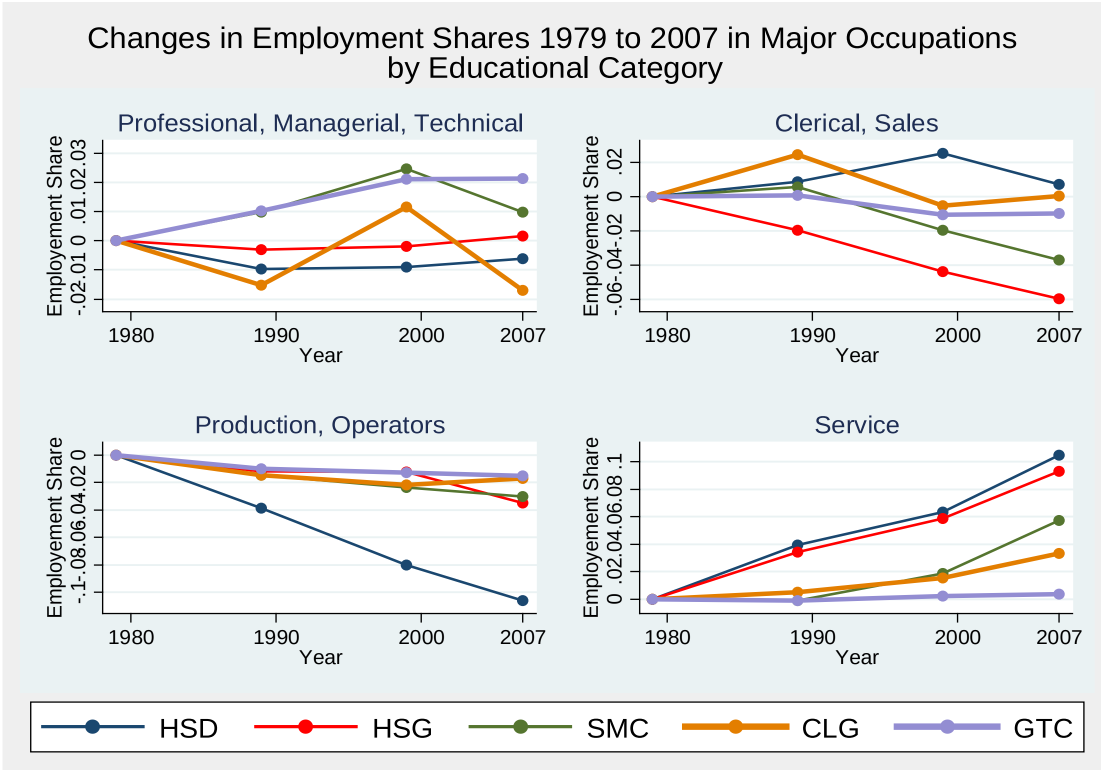


Supply and Demand of High Skill occupations: the Case of 1980s and 1990s



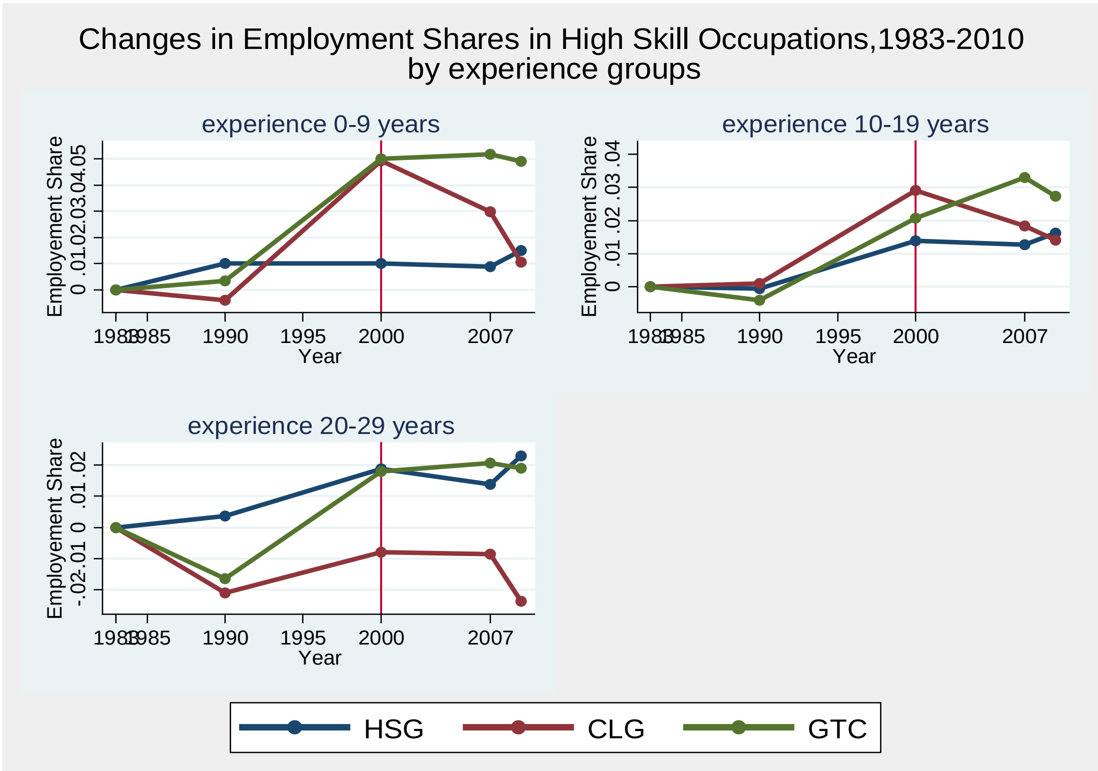
Supply and Demand of High Skill occupations: the Case of 2000s

Figure 7. Employment shares in occupational groups by education level 1980-2007



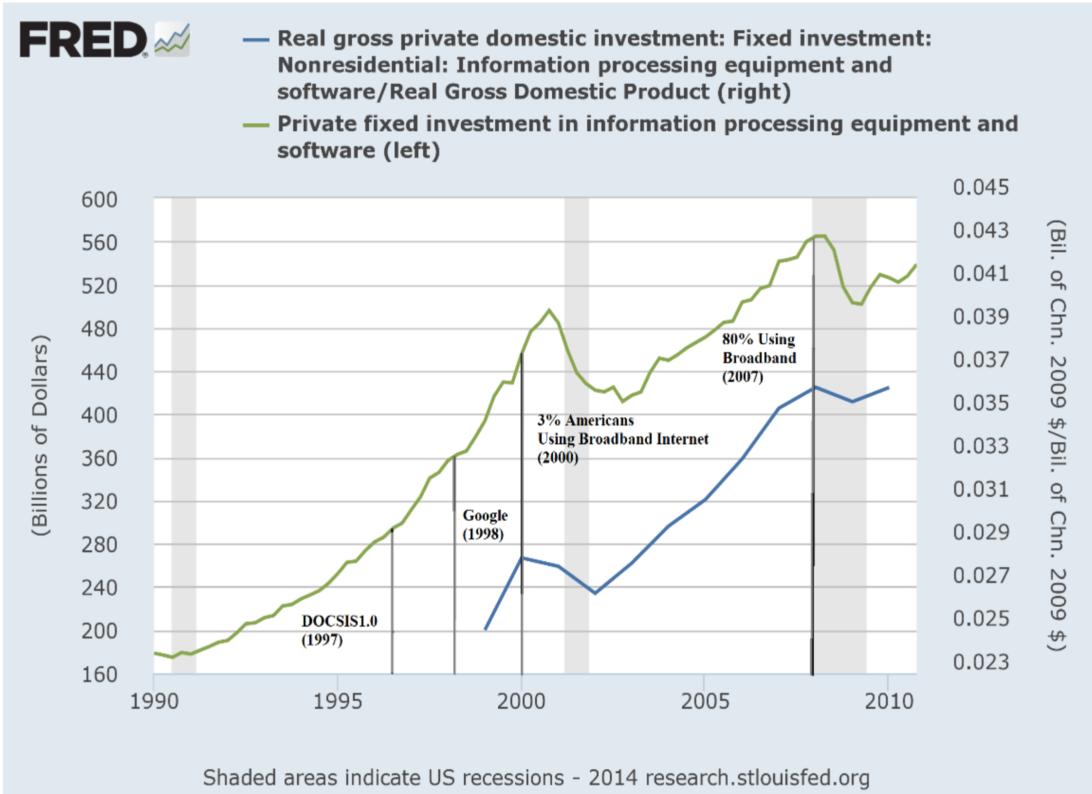
Source: CPS May/ORG data for years 1983-2007.

Figure 8. Employment shares in high skill occupational by education and experience groups



Source: CPS May/ORG data for years 1983-2007.

