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Essays on Skill Biased Technological Change and Human Capital

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Essays on Skill Biased Technological Change and Human Capital

by

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Dedicated to my parents and my loving husband, for their constant support and company during late nights of typing.

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Essays on Skill Biased Technological Change and Human Capital

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Supervisor: Sandra Black Youngblood

This dissertation studies determinants of the U.S. labor market structure and human capital development, with a focus on technological change.

A key feature of the U.S. labor market since 1980 is the substantial growth of the employment in high skill occupations and there is a substantial literature attributing this change to technological change. However, since 1999, the employment growth of high skill occupations has decelerated markedly despite continued rapid growth in technology. The first essay documents this novel trend and examines the role of technological change in explaining this phenomenon. It shows that technological advancements since the late 1990s, such as the onset of Internet, have expanded what computers can do and become substitutes for high skill occupations. This change can explain a substantial portion of the stagnancy in employment growth for high skill occupation in the 2000s.

The second essay examines the role of computer adoption in explaining the differences in the change of gender wage gap between 1980 and 2000 across cities in the United States. It uses the city-level routine task intensity in 1980 to predict the subsequent increase in computer adoption and shows that cities with one percent greater increase in computer adoption experienced a 0.7 percent more decrease in the change of

male-female wage ratio between 1980 and 2000. Computerization explains about 50 percent of the decline in the male-female wage gap between 1980 and 2000.

The third essay studies the causal effect of maternal education on the gender gap in children's non-cognitive skills. It shows that maternal education reduces boys' disadvantage in non-cognitive behaviors relative to girls at age 7. To explain the mechanism of this effect, it provides suggestive evidence that better educated mothers spend more time going outings with boys while reading to girls at age 7, and going outings could be more closely related to non-cognitive development than reading.

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Chapter 1

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

1.1 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.

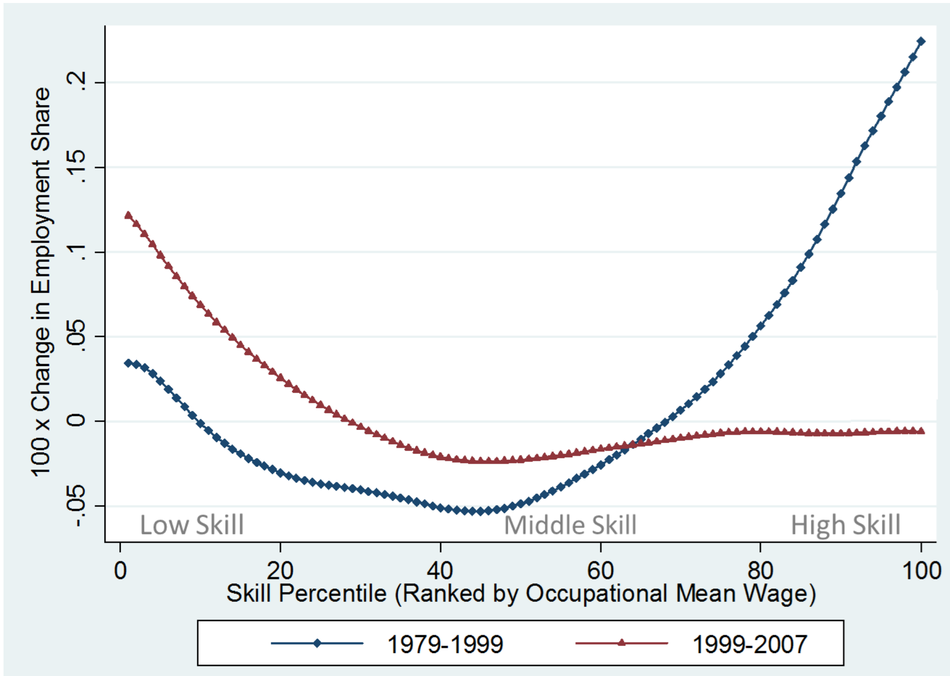
The contributions of this paper are twofold. First, I document the novel trend of employment in the U.S. after 2000. The trend suggests the polarized employment growth that has been prevailing the U.S. for two decades has changed, due to a significant deceleration in the growth of high skill employment. 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 1.2 documents the trends of employment and accompanying changes in the U.S. labor market between 1980 and 2007. Section 1.3 discusses the task-based framework. Section 1.4 describes the data sources and measures for job tasks and technological adoption at work. Section 1.5 discusses the empirical method and presents the results. Section 1.6 concludes.

1.2 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

Figure 1.1: 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.

1990s. This period is often described as a period of job polarization (Goos and Manning, 2007; Autor, Katz and Kearny, 2006, 2008, among many others).[1] The pattern is shown in Figure 1.1, 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

[1] Prior work has shown the polarization pattern is pervasive in Germany (Spitz-Oener, 2006, Dustmann, Ludsteck and Schönberg 2009), and other European countries (Goos, Manning and Salomons 2009; Michaels, Natraj and Van Reenen 2013).

occupational mean log wage in 1980.[2] 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 1.1, 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, Katz, and Kearny, 2006, 2008; 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, 2007; Grossman and Rossi-Hansberg, 2008; Feenstra and Hanson, 1999). 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, Dorn and Hanson, 2013a, 2013b; Bernard et al., 2006; Pierce and Schott, 2013).

[2] 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.

Table 1.1: 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 Technica	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.

Table 1.2: 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 Technica	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.

However, the patterns of polarized growth of the occupational distribution have undergone several important changes after 2000. As shown in Figure 1.1, while the employment share of low-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.[3] Figure 1.2 plots the change in employment share of high skill professional, managerial and technical occupations over time. Consistent with Figure 1.1, the employment share flattens out in the 2000s with a trend break at year 1999.[4] To better understand the changing pattern, in Table 1.2, 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 Table 1.2 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.[5] The share of technicians in science, engineering and health decreased by about 3 percent between 1999 and 2007.[6]

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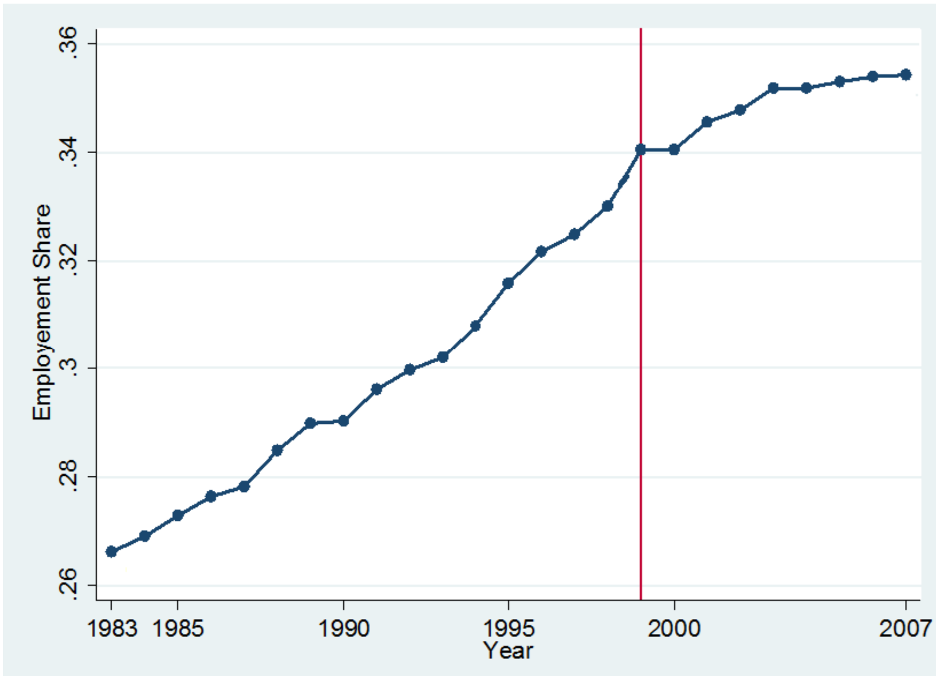
3 A concurrent paper by Autor (2014) shows similar trends of employment in the U.S. after 2000.

4 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.

5 Exceptions are health/medical professionals and primary to postsecondary instructors. These two groups of occupations have been continuously increasing in the 1990s and 2000s.

6 A key exception is the software technicians, whose employment share has increased by almost 8 percent between 1999 and 2007.

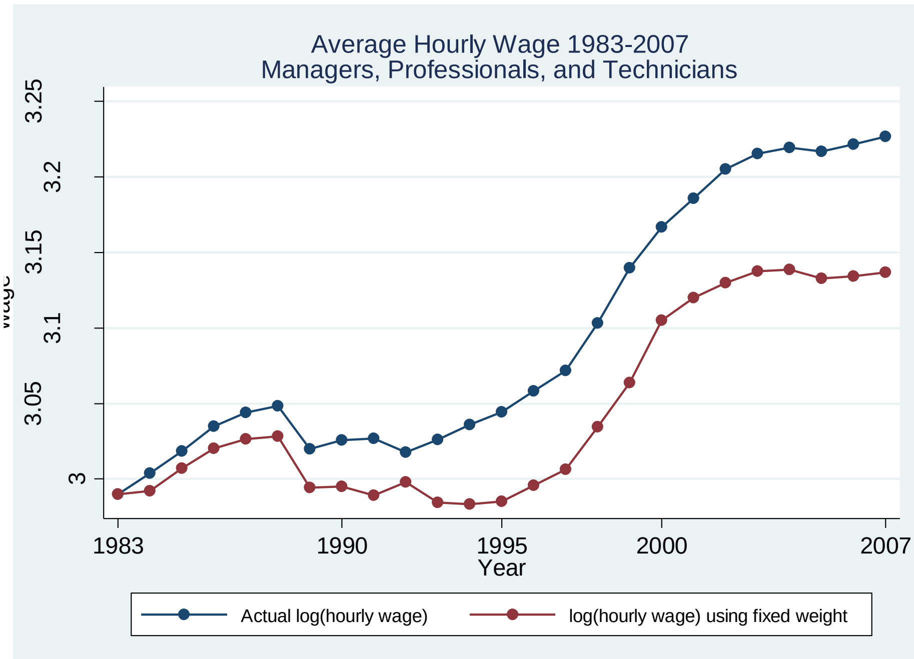
Figure 1.2: Employment Share of Professional, Managerial and Technical Occupations, 1983-2007



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.