Figure 9. Investment in Information Technology and Key Events Since 1990



Source: Federal Reserve Bank of St. Louis. http://research.stlouisfed.org/fred2/graph/?g=GXc

Table1a. Levels and Changes in Employment Share by Occupation Groups, 1983-2007

	Level of Employment Share (in Percent)				Annual Percent Change (100*Annual Log Difference)		
	1983	1989	1999	2007	Δ1983-1989	Δ1989-1999	Δ1999-2007
A. Four Broad Occupational Groups							
Managerial, Professional and Technic	26.763	29.102	34.004	35.529	1.396	1.557	0.548
Sales, Office and Administrative	28.132	27.622	25.852	24.322	-0.305	-0.662	-0.763
Production and Operators	30.035	28.877	25.777	23.284	-0.656	-1.136	-1.271
Service	13.319	13.380	13.468	16.029	0.076	0.066	2.176
B. Detaied Occupational Groups							
Managers	10.076	12.157	14.305	15.152	2.682	1.628	0.719
Managers	7.117	8.302	10.245	11.254	2.199	2.104	1.174
Management Support/Specialists	3.176	3.592	3.945	4.051	1.756	0.938	0.331
Professionals	13.096	13.326	16.157	16.623	0.249	1.927	0.355
Engineer	1.882	1.872	1.882	1.828	-0.070	0.051	-0.367
Computer system scientists	0.472	0.796	1.508	1.541	7.463	6.392	0.268
Teachers, others	0.857	1.079	1.417	1.511	3.292	2.718	0.803
Natural science scientists	0.438	0.385	0.456	0.459	-1.820	1.681	0.098
Medical scientists	2.538	2.605	3.140	3.542	0.370	1.868	1.505
Teachers, instructors	4.099	3.898	4.469	4.916	-0.717	1.366	1.191
Liberal art scientists	0.247	0.259	0.296	0.269	0.691	1.343	-1.197
Social scientists	0.919	1.010	1.181	1.199	1.348	1.567	0.187
Lawyers and judges	0.547	0.647	0.891	1.038	2.395	3.203	1.901
Art scientists	1.051	1.151	1.294	1.264	1.292	1.175	-0.297
Technicians	3.447	3.376	3.400	3.231	-0.297	0.071	-0.637
Technicians, except programmers	2.964	2.819	2.866	2.249	-0.713	0.165	-3.033
Software developers/programmers	0.483	0.556	0.534	0.982	2.018	-0.421	7.626
Sales	9.909	10.472	10.606	10.246	0.789	0.127	-0.431
Office and administrative	18.304	17.482	15.363	14.350	-0.656	-1.292	-0.853
Production, craft and repair	12.391	11.520	10.637	10.722	-1.041	-0.798	0.100
Operators,and laborers	17.540	16.631	14.947	12.108	-0.760	-1.068	-2.633
Protective service	1.964	1.929	2.045	2.314	-0.252	0.580	1.548
Personal care&services	4.548	4.379	4.597	5.654	-0.540	0.487	2.586
Food prep, cleaning	7.173	7.044	7.180	7.685	-0.258	0.191	0.849

Notes: The datasource is CPS MORG 1983-2007, including persons aged between 18-55. The level of employment share for an occupation group is calculated as 100 times the ratio between all workers in the occupation group to the total employment at each year, weighted by the CPS sampling weight. The annualized change in employment share between year t0 and t1 equals to 100*(log(shemp_t1) -log(shemp_t0))/(t1-t0), where shemp is the share of employment in that year.

Table1b. Levels and Changes in hourly wage by occupation groups, 1983-2007

	Percent Growth in the Observed Average Log Hourly Wage			Percent Growth in Average Hourly Wage Using Fixed Weight		
	Δ1983-1990	Δ1990-2000	Δ2000-2007	Δ1983-1990	Δ1990-2000	Δ2000-2007
A. Four Broad Occupational Groups						
Managerial, Professional and Technical	0.322	0.455	0.269	0.300	0.229	0.089
Sales, Office and Administrative	0.226	0.414	0.202	0.099	0.223	-0.059
Production and Operators	-0.172	0.238	0.193	-0.289	0.034	-0.002
Service	0.110	0.488	0.344	0.131	0.317	0.004
B. Detaied Occupational Groups						
Managers						
Managers	0.116	0.486	0.218	0.105	0.272	0.071
Specialists	0.140	0.465	0.203	0.080	0.154	0.019
Professionals						
Engineer	0.232	0.180	0.300	0.427	0.065	0.173
Computer system scientists	0.087	0.399	0.181	0.034	0.351	0.018
Teachers, others	0.678	0.278	0.140	0.273	0.056	-0.008
Natural science scientists	0.406	0.239	0.479	0.492	0.360	0.389
Medical scientists	0.852	0.550	0.506	0.787	0.423	0.464
Teachers, instructors	0.699	0.306	0.014	0.662	0.117	0.034
Liberal art scientists	0.453	0.504	-0.174	0.369	0.365	-0.005
Social scientists	0.511	0.815	0.282	0.478	0.473	0.216
Lawyers and judges	0.751	0.070	-0.005	0.198	0.017	-0.005
Art scientists	0.274	0.497	0.042	0.055	0.327	-0.211
Technicians						
Technicians, except programmers	0.253	0.298	0.179	0.083	0.261	0.061
Software developers/programmers	0.334	0.788	0.278	0.332	0.465	0.172
Sales	0.415	0.562	0.019	-0.318	0.383	-0.156
Office and administrative	0.166	0.305	0.058	-0.065	0.104	0.000
Production, craft and repair	-0.095	0.096	0.045	-0.267	0.003	-0.007
Operators,and laborers	-0.293	0.289	-0.016	-0.470	0.071	-0.052
Protective service	-0.025	0.632	0.090	-0.431	0.432	-0.001
Personal care&services	0.251	0.396	0.321	0.107	0.229	0.390
Food prep, cleaning	0.132	0.430	0.043	-0.739	0.325	-0.087

Notes: The data source is CPS MORG 1983-2007, including persons aged between 18-55. Columns 1-3 show the change in average log lourly wage for each of the occupational groups. Columns 4-6 show the change in the average log hourly wage using fixed weight for each of the occupational groups. The average log hourly wage using fixed weight calculates the average wage in each occupation group while holding the composition of education, age and gender constant at their 1980 levels. More details are described in the data appendix. The change between year t0 and t1 equals to 100*(lnhrwage_t0-lnhrwage_t1)/(t1-t0), which measures the annually percent growth.

Table2. Summary Statistics for Computer Use at Work

	1984	1997	2003	Δ1984-1997	Δ1997-2003
Among all workers,					
% of workers using computer at work	24.7	52	56.5	27.3	4.5
% of workers using Internet at work	-	17.5	42.8	-	25.3
Among workers who use computer at work,					
% of workers using word processing	-	**57.3**	68	-	10.7
% of workers using scheduling	-	38.1	58.2	-	20.1
% of workers using Internet	-	33.6	**75.8**	-	**42.2**
% of workers using spreadsheet	-	32.9	65.5	-	32.6
% of workers using graphs design	-	20.1	30.3	-	10.2
% of workers using programming	-	15.4	17	-	1.6

Notes: The computer use data are taken from the October 1984, 1997 and 2003 Computer and Internet Use at Work Supplements to the Current Population Survey (CPS). The samples in all three years consist of currently employed workers ages 18– 65. Computer use is derived from the question `Do you use a computer directly at work?' Internet use is derived from the question `Do you use internet at work?' Other questions for work computer use that are comparable across the 1997 and 2003 CPS are for word processing/desktop publishing, email, calendar/scheduling, graphics/design spread sheets/databases and other computer use. The percentage of workers using Computer/Internet at work is the weighted fraction of currently employed workers ages 18– 65 who answered yes to the respective question.

Table3. Task Definition and Examples

	Analytical	Managerial	Cognitive Reasoning	Information Transfer	Routine	Manual
Characteristics	Analyzing information/problem with independent or creative thinking	Making managerial decisions/plans and maintaining relationship	Performing analysis or computation by following a set of complicated rules	Delivering or searching for information	Performing repetitive and pre-determined procedures	Using hands or body to perform complex physical procedures
Examples of Tasks	Evaluate Information	Establish relationship	Problem Sensitivity	Guide	Being Structured	Use Hands
	Interpret Information	Develop Strategy	Deductive Reasoning	Coach	Follow Equipment	Manual Dexterity
	Problem Solving	Resolve Conflict	Cost Calculation	Instruct	Control Machine	Service orientated
	Originility	Build Team	System Analysis	Recrut Staff	Monitor Operation	Assist others
	Critical Thinking	Make Decision	Judging Quality	Review Information	Control Pace	Perform for public
Examples of Occupations	Economists	Chief Executives	Actuaries	HR Specialists	Telephone Operators	Truck Drivers
	Surgeons	Managers	Math Technicians	Sales Managers	Bookkeepers	Waitors
			Auditors	Coaches, Tutors		
			Accountants			
Occupational Groups with the Highest Task Importance (Top 3)	Professionals	Managers	Managers	Managers	Operators/Laborers	Protective Service
	Managers	Professionals	Professionals	Professionals	Production	Food Prep/Buiding Cleaning
	Technicians	Sales	Technicians	Technicians	Food Prep/Buiding Cleaning	Personal Care

Notes: Task measures are from the August 2000 version of the US Department of Labor's Occupational Information Network (ONET) database.