Along with the employment growth deceleration of high skill occupations, the wage growth of high skill occupations shows a contemporaneous slowdown. Figure 1.3 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

Figure 1.3: Actual and Composition-Adjusted Hourly Wage for High Skill Occupations



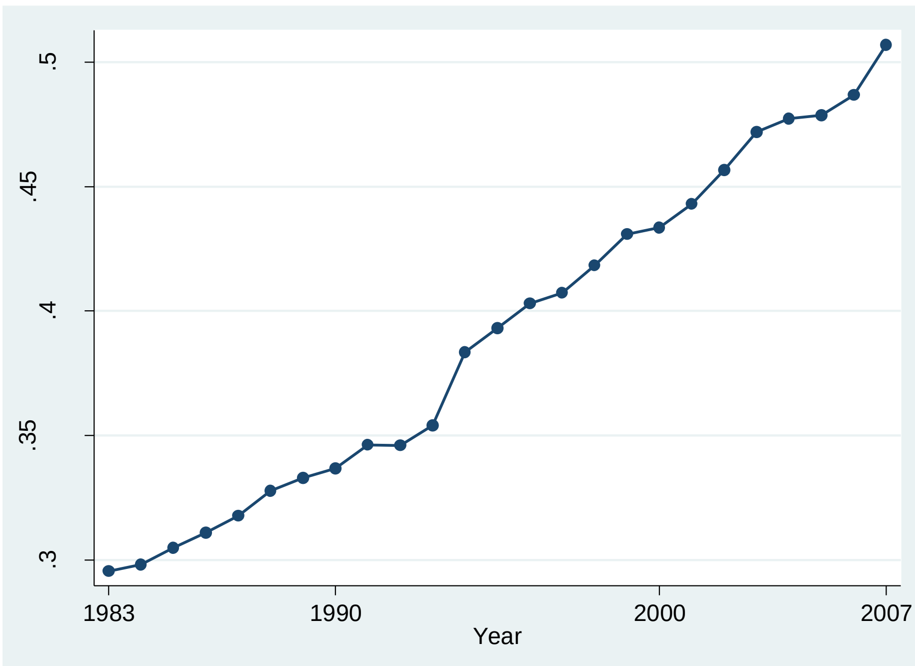
Source: CPS May/ORG data for years 1983-2007. To construct the log wage series using fixed weight, I choose the base year as 1983 and pool the base year with each year in my May/ORG data series to construct a dummy variable equal to one if an individual is observed in 1983. Then I run a logit regression, 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.

degrees (masters, PhDs, etc.) working in the high skill occupations. Therefore, I calculate the average wage in each occupation while holding the composition of education, age, gender and race constant at their 1980 levels.[7] As shown in Figure 1.3, the change of the

[7] 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, with this dummy as dependent variable, and 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 as the explanatory variables. I use the predicted values from the logit regression *yhat* to calculate the probability

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 correspondence in employment and wage change suggests an important role for demand side factors.[8]

Figure 1.4: 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.

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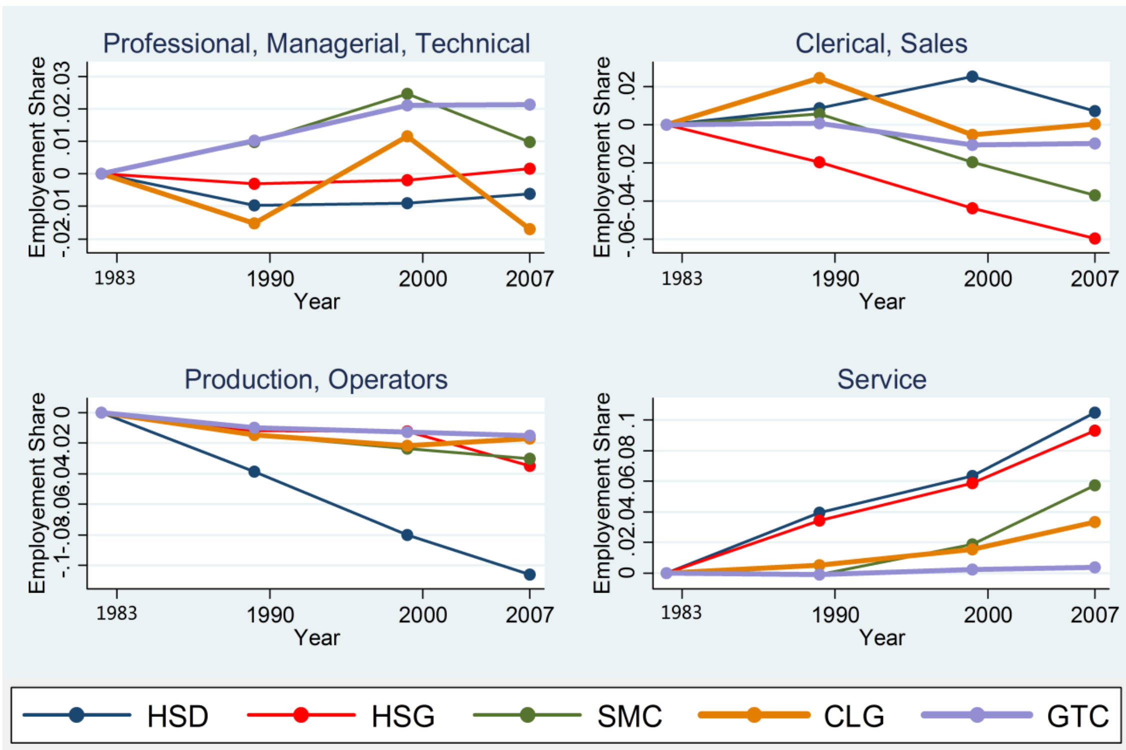
of being in the 1983 sample as *yhat/(1-yhat)* for each observation in the years 1984-2007. The compositional-adjusted wage series is constructed using the labor supply weight multiplied by *yhat/(1-yhat)* as the weight for the years between 1984 and 2007.

[8] An illustration of the demand and supply changes in high skill market in the pre and post 2000 period is shown in Figure A1.2.

In the 2000s, the relative supply of skilled workers continues to increase. Figure 1.4 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

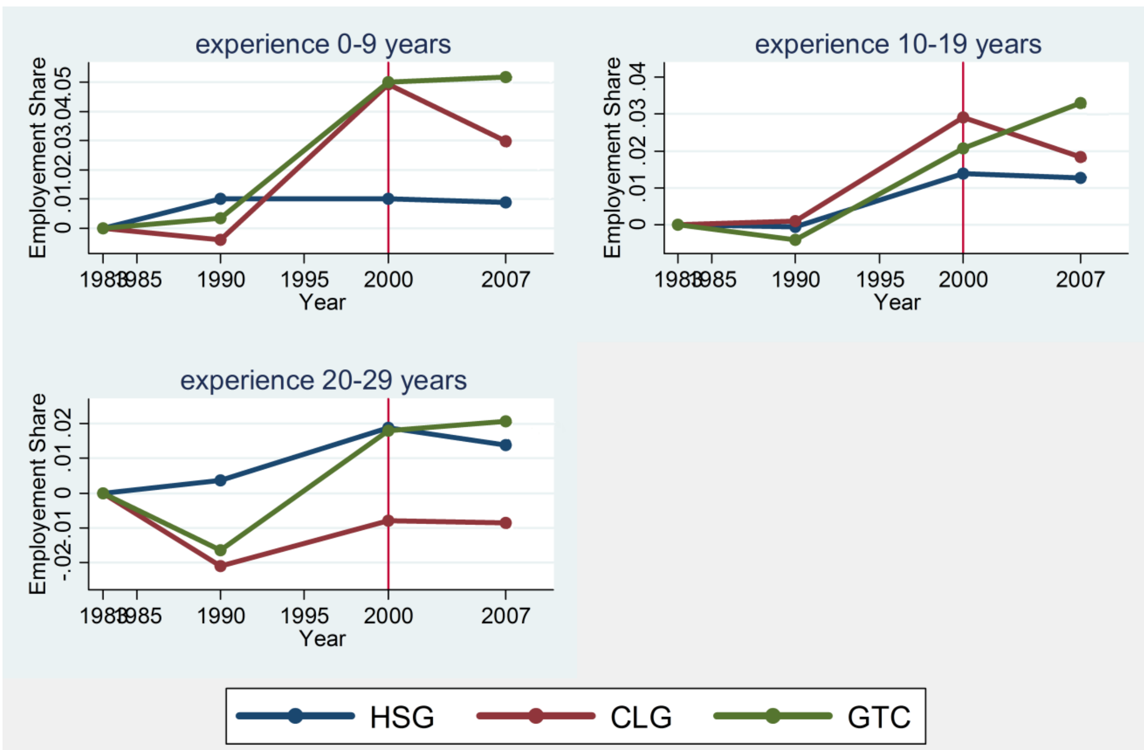
Figure 1.5: Employment Shares in Occupational Groups by Education Level 1983-2007



share prevails within education and cohort groups. Figure 1.5 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 1.6 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.

Figure 1.6: Employment Share in High Skill Occupations by Education and Experience



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 in the US.[9] 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. 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 (Bureau of Labor Statistics, 2011). 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). Internet investments are correlated with wage and employment growth in the US (Forman, Goldfarb, and Greenstein, 2012). 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

[9] One exception is a recent work by Beaudry, et al.(2013), which 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. Another recent paper by Akerman et al. (2015) look at the effect of broadband internet adoption on labor productivity in Germany and find that internet adoption complements nonroutine abstract tasks and substitutes for routine tasks. However, their task sets are limited to those used in prior work and thus do not fully characterize how internet technology affects what workers do at work (i.e. task assignment).

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

1.3 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.[10] 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 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.

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

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.[11] 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.[12] 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

[11] 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, workers that previously supplying high skills will now supply either medium or low skills. Thus, this complements the changes of skills across tasks.

[12] 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 selects 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.

complemented by new technologies, such as managing interpersonal relationships and complex problem during the post-2000 period.[13] 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.

1.4 Data Sources and Measurement

1.4.1 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 1.3. Similarly, I calculate the percentage of workers using Internet at work in 1997 and 2003 and show in the upper panel of Table 1.3 that it has increased substantially during this period, from 17.5 in 1997 to 42.8 in 2003. This

[13] 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.

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 1.3 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.

Table 1.3: 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	57.3	10.7
% of workers using scheduling	-	38.1	58.2	38.1	20.1
% of workers using Internet	-	33.6	75.8	33.6	42.2
% of workers using spreadsheet	-	32.9	65.5	32.9	32.6
% of workers using graphs design	-	20.1	30.3	20.1	10.2
% of workers using programming	-	15.4	17	15.4	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.

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. However, as shown in Figure A1.1 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.[14]

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

1.4.2 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 1.4 presents the list of tasks, 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.

Table 1.4: 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.

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 1.5 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

Table 1.5: 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.

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.

1.5 Empirical Strategy and Results

As discussed in Section 1.3, the task framework predicts that new technologies become increasingly substitutable for previously non-routine tasks, and continue to complement 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 computer adoption.

1.5.1 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:

$$\Delta T_{jt} = \beta_0 + \beta_1 \Delta PC_{jt} + \beta_2 \Delta Tech_{jt} * 1\{post2000\} + \beta_3 1\{post2000\} + X'_{j0}\theta + \varepsilon_{jt} \tag{1.1}$$

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.[15] 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 β_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

[15] 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.

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 industries are exposed to import competition.[16] The effects of offshoring and import competition are discussed in more details in Section 1.6.