Table4. Changes in Task Inputs (100*Annual Percent Change)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Analytical	Simple Average	Principle Component	Evaluate Information	Interpret Information	Problem Solving	Originility	Critical Thinking
Δ1983-1989	0.139	0.237	0.181	0.157	0.120	0.162	0.088
Δ1989-1999	0.185	0.313	0.202	0.213	0.192	0.199	0.130
Δ1999-2007	0.151	0.182	0.111	0.201	0.130	0.169	0.146
Managerial	Simple Average	Principle Component	Establishing Interpersonal	Developing Strategy	Resolving Conflict	Building Team	Making Decision
Δ1983-1989	0.150	0.287	0.088	0.176	0.217	0.162	0.130
Δ1989-1999	0.170	0.322	0.109	0.225	0.218	0.190	0.131
Δ1999-2007	0.198	0.302	0.158	0.258	0.288	0.195	0.119
Reasoning	Simple Average	Principle Component	Problem Sensitivity	Deductive Reasoning	Data Comparison	System Analysis	Judging Quality
Δ1983-1989	0.094	0.237	0.066	0.088	0.125	0.114	0.084
Δ1989-1999	0.113	0.278	0.071	0.109	0.136	0.168	0.100
Δ1999-2007	0.021	0.069	0.060	0.039	0.027	-0.102	0.045
Information	Simple Average	Principle Component	Guiding	Coaching	Instructing	Recruting Staff	Reviewing Information
Δ1983-1989	0.149	0.275	0.216	0.156	0.044	0.283	0.110
Δ1989-1999	0.190	0.348	0.238	0.229	0.113	0.242	0.163
Δ1999-2007	0.056	0.092	0.123	0.076	-0.007	-0.012	0.089
Routine	Simple Average	Principle Component	Being Structured	Following Equipment	Controlling Machine	Monitoring Operation	Controling Pace
Δ1983-1989	-0.191	-0.178	-0.141	-0.326	-0.207	-0.112	-0.182
Δ1989-1999	-0.208	-0.195	-0.124	-0.359	-0.239	-0.068	-0.286
Δ1999-2007	-0.301	-0.280	-0.087	-0.410	-0.335	-0.282	-0.408
Manual	Simple Average	Principle Component	Using Hands	Manual Dexterity	Service orientated	Assisting others	Performing for public
Δ1983-1989	0.057	-0.033	-0.166	-0.215	0.118	-0.018	0.095
Δ1989-1999	0.177	0.010	-0.204	-0.224	0.173	0.134	0.149
Δ1999-2007	0.190	0.038	-0.139	-0.202	0.085	0.167	0.246

Notes: The panel data sets for task inputs s are constructed by appending occupational level task intensities from O*NET with CPS MORG 1983-2007, based on workers' occupations. The level of labor inputs for a task is the average task intensities of the full sample, weighted by workers' labor supply weights. The change between year t0 and t1 is the annualized log difference, i.e. 100*(log(intensity_t0)-log(intensity_t1))/(t1-t0), where intensity is the level of labor inputs employed for a task.

Table 5a. Technological Change and Industry Task Input: Stacked First-Difference Estimates

Dependent Variable: 100 * Annual Log Difference in Task Input

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Composite Task Measures		Single Task Measures				
A. Analytical Tasks							
	Simple Average	Principle Component	Evaluate Information	Interpret Information	Problem Solving	Originility	Critical Thinking
ΔPC	0.046***	0.071**	0.039*	0.051**	0.048**	0.053***	0.040***
	(0.016)	(0.029)	(0.021)	(0.022)	(0.019)	(0.019)	(0.014)
ΔPC*1{post-2000}	-0.013	-0.016	-0.003	-0.008	-0.026	-0.010	-0.020
	(0.019)	(0.034)	(0.025)	(0.026)	(0.023)	(0.022)	(0.017)
R^2	0.247	0.225	0.251	0.140	0.261	0.223	0.207
Weighted mean Δ of dependent variable							
1983-1999	0.168	0.275	0.194	0.192	0.165	0.185	0.114
1999-2007	0.151	0.182	0.111	0.201	0.130	0.169	0.146
B. Managerial Tasks							
	Simple Average	Principle Component	Establishing Relationship	Developing Strategy	Resolving Conflict	Building Team	Making Decision
ΔPC	0.039***	0.068**	0.023*	0.047**	0.052***	0.039**	0.038**
	(0.014)	(0.027)	(0.012)	(0.022)	(0.020)	(0.019)	(0.014)
ΔPC*1{post-2000}	-0.014	-0.024	0.004	-0.027	-0.006	-0.027	-0.020
	(0.017)	(0.033)	(0.015)	(0.026)	(0.023)	(0.022)	(0.017)
R^2	0.177	0.172	0.087	0.201	0.110	0.189	0.224
Weighted mean Δ of dependent variable							
1983-1999	0.162	0.305	0.101	0.207	0.217	0.179	0.131
1999-2007	0.198	0.302	0.158	0.258	0.288	0.195	0.119

Notes: N is 406 (203 consistent industries in two periods). Standard errors are in parentheses. Each column in a panel is a seperate stacked-first differences OLS regression. Dependent variables are 100 times the annual log changes in task inputs between 1983 and 1999 if the dummy variable 1(post-2000) equals to 0, and that between 1999 and 2007 if 1(post-2000) equals to 1. ΔPC is the annual percentage point change in industry computer use between 1983 and 1997 when 1(post-2000) equals to 0, and that between 1997 and 2003 if 1(post-2000) equals to 1. Control variables not shown in the table include a dummy for the post-2000 period, PC use at year 1983 and 1999, industrial group dummies, propensity to offshoring and import competition, share of female, black and college educated workers in 1983 if 1(post-2000) equals to 0 and in 1999 if 1(post-2000) equals to 1. All regressions are weighted by mean industry share of total hours worked over the endpoints of the years used to form the dependent variable. Samples used are CPS MORG 1983-2007. See Table I and Appendix 1 for definitions and examples of task variables.

Table 5b. Technological Change and Industry Task Input: Stacked First-Difference Estimates

Dependent Variable: 100 * Annual Log Difference in Task Input

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Composite Task Measures		Single Task Measures				
A. Cognitive Reasoning Tasks							
	Simple Average	Principle Component	Problem Sensitivity	Deductive Reasoning	Data Comparison	System Analysis	Judging Quality
ΔPC	0.046***	0.106***	0.035***	0.038***	0.060***	0.057**	0.042***
	(0.011)	(0.028)	(0.010)	(0.010)	(0.015)	(0.023)	(0.013)
ΔPC*1{post-2000}	-0.034**	-0.078**	-0.030**	-0.022*	-0.038**	-0.052*	-0.036**
	(0.013)	(0.034)	(0.012)	(0.012)	(0.018)	(0.028)	(0.015)
R^2	0.281	0.245	0.137	0.216	0.260	0.274	0.220
Weighted mean Δ of dependent variable							
1983-1999	0.106	0.257	0.069	0.101	0.132	0.148	0.094
1999-2007	0.021	0.069	0.060	0.039	0.027	-0.102	0.045
B. Information Transfer Tasks							
	Simple Average	Principle Component	Guiding	Coaching	Instructing	Recruting Staff	Reviewing Information
ΔPC	0.053***	0.095***	0.071***	0.048**	0.033***	0.081***	0.051***
	(0.015)	(0.027)	(0.022)	(0.019)	(0.011)	(0.027)	(0.013)
ΔPC*1{post-2000}	-0.053***	-0.093***	-0.079***	-0.049**	-0.040***	-0.081**	-0.034**
	(0.017)	(0.032)	(0.026)	(0.023)	(0.013)	(0.032)	(0.015)
R^2	0.237	0.237	0.210	0.215	0.161	0.273	0.182
Weighted mean Δ of dependent variable							
1983-1999	0.175	0.311	0.230	0.201	0.087	0.257	0.143
1999-2007	0.056	0.092	0.123	0.076	-0.007	-0.012	0.089

Notes: N is 406 (203 consistent industries in two periods). Standard errors are in parentheses. Each column in a panel is a seperate stacked-first differences OLS regression. Dependent variables are 100 times the annual log changes in task inputs between 1983 and 1999 if the dummy variable 1(post-2000) equals to 0, and that between 1999 and 2007 if 1(post-2000) equals to 1. ΔPC is the annual percentage point change in industry computer use between 1983 and 1997 when 1(post-2000) equals to 0, and that between 1997 and 2003 if 1(post-2000) equals to 1. Control variables not shown in the table include a dummy for the post-2000 period, PC use at year 1983 and 1999, industrial group dummies, propensity to offshoring and import competition, share of female, black and college educated workers in 1983 if 1(post-2000) equals to 0 and in 1999 if 1(post-2000) equals to 1. All regressions are weighted by mean industry share of total hours worked over the endpoints of the years used to form the dependent variable. Samples used are CPS MORG 1983-2007. See Table I and Appendix 1 for definitions and examples of task variables.