The results for all six groups of tasks are shown in Table 1.6 & 1.7. All the specifications include the industrial level controls discussed above.[17] For the five single measures of analytical tasks and managerial tasks as well as their composite measures in Table 1.6, 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-

[16] 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.

[17] 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.

Table 1.6: Technological Change and Task Input: Stacked First-Difference Estimates for Analytical and Managerial Tasks

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 deŽnitions and examples of task variables.

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.

Table 1.7: Technological Change and Task Input: Stacked First-Difference Estimates for Cognitive Reasoning and Information Transfer Tasks

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 deŽnitions and examples of task variables.

For each of the five cognitive reasoning tasks in Table 1.7, 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.

Table 1.8: Technological Change and Task Input: Stacked First-Difference Estimates for Routine and Manual Tasks

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 deŽnitions and examples of task variables.

The results for the routine tasks and manual tasks shown in Table 1.8 show that for routine tasks, technology adoption has been negatively correlated with the change in labor 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.

1.5.2 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:

$$SkillShare_j = \alpha + \sum_{k=1}^{5} \pi_k T_j^k + \varepsilon_j \tag{1.2}$$

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 $\mathrm{T_j^k}$'s are the measures for task inputs in industry j. The coefficients $\hat{\pi}_k$ are obtained and then used to predict changes in the demand shifts in high skill employment in each period using equation (1.3):

$$\Delta \widetilde{SkillShare}_j = \alpha + \sum_{k=1}^{5} \widetilde{\pi_k} T_j^k + \varepsilon_j \qquad (1.3)$$

I also use equation (1.1) 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 (1.3) with the predicted task shifts. The results are shown in Table 1.9. 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 (1.2) and (1.3). 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.

Table 1.9: 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+information		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+information		-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.

1.5.3 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

Table 1.10: 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 1.11: 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: Propensity of import is the share of products imported from China at industrial level in the intial year of each period. See Notes for Table 1.8 for more details.

independent of new technology adoption. As shown in Table 1.10 and 1.11, 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 1.12 and Table 1.13. 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.

Table 1.12: Change in Technology Adoption and Change in Task Inputs: By Education

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 deŽnitions and examples of task variables.

Table 1.13: 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 deŽnitions and examples of task variables.

1.6 Conclusions

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.

Chapter 2

A Tale of Many Cities: The Effect of Computerization on the Change in Gender Wage Gap across Cities

2.1 Introduction

The closing of male-female wage gap in the US over the past few decades has drawn extensive research interest. The relative wages of female workers in the United States show little growth until the late 1970s and then see sharp increase until the mid-1990s, with women's share of employment increasing steadily from 1964 to 2003. While on average the ratio of female workers hourly wage relative to men increased from 65% in 1980 to 78% in 2000, there is something new and interesting to be explained: there is wide variation in the change of gender wage gap across cities over 1980 and 2000, even after accounting for compositional changes and relevant local economic characteristics. As shown in Column 6 of Table 2.1, while the average adjusted male-female log hourly wage over 1980 and 2000 declined by 0.137 log points, the change in the male-female wage gap was ranged across MSAs from -0.16 log points to 0.24 log points.

How do we explain the differences in the evolution of gender wage gap over 1980 and 2000 across cities? Since this is the period that computerization has taken place significantly at work, and previous studies suggest a robust link between computer adoption and the decline in male-female wage gap at occupational level, I focus on the role of computerization in explaining the variation in the evolution pattern of gender wage gap across local labor markets. As suggested by prior work (Welch, 2000; Baccolod and Blum, 2010; Beaudry and Lewis, 2014), computer technologies complement soft-cognitive skills (or brain skills) relatively more than hard-motor skills (or brawn skills), and thus increase the prices of brain skills relative to brawn skills. Since

Table 2.1: Male-Female Log Hourly Wage Gap in 1980 and 2000 across MSAs

	Year 1980		Year 2000		Change of M-F wage gap 1980-2000	
	Level (unadjusted)		Level (unadjusted)		Change	
	Men	Women	Men	Women	Raw	Adjusted
	(1)	(2)	(3)	(4)	(5)	(6)
10th percentile	2.774	2.376	2.858	2.617	-0.228	-0.176
25th percentile	2.875	2.436	2.943	2.688	-0.218	-0.157
50th percentile	2.943	2.513	3.001	2.774	-0.194	-0.143
75th percentile	2.994	2.590	3.111	2.863	-0.180	-0.116
90th percentile	3.058	2.629	3.158	2.974	-0.142	-0.099
Mean	2.932	2.509	3.013	2.785	-0.193	-0.137
SD	0.110	0.098	0.125	0.133	0.036	0.034
obs.	237	237	237	237	237	237

Note: The data sources are the 1980 (Ruggles et al., 2010) and 2000 public use 5% Census microdata. The worker sample is restricted to workers aged between 16 and 65, in labor force last year and with positive annual earnings. Residents of institutional group quarters such as prisons and mental institutions are dropped along with unpaid family workers and self-employed. Hourly wage for each individual worker is equal to the yearly wage and salary income divided by the product of weeks worked and usual weekly hours. Labor supply is measured by the product of weeks worked times usual number of hours per week. Individual level wage data has been collapsed using labor supply weight to an unadjusted metropolitan area average level data set (by gender, by year). Wage adjusted, separately by gender and year, for a quartic in potential experience, linear returns to education (for high school dropouts, some college, and advanced degree categories) and dummies for foreign-born, black, Hispanic, and being born after 1950.The unit of observation is MSA.

women are mostly endowed relatively more with brain skills than brawn skills compared to men (Beaudry and Lewis, 2014), they are expected to benefit more from computer adoption than men. Based on this hypothesis, in this paper I exploit the variation in the change of computer adoption for women across cities to explain the variation in the change of gender wage gap across cities. I hypothesize that cities where women experienced relatively greater increase in computer adoption would witness a greater decline in male-female wage gap.

One empirical barrier to examine the causal link between computer adoption and the change in gender wage gap is these two factors are endogenous to each other. To account for endogeneity, I apply a task-based framework developed in Autor, Levy and Murnane (2003) and later enriched by Black and Spitz-Oener (2012) to directly characterize the job contents of workers and use the relationship between tasks and computer technology to predict the change in computer adoption for women and men. The task framework categorizes the job content of occupations into abstract, routine and manual tasks. Computer technology substitutes for workers performing routine tasks, since these tasks are repetitive and pre-determined and thus can be coded with computer languages. Occupations or industries with greater routine task intensity before the onset of computerization witnessed greater increase in computer adoption (Autor et al., 2003). Moreover, men and women were differentially engaged in routine tasks prior to computerization and thus were differentially exposed to computer adoption (Black et al., 2012). Motivated by these findings, I exploit the variation in the occupation distributions of men and women across cities before computerization and use the initial difference in men and women's routine task intensities resulted from the differential occupational distribution to predict the subsequent increases in computer use at work for both groups. Since the initial routine task intensity is determined by the occupational structure that is unrelated to the subsequent changes in computer adoption or wage, it is arguably exogenous and can be used as an instrument for computer adoption. There are potentially confounding factors that may be related to the initial task intensity as well as the change in gender wage gap across cities, such as city level employment rate and share of highly educated workers for men and women. I try to control for potentially confounding factors to address this concern.

Using the 1980 and 2000 Census, I show that metropolitan statistical areas with higher relative female routine task intensity have experienced greater increase in relative female computer adoption over 1980 and 2000 and greater closing in gender wage gap over this period. The 2SLS results show that one standard deviation higher relative female PC adoption is associated with about 8%-13% greater narrowing in male-female wage gap over 1980 and 2000. The reduced form results suggest that one standard deviation higher relative female RTI in 1980 predicts around 4% greater closing in male-female wage gap over time. My estimates suggest that the gender differential computer adoption process induced by the initial gender difference in routine task intensity can explain a substantial portion of the decline in the US male-female wage gap between 1980 and 2000. I carry out robustness checks to support our causal interpretation of the link between relative computer adoption and closing in the gender wage gap over time.

The remainder of the paper is organized as follows. The next section introduces the relevant literature. Section 2.3 explains how to construct the routine task intensity as an instrument for computer adoption. Section 2.4 describes the datasets used in the analysis, paying detailed attention to the construction of task measures. Section 2.5 discusses the empirical strategies and main results. Section 2.6 discusses a few robustness checks. The final section concludes.

2.2 Related Literature

Understanding the driving force for the cross-city variation in the evolution of gender wage gap is important for understanding the change of women's labor market outcomes in major local labor markets. Since it is difficult to directly compare women's jobs to men's due to selection issues, the empirical work on examining the cause for the change in gender wage gap has been limited. One recent work that disentangles one causal force for the closing of gender wage gap across occupations is Black and Spitz-Oener (2010) (hereafter BSO2010), which applies a task-based framework (Auto, Levy and Murnane, 2003; ALM2003 hereafter) to look at the change in occupational gender wage gaps over 1980 and 2000 in Germany. The task framework characterizes the job content of an occupation with a series of tasks, and categorizes these tasks according to their relationship with computer technology into abstract, routine and manual tasks.[18] Computer technology complements abstract tasks and substitutes for routine tasks, with no clear prediction manual tasks. By examining the differential patterns of task changes for men and women at occupational level, they find that work place computerization is a major source for the within-occupation task change, and that relative task changes within-occupations account for a substantial portion of the closing of aggregate wage gap over this period in West Germany.

There is an extensive literature examining the causes for the closing of gender wage gap since 1980s. Earlier work has looked at supply side explanations, such as increasing education level and positive selection of women into the labor force (Goldin and Katz, 2002; Bailey, 2006; Mulligan and Rubinstein, 2008), an improved match between actual and potential measures of experience (Mincer and Polacek, 1974; O'Neill and Polacheck, 1993) or decreased discrimination (Black and Strahan, 2002; etc). However, the changes in measured characteristics or returns to these measured characteristics of women relative to men can only account for part of the gender pay gap. A substantial portion of the decline in gender wage gap remains unexplained.

Recent studies focus on the changes in skill demand to explain changes in wage gaps among different groups (high/low educated groups, gender groups, etc), driven by skill-biased technological change during 1980 and 2000. One strand of the studies focuses on changes in skill requirements across industries or occupations that favour female workers (Katz and Murphy, 1992; Welch, 2000; Weinberg, 2000; Borghans, ter Weel and Weinberg, 2006; Bacolod and Blum, 2010; Beaudry, Doms and Lewis, 2012).

18 Abstract tasks include analytical, non-repetitive or social tasks, such as research, teaching, coordinating or advertising. Routine tasks include repetitive and codifiable tasks, such as bookkeeping and operating a machine. Manual tasks include non-repetitive and physical tasks, such as driving a truck, serving and repairing a house.

Skills are classified into soft/cognitive and hard/motor gap, women and better educated workers are assumed to have relatively greater endowments of soft skills.[19] Due to the dramatic adoption of computer technology, returns to soft/cognitive skills increased substantially while the returns to motor skills declined. These skills price changes explain over 20% of the observed narrowing of the male-female wage gap at occupational level (Bacolod and Blum, 2010). Beaudry, Doms and Lewis (2012) provide cross-city evidence that most of the reduction in male-female wage differential observed over 1980 and 2000 was likely due to a change in the relative price of soft skills. Limitation of this classification method lies in that it does not thoroughly characterize the relationship between job skills and computer technology.[20] Therefore, it is difficult to disentangle the causal role of computerization in changing the job requirements and wage inequalities.

In this paper, I apply a task-based framework which decomposes work content into a series of tasks to construct a new instrument for the computer adoption. Based on Autor et al. (2003), computer technology complements job tasks that require abstract skills, and substitutes for routine tasks. As discussed in Autor and Acemoglu (2010), the first order effect of computer adoption is to substitute routine tasks. Thus I follow the task framework and use the city-level initial intensity of routine tasks relative to abstract and manual tasks to predict the subsequent increase in computer adoption. Using data from DOT, Census and CPS during 1960-1998, Autor et al. (2003) show that tasks have shifted from routine tasks towards abstract tasks and the shifts concentrated in most rapidly computerizing industries at all educational levels. Under the assumption that

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19 Based on this assumption, several studies have argued that the decline in gender wage gap and increase in returns to education may be caused by a common factor—the increase in the relative returns to cognitive skills (BDL 2012, Bacolod and Blum 2010).

20 For example, some job tasks using motor skills can be performed by computer and therefore the labor inputs will be substituted for by computer, such as repetitive loading, assembling or monitoring; while other job tasks using motor skills cannot be performed by computer and therefore cannot be substituted with the adoption of computer technology, such as driving trucks or repairing a house.

better educated workers have comparative advantage in performing abstract tasks relative to routine or manual tasks, the increasing wage inequality between college and high school workers can be explained by the change in task labor inputs and returns to tasks. This paper applies task framework at local labor market (city) level to look at gender differences in tasks and wages across cities, in order to understand the cross-city variation in the change of gender wage gap over 1980 and 2000 in the US. In particular, I exploit the cross-city variation in the relative female initial routine task intensity in 1980 and examine how the initial condition predicts the gender differential change in computer adoption process and wage evolution over 1980 and 2000. Cities in which women have higher routine task intensity relative to men in 1980 are expected to have a greater relative increase in PC adoption, a greater relative task shifts (women experiencing greater increase in abstract tasks and decline in routine tasks relative to men), and as a result a greater closing of gender wage gap over time.[21]

2.3 Routine Task Intensity

Based on the task-based framework proposed by ALM (2003), this paper uses the initial task structure of men and women across cities to predict the subsequent computer adoption process. The task framework characterizes job content of an occupation into a series of tasks. Based on their relationship with computer technology, the tasks can be categorized into three broad groups: abstract, routine and manual tasks.[22] Routine tasks can be either cognitive or physical tasks, but they are all repetitive and codifiable in

21 Similar to Beaudry and Lewis (2013), we exploit cross-city variation in initial conditions to explain the closing of gender wage gap over 1980 and 2000. Using direct measures of job tasks, this paper fills the latent price of cognitive skills and more clearly identifies the mechanism for the change in male-female earnings differentials.

22 Examples of the three tasks can be found in ALM2003 or BSO2012.

nature, which enables them to be automated by computer technology. Thus computer technology plays a role of substituting workers performing routine tasks. ALM framework assumes labor and computer capital to be perfect substitutes in carrying out routine tasks. Both abstract and manual tasks are non-routine in nature, i.e., they cannot be automated by computer technology using coded computer programs or machines since they require critical thinking or physical dexterity to be accomplished. Abstract tasks include non-repetitively analytical or interpersonal tasks and are associated with high skills. Computer technology complements workers performing abstract tasks by increasing workers' productivity. Manual tasks include non-repetitively interpersonal or physical tasks, and are associated with low skills.[23] They can (at least so far) neither be substituted by nor complemented with computers.

The exogenous change in the task framework is the decline of computer price since the beginning of 1980s due to advances in computer technology. The wage returns to routine tasks decline with computer price one-for-one due to perfect substitutability, while the returns to abstract tasks increase due to complementarity.[24] Thus, because of the relative decrease in return to routine task and relative increase in non-routine task, workers self-select out of routine tasks to non-routine tasks. Meanwhile, declining cost of computer price also leads to a higher demand for routine tasks. Therefore, occupations or industries that involve more routine tasks would adopt more computers to meet the

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[23] Different from the interpersonal tasks that belong to abstract task category and physical tasks that belong to routine task category, the interpersonal and physical tasks that belong to manual task category require minimal level of formal education, such as serving in a restaurant or driving a truck. Abstract and routine tasks require respectively high (college-equivalent) and medium (high school equivalent) level of education.

[24] An exogenous fall in computer price leads to a decreasing cost of routine task inputs and thus increasing demand for routine tasks. Since computers and workers performing routine tasks are substitutable, the wage rate of routine tasks decreases with computer price. The wage rate of abstract tasks increases due to complementarity. Workers shift out of routine tasks to non-routine tasks (abstract or manual) by either moving from routine-intensive occupations to non-routine-intensive occupations (between-occupation or extensive margin shifts) or shifting to performing more non-routine tasks within the same occupation (within-occupation or intensive margin shifts). As a result, the increase in demand for routine tasks is met by increase in computer adoption.

increasing demand and witness a greater shift of labor inputs from routine tasks to non-routine tasks.[25] The framework thereby can be applied to identify the mechanism for the relative change in demand for demographic groups (e.g. high educated versus medium/low educated, men versus women). For the case of gender groups, men and women were differentially involved in routine tasks prior to computerization, due to differential concentration across occupations. The gender groups with higher initial routine task intensities will experience greater rates of computer adoption, larger relative shifts away from routine tasks to non-routine tasks and differential changes in wages (Black and Spitz-Oener, 2012).

In order to explore the differential evolution patterns of gender wage gap across local labor markets, this paper uses the routine task intensity as instrument for computer adoption at local labor market level. First, because neither labor nor capital is perfectly mobile across local labor markets, each local labor market can be viewed as a single macro-economy. The ALM framework can then be applied at local labor market level to examine how the job content and returns are related to computerization if these local labor markets started with different initial conditions. Second, within each local labor market, men and women were differentially concentrated across occupations, resulting in the two gender groups differentially involved in the three tasks. Across local labor markets, variation in the gender differences in initial conditions predicts variation in the degree that men and women being differentially affected by computerization, variation in the gender differential shifts of job content and finally the variation in the change of gender wage gap over time.

[25] As shown in previous studies, most of the task shifts happened within occupations or industries (rather than across occupations or industries), supporting the computerization hypotheses (rather than changing demand for production goods).

2.4 Data

The empirical analyses focus on the links between gender difference in initial routine task intensity, computer adoption, task shifts and wage changes at local labor market (LLM) level. To this end, I construct average hourly wages, average inputs and shifts of the three tasks, routine task intensity and computer adoption rate in the unit of gender-LLM cell in the years 1980 and 2000. The year 1980 is the time point when computerization just started and used as the initial time point in our paper. Our analysis focuses on the change over 1980 and 2000 since it is the period when the gender wage gap has narrowed and computer technology has been adopted dramatically.

Local Labor Market: Metropolitan Statistical Area (MSA)

To look at geographic variation over time, I follow the literature by adopting Metropolitan Statistical Area (MSA) as a proxy for local labor markets (e.g., Beaudry et al., 2006). MSAs are defined by the US Office for Management and Budget and cover most of the metropolitan areas in the US. The measurement of MSAs suffers from two main drawbacks. One is time-inconsistency, since the geographic definition of MSAs is periodically adjusted to reflect the growth of cities. The other is it only covers the cities and excludes the rural areas.

Worker Sample and Wage

The wage data draws on the Census Integrated Public Use Metro Samples (Ruggles et al. 2004) for the years 1980 and 2000. The worker sample is restricted to workers aged between 16 and 65, in labor force last year and with positive annual earnings. Residents of institutional group quarters such as prisons and mental institutions are dropped along with unpaid family workers and self-employed. Hourly wage for each individual worker is equal to the yearly wage and salary income divided by the product of weeks worked and usual weekly hours.[26] Labor supply is measured by the product of weeks worked times usual number of hours per week. All calculations are weighted by the Census sampling weight multiplied with the labor supply weight. To account for the compositional changes that have substantial effect on gender wage gap over this period (for example, Blau and Kahn, 2006), I construct adjusted wage measures following Beaudry and Lewis (2012). Individual hourly wages are regression adjusted, separately by gender, LLM and year, for a quartic in potential work experience (age-years of schooling-6), and dummies for foreign-born, black, Hispanic, being born after 1950, years of education and its interaction with the born-after-1950 dummy, using labor supply weight.[27] The summary statistics of male-female wage gaps is shown in Table 2.1. Columns 1-4 show the unadjusted log average hourly wage for men and women across metropolitan statistical areas in 1980 and 2000 respectively. In 1980, the mean of men's log hourly wage over the 237 MSAs is 2.93, with the 10th percentile over the 237 MSAs being 2.77 and the 90th percentile being 3.06, while the mean, 10th and 90th percentile for women are 2.51, 2.38 and 2.63. In 2000, the mean of men's log hourly wage over the 237 MSAs increases to 3.01 while that of women's increases to 2.79. The unadjusted male-female wage gap over the 237 MSAs decreases by 0.19 log points (from 0.42 to 0.23) over 1980 and 2000, as shown in column 5. Column 6 shows the change in adjusted male-female wage gap for the 237 MSAs. The adjusted gender wage gap decreases by 0.14 log points on average, and the change varies across MSAs as indicated

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26 Following Autor and Dorn (2012), top-coded yearly wages are multiplied by a factor of 1.5 and hourly wages are set not to exceed this value divided by 50 weeks times 35 hours. Hourly wages below the first percentile of the national hourly wage distribution are set to the value of the first percentile.

27 Refer to Beaudry and Lewis (2012) for details of constructing adjusted male-female wage gaps. Individual hourly wages are aggregated by gender to the LLM level using labor supply weight to construct raw gender wage gaps.

by the percentiles. From Table 2.1 I observe that the average male-female wage gap exists (although smaller after adjusting for observable characteristics) and narrows over time, which is consistent with previous findings; as well as that there is wide variation in the narrowing of gender wage gap across MSAs, which is the focus of this paper.