Table 5c. Technological Change and Industry Task Input: Stacked First-Difference Estimates

Dependent Variable: 100 * Annual Log Difference in Task Input

A. Routine Tasks

	Simple Average	Principle Component	Being Structured	Following Equipment	Controlling Machine	Monitoring Operation	Controling Pace
ΔPC	-0.046*	-0.044*	-0.066***	-0.069**	-0.044	-0.011	-0.051
	(0.025)	(0.023)	(0.021)	(0.034)	(0.029)	(0.026)	(0.041)
ΔPC*1{post-2000}	-0.007	-0.006	0.038	0.020	-0.025	-0.036	-0.023
	(0.029)	(0.028)	(0.024)	(0.041)	(0.035)	(0.031)	(0.049)
R^2	0.147	0.147	0.136	0.164	0.158	0.154	0.159
Weighted mean Δ of dependent variable							
1983-1999	-0.202	-0.187	-0.347	-0.227	-0.084	-0.247	0.143
1999-2007	-0.301	-0.280	-0.087	-0.410	-0.335	-0.282	-0.408

B. Manual Tasks

	Simple Average	Principle Component	Using Hands	Manual Dexterity	Service orientated	Assisting others	Performing for public
ΔPC	0.032**	0.063***	0.002	0.039	0.052***	0.020	0.068***
	(0.013)	(0.020)	(0.023)	(0.034)	(0.016)	(0.019)	(0.025)
ΔPC*1{post-2000}	-0.036**	-0.044*	-0.032	-0.074*	-0.019	-0.020	-0.046
	(0.015)	(0.024)	(0.027)	(0.040)	(0.019)	(0.022)	(0.030)
R^2	0.191	0.131	0.140	0.164	0.180	0.172	0.084
Weighted mean Δ of dependent variable							
1983-1999	-0.006	-0.012	-0.190	-0.221	0.152	0.077	0.129
1999-2007	0.190	0.038	-0.139	-0.202	0.085	0.167	0.246

Notes: N is 406 (203 consistent industries in two periods). Standard errors are in parentheses. Each column in a panel is a seperate stacked-first differences OLS regression. Dependent variables are 100 times the annual log changes in task inputs between 1983 and 1999 if the dummy variable 1(post-2000) equals to 0, and that between 1999 and 2007 if 1(post-2000) equals to 1. ΔPC is the annual percentage point change in industry computer use between 1983 and 1997 when 1(post-2000) equals to 0, and that between 1997 and 2003 if 1(post-2000) equals to 1. Control variables not shown in the table include a dummy for the post-2000 period, PC use at year 1983 and 1999, industrial group dummies, propensity to offshoring and import competition, share of female, black and college educated workers in 1983 if 1(post-2000) equals to 0 and in 1999 if 1(post-2000) equals to 1. All regressions are weighted by mean industry share of total hours worked over the endpoints of the years used to form the dependent variable. Samples used are CPS MORG 1983-2007. See Table I and Appendix 1 for definitions and examples of task variables.

Table 6. Shifts in High Skill Occupation Share Implied by Job Tasks, 1983-2007

	(1) Observed annual changes of ONET task measures	(2) Predicted high skill employment change by ONET task shifts	(3) Task shifts induced by computer use	(4) Predicted high skill employment change by computer - induced task shifts
Period of 1983 - 1999				
Analytical	0.168	0.076	0.112	0.051
Managerial	0.162	0.105	0.102	0.078
Reasoning	0.106	0.156	0.083	0.123
Information	0.175	0.052	0.139	0.031
Routine	-0.202	0.095	-0.020	0.010
All tasks		0.485		0.293
Actual annual high skill employment share (in percentage points) = 0.458				
Percent accounted by analytical+managerial		39.520		28.036
Percent accounted by reasoning+informatior		45.415		43.774
Percent accounted by routine		20.725		2.220
Period of 1999 - 2007				
Analytical	0.151	0.096	0.065	0.061
Managerial	0.198	0.145	0.048	0.008
Reasoning	0.021	-0.127	0.020	-0.045
Information	0.056	-0.015	0.041	-0.036
Routine	-0.301	0.139	-0.052	0.019
All tasks		0.239		0.008
Actual annual high skill employment share (in percentage points) = 0.290				
Percent accounted by analytical+managerial		83.212		23.686
Percent accounted by reasoning+informatior		-48.646		-27.734
Percent accounted by routine		30.382		4.209

Notes: Observed labor share of each task is the average task intensity of the full working sample, weighted by workers' labor supply weights. The annualized change between year t0 and t1 shown in column (1) equals to 100*(log(intensity_t0)-log(intensity_t1))/(t1-t0), where intensity is the level of labor share employed for a task, same as shown in Table 4. Predicted change in high skill employment share in column (2) is calculated as the change in tasks (in column (1)) multiplying the fixed coefficients estimated using equation (2) in section 5.3. Column (3) shows the computer-induced task shifts, which is the predicted task shifts using equation (1). Column (4) equals to the computer-induced task shifts in column (3) multiplying the fixed coefficients.

Table 7a. Offshoring and Task Inputs

Dependent Variable: 100 * Annual Difference in Task Inputs. N=406

	(1)	(2)	(3)	(4)	(5)	(6)
	Analytical	Managerial	Cognitive	Information	Routine	Manual
Offshorability	0.006	0.009	0.013	0.057	0.109*	0.054*
	(0.039)	(0.034)	(0.027)	(0.035)	(0.058)	(0.031)
Offshorability*1(post2000)	0.068	0.054	0.092***	-0.072	-0.232***	-0.088**
	(0.049)	(0.043)	(0.034)	(0.044)	(0.073)	(0.039)
ΔPC	0.049***	0.041***	0.049***	0.057***	-0.023	0.019
	(0.018)	(0.015)	(0.012)	(0.016)	(0.027)	(0.014)
ΔPC*1{post-2000}	0.024	0.017	-0.037**	-0.038*	-0.088***	-0.037**
	(0.022)	(0.019)	(0.017)	(0.020)	(0.033)	(0.017)
R-squared	0.225	0.172	0.245	0.237	0.147	0.131

Notes: N is 406 (203 consistent industries in two periods). Standard errors are in parentheses. Each column in a panel is a seperate stacked-first differences OLS regression. Dependent variables are 100 times the annual log changes in task inputs between 1983 and 1999 if the dummy variable 1(post-2000) equals to 0, and that between 1999 and 2007 if 1(post-2000) equals to 1. Offshoring is the intensity of offshorable tasks at industrial level at the initial year of each period. ΔPC is the annual percentage point change in industry computer use between 1983 and 1997 when 1(post-2000) equals to 0, and that between 1997 and 2003 if 1(post-2000) equals to 1. All regressions are weighted by mean industry share of total hours worked over the endpoints of the years used to form the dependent variable. Samples used are CPS MORG 1983-2007.

Table 7b. Import Competition and Task Inputs

Dependent Variable: 100 * Annual Difference in Task Inputs. N=406

	(1)	(2)	(3)	(4)	(5)	(6)
	Analytical	Managerial	Cognitive	Information	Routine	Manual
Import	0.003	0.006	-0.003	-0.021	-0.074*	-0.014
	(0.027)	(0.024)	(0.019)	(0.024)	(0.040)	(0.021)
Import*1{post2000}	0.011	0.005	0.006	0.030	0.053	0.005
	(0.027)	(0.023)	(0.019)	(0.024)	(0.040)	(0.021)
ΔPC	0.046***	0.038***	0.046***	0.053***	-0.047*	0.032**
	(0.016)	(0.014)	(0.011)	(0.015)	(0.025)	(0.013)
ΔPC*1{post-2000}	-0.013	-0.014	-0.034**	-0.053***	-0.007	-0.036**
	(0.019)	(0.017)	(0.013)	(0.017)	(0.029)	(0.015)
R-squared	0.247	0.177	0.281	0.240	0.149	0.191

Notes: N is 406 (203 consistent industries in two periods). Standard errors are in parentheses. Each column in a panel is a seperate stacked-first differences OLS regression. Dependent variables are 100 times the annual log changes in task inputs between 1983 and 1999 if the dummy variable 1(post-2000) equals to 0, and that between 1999 and 2007 if 1(post-2000) equals to 1. Propensity of import is the share of products imported from China at industrial level in the intial year of each period. ΔPC is the annual percentage point change in industry computer use between 1983 and 1997 when 1(post-2000) equals to 0, and that between 1997 and 2003 if 1(post-2000) equals to 1. All regressions are weighted by mean industry share of total hours worked over the endpoints of the years used to form the dependent variable. Samples used are CPS MORG 1983-2007.