Task Measures and Routine Task Intensity

The occupational tasks are drawn from Autor and Dorn (2012).[28] The three task measures - abstract, routine and manual- are based on data from the 4th edition of the US Department of Labor's Dictionary of Occupational Titles (US Department of Labor, 1977; 'DOT' hereafter). The DOT contains job content evaluation along 44 objective and subjective dimensions for more than 12,000 highly detailed occupations. According to the importance of the dimension, a value from 0 to 10 is assigned to an occupation. Abstract task takes the average value of the two dimensions: one is Direction, Control and Planning of activities (DCP), which takes on high values in occupations requiring managerial and interpersonal tasks; the other is GED-MATH, which measures quantitative reasoning requirements. Routine task takes the average value of the dimensions Set limits, Tolerances, or Standards and Finger Dexterity, which have high values in occupations that require repetitive tasks. Manual task takes the value of the dimension Eye-Hand-Foot Coordination. The three task measures of the detailed DOT occupations are first aggregated into three-digit balanced panel of occupations for the 1980 and 2000 Census, of which there are 330. Then the task measures at balanced COC level are appended to the Census IPUMS five percent extracts for 1980 and 2000. For

[28] The occupational tasks data was originally constructed in ALM (2003) as five task categories. Autor and Dorn (2012) re-classifies the tasks into three groups (i.e. abstract, routine and manual) and links the tasks to a balanced panel of occupations for the 1980, 1990 and 2000 Census. Details about the balanced occupation panel can be found at http://www.cemfi.es/~dorn/data.htm.

each task, the means weighted by labor supply of each local labor market by gender in 1980 and 2000 respectively are used to measure the level of task inputs for gender groups in the local labor market at a year point. To make the task magnitude interpretable and comparable between gender groups across LLMs over time, for each task, the means are standardized over gender-LLM-year to be mean of zero and standard deviation of one.

To measure the degree to which a gender group in a local labor market is amenable to computerization, I use the variable routine task intensity (RTI). RTI measures the degree of specialization in routine tasks for men and women before the happening of computerization. The higher initial RTI is, i.e., the more intensively the gender group in a MSA was distributed in routine-intensive occupations before computerization, the faster rates of computer adoption they would experience. Following Autor and Dorn (2012), I first calculate routine task intensity at occupational level in year 1980:

$$RTI_{k,1980}=\ln(Routine_{k,1980}) -\ln(Abstract_{k,1980}) -\ln(Manual_{k,1980})$$

where $Routine_{k,1980}$, $Abstract_{k,1980}$ and $Manual_{k,1980}$ are respectively the unstandardized occupational task measures on a 0 to 10 scale. This definition of RTI measures the relative importance of routine task inputs to abstract and manual task inputs.[29] Then the occupational RTIs linked to individual workers are aggregated by gender to MSA level using labor supply weight to obtain gender-MSA level RTI in 1980, $RTI_{g,c,1980}$, where g is gender group (male, female) and c is MSA. Similar to task measures, $RTI_{g,c,1980}$ is standardized over the 474 gender-MSA units (=237 MSAs*2) into mean of zero and standard deviation of one. As shown in Table 2.2 columns 4-6, women's average RTI in

29 The results are robust to other definitions of RTI, such as the ratio of routine task inputs to the sum of three task inputs.

1980 is about 2 SD higher than men's over the 237 MSAs, although the gap varies across MSAs.

Table 2.2: Summary Statistics of RTI and PC Use

	RTI 1980						PC 1997					
	Raw			Standardized			Raw			Standardized		
	F	M	F-M	F	M	F-M	F	M	F-M	F	M	F-M
Percentile	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
10th	1.98	0.63	1.24	1.02	-0.99	1.86	0.60	0.46	0.10	0.33	-1.54	1.39
25th	2.06	0.70	1.31	1.14	-0.89	1.96	0.62	0.50	0.12	0.67	-1.01	1.58
50th	2.13	0.78	1.36	1.25	-0.77	2.03	0.65	0.52	0.13	1.04	-0.76	1.70
75th	2.19	0.82	1.41	1.33	-0.71	2.10	0.67	0.54	0.13	1.26	-0.48	1.83
90th	2.20	0.86	1.50	1.36	-0.65	2.23	0.68	0.57	0.15	1.48	-0.02	2.01
Mean	2.11	0.76	1.35	1.22	-0.79	2.02	0.64	0.52	0.13	0.94	-0.76	1.70
SD	0.10	0.10	0.10	0.14	0.15	0.15	0.03	0.04	0.02	0.47	0.58	0.25
obs.	237	237	237	237	237	237	237	237	237	237	237	237

Note: See Note of Table2 for details about the construction of task measures. Routine task intensity (RTI) is first constructed as the log difference between the unstandardized occupational level routine and abstract, manual tasks, i.e., RTIocc,1980= ln(Routineocc,1980) -ln(Abstractocc,1980) -ln(Manualocc,1980), where Routinek,1980, Abstractk,1980 and Manualk,1980 are respectively the unstandardized occupational task measures on a 0 to 10 scale.The occupational RTIs linked to individual workers are aggregated by gender to MSA level using labor supply weight to obtain gender-MSA level RTI in 1980, which is then standardized over the 474 gender-MSA units (=237 MSAs*2) into mean of zero and standard deviation of one. Columns1-3 show the means and percentiles of the unstandardized RTI for women, men and the gap and columns 4-6 are for the standardized RTI. The data for computer adoption is drawn from CPS Computer and Internet use at work 1997. The percentage of workers using computer at work in the year 1997 is used as proxy for the change of computer adoption over 1980 and 2000, based on the assumption that computer use in 1980 equals to about zero. This is our measure for computerization. The percentage of workers using computer at work (of gender-MSA cell) is constructed as ratio of number of workers using PC at work in 1997 to the total number of workers in 1997. The means and percentiles are shown in columns 7-9. PC 1997 is also standardized into mean of zero and standard deviation of one over 437 gender-MSA units. The standardized measures for women, men and the f-m difference are shown in columns 10-12.

Computer Adoption

The data for computer adoption is drawn from CPS Computer and Internet use at work 1997. The percentage of workers using computer at work in the year 1997 is used as proxy for the level of computer adoption in 2000. Based on the assumption that computer use in 1980 equals to about zero, the level of PC use in 1997 is a proxy for change in computer adoption over 1980 and 2000, which is our measure for computerization.[30] The percentage of workers using computer at work (of gender-MSA cell) is constructed by

$PC_{g,c,1997}$=Number of workers using PC at work$_{g,c,1997}$/Number of workers$_{g,c,1997}$

where g is gender (female, male) and c is MSA. Similar to RTI, PC use in 1997 is also standardized into mean of zero and standard deviation of one over 437 gender-MSA units. As shown in columns 7-12 in Table 2.2, on average women experienced 12.5% (or 1.7 SD) greater increase in computer adoption than men over 1980 and 2000; the gender difference in computer adoption varies across MSAs.

2.5 Empirical Identification and Main Results

The empirical identification session examines the hypotheses that higher relative routine task intensity of women before computerization predicts greater increase in relative computer adoption and greater increase in relative wage rate over time across MSAs. Figures B1.1 and B1.2 plot this relationship. I observe that in MSAs where women had greater relative RTI the relative PC adoption increased more for women over 1980 and 2000 in Figure 1, and that the male-female wage gap decreased most over 1980-2000 in MSAs where women experienced greater PC adoption in Figure B1.2. Figure B1.3 shows the negative reduced effect of initial relative female RTI on the change of male-female wage gap.

Since the initial routine task intensity is determined by the initial occupational structure that is unrelated to the subsequent computerization, it is arguably exogenous to technological adoption process and therefore can be used as an instrument for computer

30 The assumption that PC use in 1980 is zero is also used in Beaudry and Lewis (2012). Data supports this assumption.

adoption. I try to control for potentially confounding factors with various control sets discuss below. Further concerns are discussed in the appendix robustness session to provide support for a causal link between women's initial relative RTI, via PC adoption, and changes in the male-female wage gap over time. The main analysis contains the following two steps:

$$\mathrm{fm\Delta PC}_{c,1980-2000} = \propto_0 + \propto_1 \mathrm{fmRTI}_{c,1980} + X_c{}' + e_c \tag{2.1}$$

$$\mathrm{mflnhrwage}_{c,1980-2000} = \beta_0 + \beta_1 \mathrm{fm\Delta PC}_{c,1980-2000} + X_c{}' + e_c \tag{2.2}$$

where fmΔPCc,1980-2000 is women's PC adoption level in 1997 relative to men in MSA c, fmRTIc,1980 is women's initial routine task intensity relative to men in 1980 in MSA c, $\mathrm{mflnhrwage}_{C,1980-2000}$ is the change in adjusted male-female wage gap over 1980 and 2000, and X_c are controls. The coefficient of interest is β_1, which is expected to be negative, suggesting that greater relative PC adoption of women is associated with greater closing of male-female wage gap over time. I will show both OLS estimates and 2SLS estimates of equation (2) using equation (1) as the first stage. Standard errors are clustered at MSA level and calculated to be asymptotically robust to arbitrary error correlation within MSAs.

Panel A of Table 2.3 shows the OLS estimates of equation (2) with various controls, the effect of relative PC adoption of women on the change of adjusted male-female wage gap over 1980 and 2000. The OLS estimates are significantly negative and robust to controls, providing supportive evidence for our hypothesis. Without control variables (column 1), the wage gap declined significantly faster in MSAs where women's relative PC adoption increased more intensively, consistent with the pattern shown in Figure A2.2. The coefficient of -0.044 says that each additional SD increase in relative female PC adoption is associated with 4.4% greater decline in the male-female wage gap over 1980-2000 across MSAs. Adding controls does not change the magnitude very much.

Table 2.3: Change in Adjusted Male-Female Wage Gap and PC Adoption across MSAs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. OLS estimates of the effect of f-m PC adoption on change in adjusted gender wage gap, 1980-2000.							
f-m PC	-0.044***	-0.047***	-0.047***	-0.048***	-0.049***	-0.046***	-0.030*
	(0.012)	(0.012)	(0.012)	(0.011)	(0.010)	(0.010)	(0.016)
R-squared	0.100	0.201	0.201	0.255	0.265	0.294	0.547
B. 2SLS estimates of the effect of PC adoption on change in adjusted gender wage gap, 1980-2000.							
f-m PC	-0.104***	-0.134***	-0.116***	-0.088***	-0.089***	-0.083***	-0.093*
	(0.039)	(0.036)	(0.026)	(0.021)	(0.028)	(0.028)	(0.053)
R-squared			0.022	0.194	0.195	0.235	0.433
C. Reduced effect: f-m RTI in 1980 vs. change in adjusted wage gap over 1980 and 2000.							
f-m RTI80	-0.038***	-0.060***	-0.068***	-0.057***	-0.046***	-0.042***	-0.027
	(0.013)	(0.015)	(0.015)	(0.015)	(0.016)	(0.015)	(0.018)
R-squared	0.029	0.160	0.189	0.214	0.189	0.226	0.528
D. First stage: f-m RTI in 1980 vs. f-m PC adoption over 1980 and 2000.							
f-m RTI80	0.363***	0.445***	0.584***	0.642***	0.519***	0.504***	0.292**
	(0.110)	(0.113)	(0.099)	(0.096)	(0.118)	(0.117)	(0.110)
R-squared	0.051	0.207	0.379	0.392	0.224	0.232	0.462
city char	N	Y	Y	Y	Y	Y	Y
skills share	N	N	Y	Y	N	N	N
f empt 1980	N	N	N	Y	N	N	N
f-m skills share	N	N	N	N	Y	Y	N
f-m empt 1980	N	N	N	N	N	Y	N
state effect	N	N	N	N	N	N	Y

Note: The data sources are 1980 and 2000 Census. See the note of Table 1 for details about adjusted wage gap construction, and Table 2 for RTI and PC use. The unit of observation is MSA. For Panel A and B, the dependent variable is adjusted male-female wage gap over 1980 and 2000. Main explanatory variable is *f*-mPC, which is the difference between standardized female and male PC use in 1997. For Panel C and D, the main explanatory variable is f-mRTI, which is the difference between standardized female and male routine task intensity. f-mPC and f-mRTI are standardized measures. "city char" includes MSA level employment rate, log of labor force participation, share of black, Hispanic and foreign born. "skills share" is the initial MSA level skills share, which is the log ratio of college to high school equivalent workers in 1980. "f empt 1980" is female employment rate in 1980. "f-m skills share" is the female-male difference in initial skills share in 1980 and "f-m empt 1980" is the female-male difference in employment rate in 1980. "state effect" includes state dummies. *** p<0.01, ** p<0.05, * p<0.1

2SLS estimates with controls are shown in Panel B. These estimates use the relative female routine task intensity (RTI) in 1980 as an instrument. As Panel C shows, the initial relative RTI of women is strongly related to relative female PC adoption over time. The 2SLS estimates without controls in Column 1, Panel B is no smaller than OLS estimates in magnitude and also significant.