Table 8. Change in Technology Adoption and Change in Task Inputs: By Education Groups

Dependent Variable: 100 * Annual Difference in Task Inputs, by education group

	(1)	(2)	(3)	(4)	(5)	(6)
A. Within Industry Task Inputs Using College Educated						
	Analytical	Managerial	Reasoning	Information	Routine	Manual
ΔPC	0.029	0.032*	0.030**	0.026	-0.046	0.034
	(0.020)	(0.018)	(0.014)	(0.023)	(0.031)	(0.022)
ΔPC*1{post-2000}	-0.020	-0.030	-0.029*	-0.044*	0.077**	-0.025
	(0.023)	(0.021)	(0.016)	(0.026)	(0.035)	(0.025)
R-squared	0.179	0.127	0.193	0.158	0.096	0.160
B. Within Industry Task Inputs Using Less Than College Educated						
	Analytical	Managerial	Reasoning	Information	Routine	Manual
ΔPC	0.034**	0.021	0.035***	0.035**	-0.033	0.025**
	(0.017)	(0.015)	(0.012)	(0.016)	(0.026)	(0.012)
ΔPC*1{post-2000}	-0.013	-0.002	-0.030**	-0.039**	-0.019	-0.016
	(0.021)	(0.018)	(0.015)	(0.020)	(0.031)	(0.015)
R-squared	0.186	0.116	0.207	0.171	0.091	0.106

Notes: N is 397 for Panel A and 406 for Panel B. Standard errors are in parentheses. Each column in a panel is a seperate stacked-first differences OLS regression. Dependent variables are 100 times the annual log changes in task inputs for the relevant education group between 1983 and 1999 if the dummy variable 1(post-2000) equals to 0, and that between 1999 and 2007 if 1(post-2000) equals to 1. Task measure is the composite (simple average) measure for each of the six task category. ΔPC is the annual percentage point change in industry computer use between 1983 and 1997 when 1(post-2000) equals to 0, and that between 1997 and 2003 if 1(post-2000) equals to 1. Control variables not shown in the table include a dummy for the post-2000 period, PC use at year 1983 and 1999, industrial group dummies, propensity to offshoring and import competition, share of female, black and college educated workers in 1983 if 1(post-2000) equals to 0 and in 1999 if 1(post-2000) equals to 1. All regressions are weighted by mean industry share of total hours worked over the endpoints of the years used to form the dependent variable. Samples used are CPS MORG 1983-2007. See Table I and Appendix 1 for definitions and examples of task variables.

Table 9. Change in Technology Adoption and Change in Task Inputs: By Gender

Dependent Variable: 100 * Annual Difference in Task Inputs, by gender

	(1)	(2)	(3)	(4)	(5)	(6)
A. Female						
	Analytical	Managerial	Reasoning	Information	Routine	Manual
ΔPC	0.070***	0.066***	0.074***	0.072***	-0.066**	0.045***
	(0.020)	(0.018)	(0.016)	(0.021)	(0.028)	(0.016)
ΔPC*1{post-2000}	-0.046**	-0.052**	-0.057***	-0.080***	0.076**	-0.023
	(0.023)	(0.020)	(0.018)	(0.024)	(0.032)	(0.018)
R-squared	0.308	0.230	0.310	0.307	0.207	0.184
B. Male						
	Analytical	Managerial	Reasoning	Information	Routine	Manual
ΔPC	0.060***	0.047***	0.033***	0.041**	-0.089***	-0.007
	(0.019)	(0.016)	(0.012)	(0.017)	(0.034)	(0.016)
ΔPC*1{post-2000}	0.015	0.011	-0.023**	-0.021**	-0.022	-0.034*
	(0.022)	(0.018)	(0.011)	(0.012)	(0.038)	(0.018)
R-squared	0.222	0.184	0.191	0.146	0.144	0.195

Notes: N is 397 for Panel A and 406 for Panel B. Standard errors are in parentheses. Each column in a panel is a seperate stacked-first differences OLS regression. Dependent variables are 100 times the annual log changes in task inputs for the relevant gender group between 1983 and 1999 if the dummy variable 1(post-2000) equals to 0, and that between 1999 and 2007 if 1(post-2000) equals to 1. Task measure is the composite (simple average) measure for each of the six task category. ΔPC is the annual percentage point change in industry computer use between 1983 and 1997 when 1(post-2000) equals to 0, and that between 1997 and 2003 if 1(post-2000) equals to 1. Control variables not shown in the table include a dummy for the post-2000 period, PC use at year 1983 and 1999, industrial group dummies, propensity to offshoring and import competition, share of female, black and college educated workers in 1983 if 1(post-2000) equals to 0 and in 1999 if 1(post-2000) equals to 1. All regressions are weighted by mean industry share of total hours worked over the endpoints of the years used to form the dependent variable. Samples used are CPS MORG 1983-2007. See Table I and Appendix 1 for definitions and examples of task variables.

Appendix Tables

Appendix Table 2. Technological Change and Changes in Industry Task Input (N=406, No Controls)
Dependent Variable: 100 * Annual Log Difference in Task Inputs

Robustness Check: Do the results hold without controlling for industry characteristics?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Composite Task Measures		Single Task Measures				
A. Analytical Tasks							
	Principle Component	Simple Average	Evaluate Information	Interpret Information	Problem Solving	Originility	Critical Thinking
ΔPC	0.036**	0.053**	0.035*	0.036*	0.043**	0.034**	0.033***
	(0.014)	(0.026)	(0.018)	(0.020)	(0.017)	(0.016)	(0.013)
ΔPC*1{post-2000}	-0.006	-0.003	-0.001	0.000	-0.020	0.003	-0.014
	(0.019)	(0.033)	(0.024)	(0.025)	(0.022)	(0.021)	(0.016)
R-squared	0.221	0.201	0.239	0.119	0.220	0.200	0.184
B. Managerial Tasks							
	Principle Component	Simple Average	Establishing Interpersonal	Developing Strategy	Resolving Conflict	Building Team	Making Decision
ΔPC	0.031**	0.053**	0.013	0.038**	0.035**	0.040**	0.031**
	(0.012)	(0.024)	(0.011)	(0.019)	(0.017)	(0.016)	(0.013)
ΔPC*1{post-2000}	-0.009	-0.014	0.008	-0.018	0.001	-0.026	-0.013
	(0.016)	(0.031)	(0.014)	(0.025)	(0.023)	(0.021)	(0.017)
R-squared	0.157	0.153	0.051	0.186	0.087	0.181	0.199
C. Cognitive Reasoning Tasks							
	Principle Component	Simple Average	Problem Sensitivity	Deductive Reasoning	Data Comparison	System Analysis	Judging Quality
ΔPC	0.035***	0.080***	0.027***	0.028***	0.043***	0.045**	0.035***
	(0.010)	(0.025)	(0.009)	(0.009)	(0.014)	(0.021)	(0.011)
ΔPC*1{post-2000}	-0.028**	-0.060*	-0.024**	-0.015	-0.029	-0.044*	-0.033**
	(0.013)	(0.033)	(0.012)	(0.012)	(0.018)	(0.027)	(0.015)
R-squared	0.239	0.202	0.097	0.184	0.198	0.247	0.207
D. Information Transfer Tasks							
	Principle Component	Simple Average	Guiding	Coaching	Instructing	Staffing Unit	Reviewing Information
ΔPC	0.043***	0.076***	0.060***	0.043**	0.026***	0.071***	0.030***
	(0.013)	(0.024)	(0.019)	(0.017)	(0.010)	(0.024)	(0.012)
ΔPC*1{post-2000}	-0.045***	-0.079**	-0.070***	-0.044**	-0.034***	-0.077**	-0.020
	(0.017)	(0.031)	(0.025)	(0.022)	(0.013)	(0.031)	(0.015)
R-squared	0.222	0.222	0.196	0.211	0.138	0.244	0.138
E. Routine Tasks							
	Principle Component	Simple Average	Being Structured	Following Equipment	Controlling Machine	Monitoring Operation	Controling Pace
ΔPC	-0.038*	-0.036*	-0.045**	-0.070**	-0.043	-0.000	-0.046
	(0.022)	(0.021)	(0.018)	(0.031)	(0.026)	(0.023)	(0.036)
ΔPC*1{post-2000}	-0.011	-0.010	0.028	0.014	-0.024	-0.040	-0.023
	(0.029)	(0.027)	(0.024)	(0.040)	(0.034)	(0.030)	(0.047)
R-squared	0.119	0.119	0.098	0.118	0.135	0.122	0.138
F. Manual Tasks							
	Principle Component	Simple Average	Using Hands	Manual Dexterity	Service orientated	Assisting others	Performing for public
ΔPC	0.009	0.024	-0.012	0.004	0.028**	-0.002	0.035
	(0.012)	(0.018)	(0.020)	(0.030)	(0.014)	(0.017)	(0.022)
ΔPC*1{post-2000}	-0.021	-0.020	-0.020	-0.053	-0.005	-0.006	-0.026
	(0.015)	(0.024)	(0.026)	(0.039)	(0.018)	(0.022)	(0.029)
R-squared	0.145	0.089	0.115	0.113	0.139	0.147	0.055

Notes: N is 406 (203 consistent industries in two periods). Standard errors are in parentheses. Each column in a panel is a seperate stacked-first differences OLS regression. Dependent variables are 100 times the annual log changes in task inputs between 1983 and 1999 if the dummy variable 1(post-2000) equals to 0, and that between 1999 and 2007 if 1(post-2000) equals to 1. ΔTech is the annual percentage point change in industry computer use between 1983 and 1997 when 1(post-2000) equals to 0, and that between 1997 and 2003 if 1(post-2000) equals to 1. **Control** variables not shown in the table include a dummy for the post-2000 period, computer use at initial year, and industrial group dummies. All regressions are weighted by mean industry share of total hours worked over the endpoints of the years used to form the dependent variable. Samples used are CPS MORG 1983-2007. See Table I and Appendix 1 for definitions and examples of task variables.

Appendix Table 3. Technological Change and Changes in Industry Task Input (N=406, With Controls)
Dependent Variable: 100 * Annual Log Difference in Task Inputs

Robustness Check: Does it matter that the post-2000 period start from 1999 or 2000?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Composite Task Measures		Single Task Measures				
A. Analytical Tasks							
	Principle Component	Simple Average	Evaluate Information	Interpret Information	Problem Solving	Originility	Critical Thinking
ΔPC	0.002***	0.003***	0.001*	0.002**	0.002**	0.002***	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ΔPC*1{post-2000}	-0.000	-0.001	0.000	-0.000	-0.001	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R-squared	0.237	0.235	0.238	0.137	0.263	0.196	0.213
B. Managerial Tasks							
	Principle Component	Simple Average	Establishing Interpersonal Relationship	Developing Strategy	Resolving Conflict	Building Team	Making Decision
ΔPC	0.001**	0.003**	0.001*	0.002*	0.002**	0.001*	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ΔPC*1{post-2000}	-0.000	-0.001	0.000	-0.001	0.000	-0.001	-0.001
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R-squared	0.163	0.164	0.092	0.202	0.093	0.172	0.207
C. Cognitive Reasoning Tasks							
	Principle Component	Simple Average	Problem Sensitivity	Deductive Reasoning	Data Comparison	System Analysis	Judging Quality
ΔPC	0.002***	0.004***	0.001***	0.001***	0.002***	0.001**	0.001***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
ΔPC*1{post-2000}	-0.001**	-0.003**	-0.001*	-0.001	-0.001*	-0.001	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R-squared	0.243	0.225	0.118	0.183	0.231	0.253	0.191
D. Information Transfer Tasks							
	Principle Component	Simple Average	Guiding	Coaching	Instructing	Staffing Unit	Reviewing Information
ΔPC	0.002***	0.004***	0.002***	0.001**	0.001**	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
ΔPC*1{post-2000}	-0.002***	-0.004***	-0.002***	-0.001*	-0.002***	-0.002**	-0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R-squared	0.185	0.184	0.167	0.171	0.140	0.228	0.158
E. Routine Tasks							
	Principle Component	Simple Average	Being Structured	Following Equipment	Controlling Machine	Monitoring Operation	Controling Pace
ΔPC	-0.001*	-0.002*	-0.001**	-0.002*	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ΔPC*1{post-2000}	-0.000	-0.000	0.001	0.000	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R-squared	0.170	0.169	0.121	0.168	0.181	0.171	0.166
F. Manual Tasks							
	Principle Component	Simple Average	Using Hands	Manual Dexterity	Service orientated	Assisting others	Performing for public
ΔPC	0.001**	0.003***	-0.000	0.001	0.002***	0.001	0.003***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ΔPC*1{post-2000}	-0.001**	-0.002	-0.002	-0.002*	-0.001	-0.000	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R-squared	0.194	0.137	0.135	0.157	0.162	0.186	0.082

Notes: N is 406 (203 consistent industries in two periods). Standard errors are in parentheses. Each column in a panel is a seperate stacked-first differences OLS regression. Dependent variables are 100 times the annual log changes in task inputs between 1983 and 1999 if the dummy variable 1(post-2000) equals to 0, and that between **2000** and **2007** if 1(post-2000) equals to 1. ΔTech is the annual percentage point change in industry computer use between 1983 and 1997 when 1(post-2000) equals to 0, and that between 1997 and 2003 if 1(post-2000) equals to 1. Control variables not shown in the table include a dummy for the post-2000 period, PC use at year 1983 and 1999, industrial group dummies, propensity to offshoring and import competition, share of female, black and college educated workers in 1983 if 1(post-2000) equals to 0 and in 1999 if 1(post-2000) equals to 1. All regressions are weighted by mean industry share of total hours worked over the endpoints of the years used to form the dependent variable. Samples used are CPS MORG 1983-2007. See Table I and Appendix 1 for definitions and examples of task variables.

Appendix Table 4. Technological Change and Changes in Industry Task Input (N=406, With Controls)
Dependent Variable: 100 * Annual Difference in Task Inputs

Robustness Check: Does it matter to use the log differences of task inputs or simple differences?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Composite Task Measures		Single Task Measures				
A. Analytical Tasks							
	Principle Component	Simple Average	Evaluate Information	Interpret Information	Problem Solving	Originility	Critical Thinking
ΔPC	0.002***	0.003***	0.001*	0.002**	0.002**	0.002***	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ΔPC*1{post-2000}	-0.000	-0.001	0.000	-0.000	-0.001	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R-squared	0.237	0.235	0.238	0.137	0.263	0.196	0.213
B. Managerial Tasks							
	Principle Component	Simple Average	Establishing Interpersonal Relationship	Developing Strategy	Resolving Conflict	Building Team	Making Decision
ΔPC	0.001**	0.003**	0.001*	0.002*	0.002**	0.001*	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ΔPC*1{post-2000}	-0.000	-0.001	0.000	-0.001	0.000	-0.001	-0.001
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R-squared	0.163	0.164	0.092	0.202	0.093	0.172	0.207
C. Cognitive Reasoning Tasks							
	Principle Component	Simple Average	Problem Sensitivity	Deductive Reasoning	Data Comparison	System Analysis	Judging Quality
ΔPC	0.002***	0.004***	0.001***	0.001***	0.002***	0.001**	0.001***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
ΔPC*1{post-2000}	-0.001**	-0.003**	-0.001*	-0.001	-0.001*	-0.001	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R-squared	0.243	0.225	0.118	0.183	0.231	0.253	0.191
D. Information Transfer Tasks							
	Principle Component	Simple Average	Guiding	Coaching	Instructing	Staffing Unit	Reviewing Information
ΔPC	0.002***	0.004***	0.002***	0.001**	0.001**	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
ΔPC*1{post-2000}	-0.002***	-0.004***	-0.002***	-0.001*	-0.002***	-0.002**	-0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R-squared	0.185	0.184	0.167	0.171	0.140	0.228	0.158
E. Routine Tasks							
	Principle Component	Simple Average	Being Structured	Following Equipment	Controlling Machine	Monitoring Operation	Controling Pace
ΔPC	-0.001*	-0.002*	-0.001**	-0.002*	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ΔPC*1{post-2000}	-0.000	-0.000	0.001	0.000	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R-squared	0.170	0.169	0.121	0.168	0.181	0.171	0.166
F. Manual Tasks							
	Principle Component	Simple Average	Using Hands	Manual Dexterity	Service orientated	Assisting others	Performing for public
ΔPC	0.001**	0.003***	-0.000	0.001	0.002***	0.001	0.003***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ΔPC*1{post-2000}	-0.001**	-0.002	-0.002	-0.002*	-0.001	-0.000	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R-squared	0.194	0.137	0.135	0.157	0.162	0.186	0.082

Notes: N is 406 (203 consistent industries in two periods). Standard errors are in parentheses. Each column in a panel is a seperate stacked-first differences OLS regression. Dependent variables are 100 times the **annual changes** in task inputs between 1983 and 1999 if the dummy variable 1(post-2000) equals to 0, and that between 1999 and 2007 if 1(post-2000) equals to 1. ΔTech is the annual percentage point change in industry computer use between 1983 and 1997 when 1(post-2000) equals to 0, and that between 1997 and 2003 if 1(post-2000) equals to 1. Control variables not shown in the table include a dummy for the post-2000 period, PC use at year 1983 and 1999, industrial group dummies, propensity to offshoring and import competition, share of female, black and college educated workers in 1983 if 1(post-2000) equals to 0 and in 1999 if 1(post-2000) equals to 1. All regressions are weighted by mean industry share of total hours worked over the endpoints of the years used to form the dependent variable. Samples used are CPS MORG 1983-2007. See Table I and Appendix 1 for definitions and examples of task variables.