Column 2 controls for city level characteristics in 1980 that may have a compositional impact on the change of gender wage gap, including employment rate, log of labor force participation, share of black, Hispanic and foreign born. These controls jointly have little impact on the relationship between relative PC adoption and change of gender wage gap.

Column 3 controls for initial MSA level skills share, which is the log ratio of college to high school equivalent workers in 1980. As suggested by BDL (2013), part of the relationship between computer adoption and closing of gender wage gap could be due to differences in skills share across MSAs. Cities with more abundant skilled workers will adoption computer more intensively and thus expect greater closing in gender wage gap. Comparing to column 2, controlling for initial MSA level skills share decreases the magnitude of the estimate but not the significance of the 2SLS estimate, which is consistent with that BDL2013 that part of the link is driven by initial city skills share and also shows the robustness of the 2SLS estimates.[31,32]

Column 4 controls for female employment rate in 1980 as a simple attempt to control for selection of women into workforce. The initial level of female employment rate is used as a proxy for the subsequent change in employment, as the change in employment over 1980-2000 may be endogenous and simultaneously related with change in wage gap. The coefficient is affected very little by this control. However, the

[31] Also consistent with BDL 2013, the initial city level skills share is significantly negatively related to the change in male-female wage gap over 1980-2000.

[32] I also try to control MSA level share of high school, some college, college and graduate degrees as more detailed controls for the educational composition of an MSA. The results are robust to these education share controls.

employment rate in 1980 is still potentially endogenous to initial task intensity (or occupational structure), so the results provide limited evidence about whether selection is driven our results. The robustness section gives a more thorough discussion of selection.

Since my findings suggest that the status of women relative to men across MSAs may matter more than the absolute terms of women across MSAs, I control for the relative female skills share and employment rate in column 5 and 6. Adding relative female skills share decreases the magnitude of estimate, suggesting that relative female skills share is driving the change in gender wage gap. Relative female employment rate has little effect on the estimate, but it is at most suggestive since the control may be endogenous. In both cases our estimates remain significant.

Column 7 adds state dummies as an attempt to control for regional differences in policies or gender discrimination. The estimate is smaller comparing to column 2 and noisier, but remains significant, suggesting the state polities that might affect the male-female wage gap are not systematically correlated with computerization.

Overall Panel B shows that there is a robust causal link between relative PC adoption and change in male-female wage gap. The 2SLS estimates range from -0.13 to -0.08, suggesting that one standard deviation higher relative female PC adoption is associated with about 8%-13% greater narrowing in male-female wage gap over 1980 and 2000. The reduced estimates are around -0.04, indicating that one standard deviation higher relative female RTI in 1980 predicts around 4% greater closing in male-female wage gap over time. In order to understand how much of the closing in the average level can be attributed to differential computer adoption process induced by initial difference in routine task intensity, I can look at the 2SLS estimates for the coefficient on relative female PC adoption or the reduced effect estimates for the coefficient on relative female RTI and apply the estimates to the average increase in relative female PC adoption and average initial female relative RTI. Specifically, the 2SLS coefficient for relative female PC adoption is about -0.09, with average female PC adoption being 1.695 in Table 2.2, predicting a decline in gender wage gap of about 0.153. With the actual average decline in adjusted male-female wage gap being 0.137 in Table 2.1, the gender-differential PC adoption process accounts for more than the entire closing in gender wage gap. However, the average increase in relative female PC adoption may be partly driven by a fall in computer price, while our main analyses assume the price to be constant over the twenty years (only declining sharply at the beginning). Therefore, the contribution may be overstated. Another way to examine the contribution is to use the reduced effect estimates -0.4 and multiply it with the average relative female RTI 2.022, predicting a decline in gender wage gap of about 0.08, which is about 58% of the average decline in adjusted male-female wage gap over 1980 and 2000.

2.6 Robustness Checks

2.6.1 Within-Cohort Changes

Next I turn to look at the effect of computer adoption on change in gender wage gap within cohorts. As suggested by Bailey, Hershblei and Miller (2012), much of the closing of gender wage gap over 1980 and 2000 was “across cohorts”, because younger women tend to be more skilled/educated and have greater labor force attachment than the older cohorts. If the local labor markets with women experiencing relatively faster computer adoption tend to have younger female workforces, then our main results may be overstated. To address this concern, I examine the adjusted “within cohort” changes in male-female wage gap measured in five-year cells by birth year. The results are shown in Table 2.4. The worker sample used for Table 2.4 is further restricted to workers born before 1940 to 1960. Wages are regression adjusted, separately by cohort, gender and year, for a quartic in potential experience, linear returns to education (for high school dropouts, some college, and advanced degree categories) and dummies for foreign-born, black and Hispanic. PC use and RTI variables are constructed by cohorts and standardized over cohort-gender-MSA cells. The main explanatory variables are the difference between standardized female and male PC use in 1997 (fmPC), and its interactions with cohort dummies for Panel A, and the difference between standardized female and male routine task intensity (fmRTI) and its interactions with cohort dummies in Panel B. In Panel C, female relative RTI (fmRTI) and its interactions with cohort dummies are used as instruments for female relative PC adoption (fmPC), and its interactions with cohort dummies to obtain 2SLS estimates. The omitted cohort category is cohort born before 1940. The OLS estimates suggest that relative computer adoption has stronger effect on the closing of gender wage gap for younger cohorts (Panel A), but the reduced effect shown in Panel B and 2SLS results in Panel C show little evidence about this pattern. The 2SLS results suggest that the negative link between relative computer adoption and change in gender wage gap is significant for most cohorts, and stronger for older cohorts. Overall, the significant effects within cohort suggest that our results are not mainly driven by differential changes in cohort composition.

2.6.2 Selection

Another important concern is that rising returns to skill have induced more positive selection of women into work. Women are more likely to attain more schooling, and high-skill women are less likely to drop out of the labor force because the returns to skills are rising significantly over the recent decades (See Mulligan and Rubinstein). If the returns to skills are systematically correlated with relative female task shifts (relative decrease in routine task inputs and relative increase in abstract and routine), then the

Table 2.4: Change in Male-Female Employment Rate across MSAs vs PC Adoption

	(1)	(2)	(3)	(4)	(5)
A. OLS estimates of the effect of f-m PC adoption on change in m-f employment rate, 1980-2000. (N=237)					
f-m PC	-0.027***	-0.012	0.002	-0.012	-0.016
	(0.009)	(0.008)	(0.007)	(0.008)	(0.010)
R-squared	0.045	0.403	0.463	0.406	0.626
B. 2SLS estimates of the effect of PC adoption on change in m-f employment rate, 1980-2000. (N=237)					
f-m PC	0.110*	0.021	-0.002	0.027	0.063
	(0.062)	(0.032)	(0.021)	(0.027)	(0.060)
R-squared		0.343	0.462	0.324	0.406
C. Reduced effect: f-m RTI in 1980 vs. m-f employment rate over 1980 and 2000. (N=237)					
f-m RTI80	0.040**	0.010	-0.001	0.014	0.018
	(0.015)	(0.014)	(0.013)	(0.013)	(0.014)
R-squared	0.039	0.397	0.463	0.401	0.621
city char	N	Y	Y	Y	Y
skills share	N	N	Y	N	N
f-m skills share	N	N	N	Y	N
state effect	N	N	N	N	Y

Note: The data sources are 1980 and 2000 Census. See the note of Table 2 for RTI and PC use. The unit of observation is gender-MSA. The dependent variable is the male-female difference in employment rate over 1980 and 2000. i.e. (emptm,2000-emptm,1980)-(emptf,2000-emptf1980). In Panel A and B, the main explanatory variable is f-mPC, which is the difference between standardized female and male PC use in 1997. f-mRTI80 is used as an instrument for f-mPC in Panel B. For Panel C, the main explanatory variable is f-mRTI, which is the differnece between standardized female and male routine task intensity. f-mPC and f-mRTI are standardized measures. "city char" includes MSA level employment rate, log of labor force participation, share of black, Hispanic and foreign born. "skills share"is the initial MSA level skills share, which is the log ratio of college to high school equivalent workers in 1980. "f empt 1980" is female employment rate in 1980. "f-m skills share" is the female-male difference in initial skills share in 1980 and "f-m empt 1980" is thefemale-male difference in employment rate in 1980. "state effect" includes state dummies. *** p<0.01, ** p<0.05, * p<0.1

areas with greater relative task shifts would be more likely to induce (high skilled) women into workforce and thus see greater closing in gender wage gap.