Appendix Table 5. Technological Change and Changes in Industry Task Input By Education Group
Dependent Variable: 100 * Annual Log Difference in Task Inputs Using an Education Group

COLLEGE

	(1)	(2)	(3)	(4)	(5)
A. Analytical Tasks					
	Evaluate Information	Interpret Information	Problem Solving	Originility	Critical Thinking
ΔPC	0.022	0.030	0.026	0.050**	0.021
	(0.028)	(0.023)	(0.027)	(0.021)	(0.017)
ΔPC*1{post-2000}	-0.007	-0.009	-0.046	-0.024	-0.021
	(0.032)	(0.027)	(0.031)	(0.024)	(0.020)
R-squared	0.153	0.161	0.177	0.138	0.211
B. Managerial Tasks					
	Interpersonal	Developing Strategy	Resolving Conflict	Building Team	Making Decision
ΔPC	0.025*	0.050*	0.024	0.032	0.030*
	(0.015)	(0.029)	(0.026)	(0.027)	(0.017)
ΔPC*1{post-2000}	-0.028*	-0.038	-0.032	-0.031	-0.022
	(0.017)	(0.033)	(0.030)	(0.031)	(0.020)
R-squared	0.081	0.118	0.077	0.154	0.149
C. Cognitive Reasoning Tasks					
	Problem Sensitivity	Deductive Reasoning	Data Comparison	System Analysis	Judging Quality
ΔPC	0.015	0.018	0.052***	0.040	0.026
	(0.012)	(0.013)	(0.019)	(0.031)	(0.017)
ΔPC*1{post-2000}	-0.018	-0.014	-0.057***	-0.019	-0.043**
	(0.014)	(0.015)	(0.021)	(0.036)	(0.020)
R-squared	0.087	0.152	0.198	0.190	0.142
D. Information Transfer Tasks					
	Guiding	Coaching	Instructing	Staffing Unit	Reviewing Information
ΔPC	0.017	0.015	0.021	0.046	0.038**
	(0.033)	(0.029)	(0.018)	(0.041)	(0.019)
ΔPC*1{post-2000}	-0.044	-0.035	-0.033	-0.086*	-0.044**
	(0.038)	(0.033)	(0.020)	(0.046)	(0.022)
R-squared	0.137	0.117	0.097	0.225	0.140
E. Routine Tasks					
	Being Structured	Following Equipment	Controlling Machine	Monitoring Operation	Controling Pace
ΔPC	-0.059**	-0.037	-0.048	-0.015	-0.079*
	(0.026)	(0.045)	(0.041)	(0.036)	(0.046)
ΔPC*1{post-2000}	0.069**	0.065	0.094**	0.064	0.088*
	(0.030)	(0.051)	(0.047)	(0.041)	(0.053)
R-squared	0.147	0.105	0.111	0.116	0.110
F. Manual Tasks					
	Using Hands	Manual Dexterity	Service orientated	Assisting others	Performing for public
ΔPC	0.020	0.065	0.039*	0.020	0.054
	(0.032)	(0.046)	(0.021)	(0.029)	(0.040)
ΔPC*1{post-2000}	0.012	-0.030	-0.039	-0.021	-0.063
	(0.037)	(0.052)	(0.024)	(0.033)	(0.045)
R-squared	0.107	0.158	0.138	0.133	0.103

Notes: N is 406 (203 consistent industries in two periods). Standard errors are in parentheses. Each column in a panel is a seperate stacked-first differences OLS regression. Dependent variables are 100 times the annual log changes in task inputs between 1983 and 1999 if the dummy variable 1(post-2000) equals to 0, and that between 1999 and 2007 if 1(post-2000) equals to 1. ΔTech is the annual percentage point change in industry computer use between 1983 and 1997 when 1(post-2000) equals to 0, and that between 1997 and 2003 if 1(post-2000) equals to 1. Control variables not shown in the table include a dummy for the post-2000 period, PC use at year 1983 and 1999, industrial group dummies, propensity to offshoring and import competition, share of female, black and college educated workers in 1983 if 1(post-2000) equals to 0 and in 1999 if 1(post-2000) equals to 1. All regressions are weighted by mean industry share of total hours worked over the endpoints of the years used to form the dependent variable. Samples used are CPS MORG 1983-2007. See Table I and Appendix 1 for definitions and examples of task variables.

Appendix Table 6. Technological Change and Changes in Industry Task Input By Education Group
Dependent Variable: 100 * Annual Log Difference in Task Inputs Using an Education Group

LESS THAN COLLEGE

	(1)	(2)	(3)	(4)	(5)
A. Analytical Tasks					
	Evaluate Information	Interpret Information	Problem Solving	Originility	Critical Thinking
ΔPC	0.033	0.032	0.038*	0.034	0.034**
	(0.022)	(0.025)	(0.021)	(0.021)	(0.015)
ΔPC*1{post-2000}	-0.014	-0.005	-0.021	-0.003	-0.023
	(0.027)	(0.030)	(0.025)	(0.025)	(0.018)
R-squared	0.228	0.087	0.195	0.171	0.131
B. Managerial Tasks					
	Interpersonal	Developing Strategy	Resolving Conflict	Building Team	Making Decision
ΔPC	0.008	0.013	0.038*	0.022	0.024
	(0.013)	(0.024)	(0.022)	(0.021)	(0.016)
ΔPC*1{post-2000}	0.015	-0.009	0.015	-0.020	-0.013
	(0.016)	(0.028)	(0.027)	(0.025)	(0.019)
R-squared	0.079	0.149	0.089	0.115	0.181
C. Cognitive Reasoning Tasks					
	Problem Sensitivity	Deductive Reasoning	Data Comparison	System Analysis	Judging Quality
ΔPC	0.028**	0.028**	0.049***	0.049*	0.024*
	(0.012)	(0.011)	(0.017)	(0.025)	(0.014)
ΔPC*1{post-2000}	-0.024	-0.017	-0.033	-0.071**	-0.020
	(0.014)	(0.013)	(0.021)	(0.030)	(0.017)
R-squared	0.097	0.149	0.190	0.223	0.184
D. Information Transfer Tasks					
	Guiding	Coaching	Instructing	Staffing Unit	Reviewing Information
ΔPC	0.058**	0.035	0.021*	0.045	0.029**
	(0.025)	(0.022)	(0.012)	(0.031)	(0.014)
ΔPC*1{post-2000}	-0.079***	-0.043*	-0.024	-0.051	-0.016
	(0.030)	(0.026)	(0.015)	(0.037)	(0.017)
R-squared	0.143	0.198	0.165	0.157	0.124
E. Routine Tasks					
	Being Structured	Following Equipment	Controlling Machine	Monitoring Operation	Controling Pace
ΔPC	-0.044**	-0.053	-0.029	-0.016	-0.016
	(0.022)	(0.036)	(0.030)	(0.029)	(0.045)
ΔPC*1{post-2000}	0.028	0.017	-0.041	-0.046	-0.047
	(0.027)	(0.043)	(0.036)	(0.034)	(0.054)
R-squared	0.069	0.081	0.091	0.139	0.108
F. Manual Tasks					
	Using Hands	Manual Dexterity	Service orientated	Assisting others	Performing for public
ΔPC	0.011	0.043	0.042**	0.001	0.047*
	(0.024)	(0.036)	(0.017)	(0.020)	(0.027)
ΔPC*1{post-2000}	-0.028	-0.055	-0.006	0.012	-0.015
	(0.028)	(0.043)	(0.020)	(0.024)	(0.033)
R-squared	0.082	0.081	0.151	0.128	0.069

Notes: N is 406 (203 consistent industries in two periods). Standard errors are in parentheses. Each column in a panel is a seperate stacked-first differences OLS regression. Dependent variables are 100 times the annual log changes in task inputs between 1983 and 1999 if the dummy variable 1(post-2000) equals to 0, and that between 1999 and 2007 if 1(post-2000) equals to 1. ΔTech is the annual percentage point change in industry computer use between 1983 and 1997 when 1(post-2000) equals to 0, and that between 1997 and 2003 if 1(post-2000) equals to 1. Control variables not shown in the table include a dummy for the post-2000 period, PC use at year 1983 and 1999, industrial group dummies, propensity to offshoring and import competition, share of female, black and college educated workers in 1983 if 1(post-2000) equals to 0 and in 1999 if 1(post-2000) equals to 1. All regressions are weighted by mean industry share of total hours worked over the endpoints of the years used to form the dependent variable. Samples used are CPS MORG 1983-2007. See Table I and Appendix 1 for definitions and examples of task variables.

Data Appendix

1. May/Outgoing Rotation Groups Current Population Survey

I use the May/Outgoing Rotation Groups Current Population Survey from 1983 to 2007. The base sample includes workers aged between 18 and 65, with positive potential work experience (max(age-years of schooling-6,0)), not in group quarters or self-employed. The level of employment share for an occupation group is calculated as the ratio between all workers in the occupation group to the total employment at each year, weighted by the CPS sampling weight. The change between year t0 and t1 equals to 100*(log(shemp_t0)-log(shemp_t1))/(t1-t0), where shemp is the share of employment.

The task analysis procedure in this paper requires us to assign workers to occupation, industry and education categories that are consistent over time. The industry classifications used in the CPS have changed repeatedly since 1960. To obtain a consistent set of industry codes, I first use the IPUMS "ind1990" variable to convert workers in the post-1990 samples into 1990 Census industry codes. I then assign workers in all samples to a consistent set of 203 detailed industries using the crosswalk from AA2011. To obtain a consistent set of occupation codes, I follow Autor and Dorn (2011) and use a modified version of the crosswalk developed by Meyer and Osborne (2005) to create time-consistent occupation categories. The classification creates a balanced panel of 326 occupations for the years 1980–2005 that allows us to follow a consistently defined set of occupations over time. Since the new emerging IT-related occupations are potentially very important to my analysis, and excluding these occupations may bias the results towards no/smaller effect of computer adoption (because these occupations are expected to be strongly complemented by internet or computer adoption), I choose to include these new occupations that emerge after 2000 and put them in the occupation "managerial occupations, not elsewhere specified". To attain comparable educational categories across the redefinition of the Census Bureau s education variable introduced in the 1990 Census, I follow the literature (for example, AA2011) and use the method proposed by Jaeger (1997).

2. O*NET

O*NET task measures used in this paper are single measures of O*NET Work Activities and Work Context Importance scales. The definitions and examples of the tasks are listed in Appendix Table1. I assign task scores to each worker on the basis of the worker s occupation following AA2011 and ALM2003. Each task in O*NET is on a scale of [1, 5]. Since the O*NET data set has a much detailed occupation code than CPS, I first collapse the O*NET-SOC occupational classification scheme into SOC occupations using labor supply weights from the pooled 2005/6/7 Occupational Employment Statistics (OES) Survey. In order to merge with the CPS data, the task measures are collapsed to the Census 2000 occupational code level, using the OES Survey labor supply weights and then collapsed to the 326 consistent occupations, using Census 2000 labor supply weights. Then I use the crosswalk between 2000 occupation code and the consistent occupation code (occ1990) and collapse the task means for each occupation in the consistent occupation scheme. To calculate the labor shares of tasks over time, I append the task means at occ1990 level to CPS MORG between 1983 and 2007 based on worker s occupation. Then I calculate the task means at each year at industrial level or national level.

3. The Industry Level MORG CPS Data

For the industry level analysis, I use the Merged Outgoing Rotation Groups for 1983 and 2007 for all employed workers. An industry level crosswalk was generated to generate 203 common industrial categories over time. Employment shares are constructed by summing all workers by industry and year. For an industry j, the labor inputs for task k in year t is measured as a (occupational employment share) weighted sum of occupational task importance. i.e. $k_{j,t} = \sum_{i \in j} w_{i,t}\, k_{i,o} / \sum_{i \in j} w_{i,t}$, where i is an individual in industry j working in occupation o and $w_{i,t}$ is the weight of individual i. Due to fixing the occupational task importance $k_{i,o}$, the within-occupational change in task content cannot be measured. The source of variation we exploit for measuring changes in job task (labor) demand consists of changes over time in the occupational distribution of workers, holding constant the task content within occupations. For the industrial analysis, the change in labor inputs for task k between year t and t+1 of an industry reflect changes in within-industry occupational employment shares.

4. The Computer Use Data

The computer use data are taken from the October 1984, 1997 and 2003 Computer and Internet Use at Work Supplements to the Current Population Survey (CPS). The samples in all three years consist of currently employed workers ages 18– 65. CPS computer use is derived from the question `Do you use a computer directly at work?  The CPS supplements also have questions on `Do you use internet at work? Other questions for work computer use that are comparable across the 1997 and 2003 CPS are for word processing/desktop publishing, email, calendar/scheduling, graphics/design spread sheets/databases and other computer use. I use these questions to construct the descriptive statistics for the purposes/applications of computer use at work.

Theoretical Appendix

The task framework used in this paper builds on Acemoglu and Autor (2010). They propose a model to understand how technological changes affect workers of different skill levels. Consider an economy with one final good Y produced by combining a continuum of tasks on an interval [0, 1].

$$Y = \exp[\int_0^1 lny(i)di].$$

Each task i produces the services y(i) following the production function:

$$y(i) = A_L\alpha_L(i)l(i) + A_M\alpha_M(i)m(i) + A_H\alpha_H(i)h(i) + A_K\alpha_K(i)k(i)$$

There are three types of labor: low-skilled (L), middle-skilled (M) and high-skilled (H) workers and capital K. l(i) is the number of low-skilled workers allocated to task i. A is factor-augmenting technology and α is the productivity of workers at each skill level in performing task i. The structure of α is assumed that $\alpha_L(i)/\alpha_M(i)$ and $\alpha_M(i)/\alpha_H(i)$ are continuously differentiable and strictly decreasing. Therefore, high skilled workers have comparative advantage in the higher numbered tasks. First consider $\alpha_K(.)$=0 and assume all markets to be competitive. Assuming market clearing, in any equilibrium there exists two threshold points, I_L and I_H, such that the tasks can be partitioned into three (convex) sets. All tasks with indices $i < I_L$(mostly manual tasks) will be performed by low skilled workers, all tasks with $i > I_H$ (mostly non-routine analytical or interpersonal tasks) will be performed by high skilled workers and all tasks with $I_L < i < I_H$ (mostly routine tasks) will be performed by middle skilled workers. The two cutoff points are endogenous to changes in technology and skill supplies. Under three equilibrium condition, 1) law of one price for skills - workers of same skill level are paid the same wage though they may be assigned to different tasks; 2) no arbitrage between tasks - the cost of producing task I_H (I_L) is the same using either H or M (M or L); 3) equal division of labor among tasks within a skill group, relative wages can be written as a function of labor supplies and task thresholds:

$$\frac{w_H}{w_M} = \left(\frac{1 - I_H}{I_H - I_L}\right)\left(\frac{H}{M}\right)^{-1}$$

$$\frac{w_M}{w_L} = \left(\frac{I_H - I_L}{I_L}\right)\left(\frac{M}{L}\right)^{-1}$$

The equilibrium thresholds can be expressed as:

$$\frac{A_M \alpha_M(I_H)M}{I_H - I_L} = \frac{A_H \alpha_H(I_L)H}{1 - I_H}$$
$$\frac{A_L \alpha_L(I_L)L}{I_L} = \frac{A_M \alpha_M(I_L)M}{I_H - I_L}$$

Labor supplies L, M, H plus compare advantage. a (L), a (M), a (L) determine task allocation, I_H and I_L, and hence wages.

Suppose technology can replace workers in performing routine tasks, i.e. Capital that out-competes M in a subset of tasks i (denoted by ε in the following equations) in the interval $I_L < i' < I_H$. This lowers the wage of M relative to H and L by narrowing set of M tasks. More specifically, the introduction of machines replacing tasks leads to a new equilibrium characterized by new thresholds $\hat{I}_L$ and $\hat{I}_H$.

$\frac{dI_H}{d\varepsilon} > 0, \frac{dI_L}{d\varepsilon} < 0, \frac{dI_{H-I_L}}{d\varepsilon} > 0 , \frac{dln(w_H/w_M)}{d\varepsilon} > 0, \ \frac{dln(w_M/w_L)}{d\varepsilon} < 0$

Now assume the economy achieves the new equilibrium with new thresholds $\hat{I}_L$ and $\hat{I}_H$. This paper analyzes a case where a subset of tasks $i'' > \hat{I}_H$ become replaceable by new types of technologies, while at the same time more tasks in the interval $[\hat{I}_L, \hat{I}_H]$ continue to be replaced by technologies. The replacing of tasks $i'' > \hat{I}_H$ shrinks the set of tasks that can be performed by H, and would decrease the relative wage of H to M. This force puts an end to the continuous increase in the relative wage of H to M, driven by the replacing of tasks in the interval $[\hat{I}_L, \hat{I}_H]$ with machines. [15]

[15] It is important to distinguish between the wages paid to a skill group and the wages paid to a given task, because the assignment of skills to tasks is endogenous. If a technological change raises the productivity of high skill workers in all tasks, (e.g. an increase in Ah), the set of tasks performed by high skill workers will expand so that some of the tasks formerly performed by medium skilled workers would now be performed by high skill workers instead. The relative wage paid to workers performing these (formerly) middle skill tasks would actually increase, since they are now being performed by the more productive high skill workers. But crucially the model implies that the relative wage of medium skill workers would fall. The relative wage paid to a given skill group always moves in the same direction as its comparative advantage.