As an attempt to test the effect of selection on our results, I first look at the link between relative female computer adoption and the change in employment demand for women and men over time. The results for employment rate are shown in Table 2.5. The

OLS estimate is negative and significant (Panel A, column1) but explained away by the control variables. The 2SLS estimates suggest that the relative female PC adoption has little to do with the change in male-female employment rate over time. If anything, it

Table 2.5: Change in Adjusted Male-Female Wage Gap 1980-2000 vs PC Adoption, for Young Women with Children<6 Years Old (N=237)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. OLS estimates of the effect of f-m PC adoption on change in adjusted gender wage gap, 1980-2000.							
f-m PC	-0.009	-0.020**	-0.031***	-0.033***	-0.021**	-0.019**	-0.016*
	(0.008)	(0.009)	(0.010)	(0.010)	(0.008)	(0.008)	(0.009)
R-squared	0.007	0.055	0.077	0.114	0.066	0.074	0.478
B. 2SLS estimates of the effect of PC adoption on change in adjusted gender wage gap, 1980-2000.							
f-m PC	-0.021	-0.085	-0.083	-0.070	-0.064	-0.065	-0.118
	(0.041)	(0.061)	(0.055)	(0.047)	(0.051)	(0.050)	(0.088)
R-squared				0.053			0.082
C. First stage: f-m RTI in 1980 vs. f-m PC adoption over 1980 and 2000.							
f-m RTI80	0.242*	0.220*	0.224**	0.234**	0.245**	0.249**	0.171*
	(0.127)	(0.117)	(0.091)	(0.090)	(0.117)	(0.114)	(0.100)
R-squared	0.036	0.275	0.452	0.458	0.280	0.291	0.524
D. Reduced effect: f-m RTI in 1980 vs. change in adjsuted gender wage gap over 1980 and 2000.							
f-m RTI80	-0.005	-0.019*	-0.019	-0.016	-0.016	-0.016	-0.020
	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.014)
R-squared	0.001	0.043	0.046	0.073	0.049	0.061	0.476
city char	N	Y	Y	Y	Y	Y	Y
skills share	N	N	Y	Y	N	N	N
f empt 1980	N	N	N	Y	N	N	N
f-m skills share	N	N	N	N	Y	Y	N
f-m empt 1980	N	N	N	N	N	Y	N
state effect	N	N	N	N	N	N	Y

Note: The data sources are 1980 and 2000 Census. The worker sample is further restricted to men aged between 25 and 44, and women aged between 25 and 44 and with youngest kids less than 6 years old based on the worker sample used in Table5. The unit of observation is MSA. For Panel A and B, the dependent variable is adjusted male-female wage gap over 1980 and 2000. Main explanatory variable is f-mPC, which is the difference between standardized female and male PC use in 1997. For Panel C, the dependent variable is f-mPC and main explanatory variable is f-mRTI, which is the differnece between standardized female and male routine task intensity. f-mPC and f-mRTI are standardized measures. "city char" includes MSA level employment rate, log of labor force participation, share of black, Hispanic and foreign born. "skills share"is the initial MSA level skills share, which is the log ratio of college to high school equivalent workers in 1980. "f empt 1980" is female employment rate in 1980. "f-m skills share" is the female-male difference in initial skills share in 1980 and "f-m empt 1980" is thefemale-male difference in employment rate in 1980. "state effect" includes state dummies. *** p<0.01, ** p<0.05, * p<0.1

goes the opposite direction as its effect on the change in gender wage gap. The reduced effect shown in Panel C further shows that there is no significant link between the initial task intensity and change in gender employment rate. I also check whether the change in female employment rate over 1980 and 2000 is related to relative female computer adoption and relative initial RTI and find no significant correlation. Therefore, it is unlikely that our results are driven by women's selection into employment.

Next I separate women into "always-working" and others. The "always-working" women are those working women with young kids, who have high labor force attachment and are more comparable to men (Machado, 2013; BDL, 2013). I use a young worker sample that is restricted to men aged between 25 and 45 and women aged between 25 and 45 and with kids younger than 10 years old. The construction of adjusted male-female wage gap, PC adoption, RTI and control variables are similar to the main analyses. The results for this young subsample are shown in Table 2.6. The OLS estimates show similar pattern as the full sample shown in Table 2.3, with smaller magnitude. Since the estimates are unsatisfyingly noisy, the first stage is only marginally significant and the 2SLS estimates are not significant. However, the magnitude of 2SLS estimates with controls is comparable to that in Panel B, Table 2.3, suggesting that there is still a negative link between relative female computer adoption and the closing in gender wage gap over time. The estimates for the reduced effect shown in Panel D remain marginally significant, providing evidence that the male-female wage gaps closed more in MSAs with greater initial relative female RTI. In general Table 2.6 suggests that our results are not mainly driven by selection.

2.7 Conclusions

This paper applies task framework at local labor market level to examine the causal force for the cross-city variation in the change of gender wage gap over 1980 and 2000 in the US. The framework predicts that cities where women have higher relative routine task intensity in 1980 are expected to have a greater increase in women's computer adoption rate, which leads to a greater relative task shifts of women (women experiencing greater increase in abstract tasks and decline in routine tasks relative to men). The differential task shift patterns across cities account for part of the variation in the change of gender wage gap over time. That is, cities in which women experience greater increase in abstract tasks and decline in routine tasks relative to men witness a greater closing of gender wage gap over time. To empirically test these hypotheses, I exploit the cross-city variation in the male-female difference in the routine task intensity in 1980 (pre-computerization) and examine how the initial condition predicts the gender differential change in computer adoption process and wage evolution over 1980 and 2000, using data from Census 1980 and 2000, DOT and CPS. The results suggest that cities where women had one percent higher relative RTI in 1980 are expected to have a relative change in PC adoption for women over 1980 and 2000 33% higher than average. They are also expected to experience greater decrease in women's relative routine task inputs, and greater increase in women's relative abstract and manual task inputs. Since it is not straightforward to look at returns to tasks due to simultaneity/instantaneous causation issue and most of the task shifts are caused by computer adoption, I examine the role of computer adoption in explaining the change in gender wage gap, using initial routine task intensity as instrument for computer adoption rate. The results suggest that one percentage greater of women's relative computer adoption rate would result in a 0.6

percent greater increase in women's relative wage growth over 1980 and 2000, or equivalently, a greater narrowing of gender wage gap over time by 0.6 percent. On average about 70 percent of the narrowing of gender wage gap over time across cities can be explained by the change in relative computer adoption. As suggested by R-squared, about one-fifth of the cross-city variation in the change of gender wage gap over time can be explained by the cross-city variation in the relative change in PC adoption.

Chapter 3

The Causal Effect of Maternal Education on the Gender Gap in Children's Non-Cognitive Development

3.1 Introduction

Maternal education plays an important role in children's skill development. Parents with higher level of education are more likely to have children with better outcomes - higher skill and education levels, better health status, and greater labor market achievement (Dearden et al, 1997; Solon, 1999; Chevalier , 2004; Oreopoulos et al., 2003; Black et al., 2005; Currie and Moretti, 2003). Increasing attention has been drawn on understanding the development of noncognitive skills, especially the gender differences in children's noncognitive skills. Prior work suggests that boys perform worse than girls on many noncognitive dimensions, as they develop slower in mental maturity.[33] At the same time, mothers with higher education are more likely to spend more time with children – but engage in different activities for boys and girls, which may have different effects on children's skill development (Guryan, Hurst and Kearney, 2008; Baker and Miligan, 2011). This paper examines whether maternal education affects the noncognitive development of boys and girls differentially and how it is related to gender gap in children's noncognitive skills.

The importance of this research question lies in the role of noncognitive skills in explaining the acquisition of skills, productivity in the labor market and a variety of behaviors. A telling example is that conditional on achievement test scores, GED

[33] Boys have higher rates of experiencing attention and behavioral difficulties, attention deficit hyperactivity disorder, lower level of inhibitory control and perceptual sensitivity, higher arrest rate and suspension rate in middle school. Some studies on the behavioral deficiencies of boys have been carried out in sociology and psychology (Entwisle et al., 2007; Szatmari, 1989). Other evidences are provided in Beamen et al.(2006), Godlin et al. (2006), and Bertrand and Pan (2011).

recipients (high school dropouts who exam certify as high school equivalents) earn lower wages on average than high school graduates who do not go on to college due to their low levels of noncognitive skills (Heckman and Rubinstein, 2001). Moreover, the disadvantage that boys experience in noncognitive development relative to girls manifests itself in the higher incidence of arrest rates among teenage boys and the rising trends of female advantage in college enrollment rate and graduation rate that currently exist in the US and many other developed countries (Jacob, 2002; Becker et al., 2010). Jacob (2002) shows that the noncognitive behavioral factors (i.e. the greater risk of noncognitive deficiencies among boys) can explain virtually the entire female advantage in college attendance. Therefore, it is important to understand the driving forces for the noncognitive development of boys and girls.

Evidence suggests that noncognitive skills are quite malleable and can be shaped by early intervention programs, family and school influences. Previous studies have looked at the correlations between parental and school characteristics and the noncognitive skills of their children, but the causal link between parents and the noncognitive development of children, especially of boys and girls separately, has not been systematically examined. From a policy perspective, evidence of a causal relationship between mother's education and children's noncognitive behaviors provides empirical support for the role of schooling as equalizing economic opportunities and for policy interventions that aim at subsidizing low educated and/or low income parents.

This paper contributes to the literature relating parental influences and noncognitive skills by examining the causal effect of mother's education on the gender gap in children's noncognitive skills, using longitudinal data from the British National Child Development Study (NCDS). One issue for the empirical analysis is that mother's education may be correlated with unobservable factors that also affect children's skills, which leads to omitted variable bias. To disentangle the causal link between mother's education and children's noncognitive skills, I use the 1947 education reform in UK, which raised the minimum school leaving age from 14 to 15, as an exogenous source of variation for mother's education. The OLS estimates suggest a significantly positive association between mother's education and children's noncognitive skills with no evidence for a differential relationship by gender. Using the reform to instrument for mother's education, the IV results show an increase in mother's years of schooling significantly reduce the gender gap in children's noncognitive behaviors at age 7. There is a positive effect of mother's education on the level of children's noncognitive skills at age 11, but the causal link with the gender gap becomes weaker. There is little evidence for an effect on children at age 16. This suggests that better educated mothers erase some of the disadvantage of boys in noncognitive skills during the early stage of childhood.

The structure of the paper is as follows: Section 2 and 3 discusses relevant literature and the conceptual framework. Section 4 describes the data and the 1947 education reform in UK. Section 5 discusses the identification strategy. Section 6 and 7 present the main results and robustness check for the effect of father's education. Section 8 explores mother's inputs as a potential channel for the causal link between mother's education and the gender gap. Section 9 then concludes.

3.2 Literature Review

There is an extensive literature on the connection between investments in human capital in the present and future generations. Parents play a powerful role in shaping children's abilities through genetics, parental investments and choice of environment. A number of studies have found a strong link between education of the parents and of the child. More educated parents have children with more years of schooling, with estimates of the elasticity for intergenerational mobility in education lie between 0.14 to 0.45 in the US and 0.25 to 0.40 in the UK (Dearden et al, 1997; Solon, 1999). The schooling of parents also affects children's labor market outcomes, health status, personality and other outcomes (Currie and Moretti, 2003; Duncan et al.; 1991).

While children's outcomes such as education, earnings and health have been extensively studied, the role of noncognitive skills has recently received growing interest. The noncognitive traits investigated to date, include social and leadership skills and various personality traits such as aggression, externality, self-esteem, and locus of control. A strand of studies focuses on the importance of noncognitive skills in explaining adult outcomes. For example, Heckman et al.(2006) show that noncognitive skills raise wages through their direct effects on productivity, and indirect effects on schooling and work experience.[34] Another strand is interested in how family and social environments affect the development of noncognitive skills. The motivation lies in that noncognitive skills are quite malleable over the life time, and most critically influenced in early life stages. Early intervention programs, such as the Perry preschool program and Tennessee STAR class size experiment, improve the treated students' future labor market outcomes primarily through the noncognitive channel by increasing effort, motivating initiative and reducing disruptive behaviors (Heckman et al., 2010; Chetty et al. 2010). They may also be affected by parental and school characteristics (Segal, 2008).

Increasing attention has been drawn on the gender differences in children's noncognitive skills. Evidence suggests that boys perform worse than girls on many

[34] Also see Heckman and Rubinstein, 2001; Jacob, 2002; Segal, 2011.

noncognitive dimensions, as they develop slower in mental maturity.[35] The higher incidence of behavioral problems among boys manifests itself in the rising trends of higher college enrollment rate and graduation rate of female students. Jacob (2002) shows that controlling for the noncognitive behavioral factors can explain virtually the entire female advantage in college attendance in the US, after adjusting for family background, test scores and high school achievement. Becker et al. (2010) confirm and generalize the results from the US to other developed countries. Thus, understanding the sources of boys' behavioral and socio-emotional problems is if anything an even more pressing issue today than it was in the past.

A few studies have looked at the gender differential effect of family and school factors on children's cognitive and noncognitive development (Jacob, 2002; Goldin et al. 2006; Dahl and Moretti, 2008; Thomas, 2006; Becker, Hubbard and Murphy, 2010; Bertrand et al. 2012). For example, Thomas (2006) finds that a teacher's gender affects student test performance and academic engagement in the way that girls have educational outcomes when taught by women and boys are better off when taught by men. Bertrand and Pan (2011) examine the effect of family and school environment on the gender gap in children's externalizing behaviors and school suspension rates. They find that family structure is critically correlated with the gender gap in children's disruptive behaviors. Boys are much more likely to act out in broken families and the gender gap in externalizing problems is twice as large for children raised by single mothers compared to children raised in traditional families. Although the results confirm the importance of parental characteristics in explaining the gender differences, they cannot distinguish

[35] Boys have higher rates of experiencing attention and behavioral difficulties, attention deficit hyperactivity disorder, lower level of inhibitory control and perceptual sensitivity, higher arrest rate and suspension rate in middle school. Some studies on the behavioral deficiencies of boys have been carried out in sociology and psychology (Entwisle et al., 2007; Szatmari, 1989). Other evidences are provided in Beamen et al.(2006), Godlin et al. (2006), and Bertrand and Pan (2011).

between the effects of family structure, SES and mother's characteristics due to data limitations. Also, they did not look at the effect of parental education because ECLS-K data set does not match mother's education with the child.

So far, little is known about the causal effect of mother's education on the gender gap in children's noncognitive skills. My paper provides an important complement to the existing literature by assessing the causality using longitudinal data from the British National Child Development Study (NCDS). To account for the endogeneity of mother's education, I adopt an instrumental variable strategy. It is based on a policy reform which changes the educational distribution of the parents without directly affecting children.[36] In 1974, The UK raised the minimum school leaving age from 14 to 15 years. This reform exogenously affected the educational choice of parents and increased the average years of schooling of both mothers and fathers. This discontinuity is exploited to identify the causal effect of parental education on children's outcomes. Using the 1974 education reform in UK, Chevalier (2004) finds a large positive effect of a parent's education on the education outcome of child of the same gender. Galindo-Rueda (2003) exploits the earlier 1947 reform and, relying on regression discontinuity, finds significant causal effect on child's education but only for fathers. In this paper I also use this reform to provide exogenous variation in mothers' education.

Closest to my paper is a recent study by Silles (2011). She examines the effect of parental education on children's cognitive and noncognitive behaviors. The least squares

36 There are two principal hypotheses that may explain why parents' and children's human capital are related. One is based on selection theory, which argues that the genetic characteristics primarily determine the level of education of parents and that of children and the contribution of parents' education to their children's human capital is a statistical artifact reflecting positive selection. The other is based on causation theory; more years of schooling better places parents to influence the human capital of their children by virtue of their additional education. To distinguish between positive selection and causation, three strategies have been employed to assess the causal effect of parental education on children's outcomes: identical twins, adoptees, and instrumental variables. For studies on the effect of parental education using education reforms as IV, see Oreopoulos et al., 2003; Black et al., 2005; Currie and Moretti, 2003.

estimates suggest strong correlations between parental education and children's cognitive and noncognitive behaviors, but the 2SLS estimates using education reform to instrument for parental education are not sufficiently precise to find a significantly beneficial effect of either parent's schooling on children's cognitive and noncognitive development.

My paper contributes to the noncognitive literature by exploring the causal link between mothers' education and the gender gap in children's noncognitive skills, as well as why the effect may be gender differential. Consistent with Baker and Milligan (2011), I provide suggestive evidence that mothers with more years of schooling spend more time and attention to children. They spend time going outing with boys while reading to girls. While reading to children is particularly beneficial to the cognitive development, going outing or walking with children may help with the foster of noncognitive skills more. Thus, the differential time use of better educated mothers benefits the noncognitive development of boys more than girls and narrows the gender gap in children's noncognitive skills.

3.3 Economic Framework

Mother's education can affect child quality, such as education level, health status, cognitive and noncognitive skills, by improving the behaviors of mothers or changing the household budget. Education may also provide mothers with important skills, values and knowledge that better support and facilitate their children's learning and development. For example, mothers with higher levels of education show greater average levels of warmth and emotional supportiveness in parent–child interactions and lower levels of harsh and/or erratic discipline (Klebanov et al., 1994; Fox et al., 1995). Guryan, Hurst and Kearney (2008) find that in the US, mothers with a college education or greater spend roughly 4.5 hours more per week in child care than mothers with a high school degree or less. The higher level of maternal investments effectively improves children's socio-emotional development and behavioral adjustment.

Mothers' time inputs for children may be different for boys and girls. Furthermore, Baker and Miligan (2011) find that mothers spend their time engaging in different activities for boys and girls. For example, mothers tend to spend time reading to girls while go outing with boys. This may have differential effect on the noncognitive skill development of girls and boys, since reading is shown to be benefit the development of cognitive skills and outing on the other hand benefits more for noncognitive skills. This motivates this paper to examine whether maternal education affects the noncognitive development of boys and girls differentially.

As pointed out in the life-cycle model of learning in Heckman and Cunha (2008), the time profile of investments in human capital is critical and inputs into the production of human capital at different stages in the lifecycle are not perfect substitutes. Ages where parental inputs have higher marginal productivity, holding all inputs constant, are called "sensitive" periods. For the development of cognitive skills parental investments have large impacts mainly during the first 8 years of life, while noncognitive skills are more malleable during later childhood (6-12 years old). Self-productivity becomes stronger when children become older. This predicts that at different ages, the gender gap in children's noncognitive skills will respond differently to the change in mother's education, and will be mostly affected during at earlier ages (Heckman and Cunha, 2008). This motivates my analysis to look at children's noncognitive behaviors at different ages (age 7, 11 and 16). The empirical findings are consistent with the model: the gender gap in noncognitive skills is most sizable when children are 7 and 11 years old, and significantly affected by changes in mother's education, while that of 16 year olds conveys no such pattern.

3.4 Data

The data source for my analysis is the National Child Development Study (NCDS). NCDS is a continuing longitudinal study of cohort born in UK between 3rd and 9th of March 1958. Following the initial survey in 1958, the Perinatal Mortality Survey (PMS), several attempts were carried out in 1965 (age 7), 1969 (age 11), 1974 (age 16), 1978 (age 20), 1981 (age 23), 1991 (age 33), 1999 (age 41) to trace all members of the birth cohort in order to monitor their physical, educational and social development. This paper draws on the initial 1958 survey and three subsequent sweeps taken in 1965 (age 7), 1969 (age 11) and 1974 (age 16). The original sample contains 17,415 individuals. The sample for the main analysis in this paper is restricted to individuals (i.e. the child cohort) with natural mothers and no missing data for the key variables, and the sample size is reduced to 7,634.[37] Summary statistics for the main sample are presented in Table 3.1.

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37 The key variables include sex of child, mother's age, schooling, Parity in 1958, children's non-cognitive behaviors measures in age 7, 11 and 16. Observations with missing values for these key variables are dropped for the main analysis. 4291 observations are dropped due to missing values for the relationship with mothers (i.e. whether it is "natural mother"). These dropped observations have similar average maternal schooling leaving age and socio-economics status as those with natural mothers. 502 observations are then dropped due to missing values for mothers' schooling leaving age. Furthermore, 483 observations whose mothers' schooling leaving ages are less than 13 or older than 18 are dropped, because mother's years of schooling are not precisely recorded in this range. Finally observations with missing values for noncognitive behaviors at age 7, 11 and 16 are dropped. Comparing available characteristics (family ses status, mothers' occupation, fathers' education) of the dropped sample with the main sample shows that the dropped observations have slightly less privileged socio-economic backgrounds. Since the differences are quite small, the problem of non-random attrition bias is likely to be minor.

Table 3.1: Summary Statistics

	Total	SD	Boys	SD	Girls	SD	Diff(B-G)	SD
Noncognitive behaviors at age 7								
Aggregate Measure	0.000	(1.000)	-0.162	(0.016)	0.170	(0.016)	-0.332***	(0.023)
Externalizing	0.000	(1.000)	-0.149	(0.016)	0.156	(0.016)	-0.305***	(0.023)
Internalizing	0.000	(1.000)	-0.148	(0.016)	0.155	(0.016)	-0.303***	(0.023)
Noncognitive behaviors at age 11								
Aggregate Measure	0.000	(1.000)	-0.160	(0.016)	0.168	(0.016)	-0.327***	(0.023)
Externalizing	0.000	(1.000)	-0.137	(0.016)	0.143	(0.016)	-0.280***	(0.023)
Internalizing	0.000	(1.000)	-0.151	(0.016)	0.159	(0.016)	-0.310***	(0.023)
Noncognitive behaviors at age 16								
Aggregate Measure	0.000	(1.000)	0.002	(0.016)	-0.003	(0.016)	0.005	(0.023)
Externalizing	0.000	(1.000)	-0.039	(0.016)	0.041	(0.016)	-0.080***	(0.023)
Internalizing	0.000	(1.000)	0.051	(0.016)	-0.054	(0.016)	0.105***	(0.023)
Mother's School Leaving Age	14.767	(0.983)	14.754	(0.016)	14.783	(0.016)	0.029	(0.023)
Mother's School Leaving Age (pre-reform)	14.582	(1.032)	14.567	(1.011)	14.591	(1.053)	-0.032	(0.031)
Mother's School Leaving Age (post-reform)	15.145	(0.746)	15.132	(0.740)	15.150	(0.752)	-0.027	(0.029)
Mother affected by Min Schooling Law	0.330		0.330		0.329		0.003	(0.009)
Children's Gender Composition	1.000		0.512					
Number of Observations	7,634		3,906		3,728			

Notes: Sample includes children born between the 3rd and 9th of March 1958 in UK, with natural mothers and no missing data for the sex of child, mothers'age, mothers' school leaving age (between 13 and 18 years), Parity in 1958, children's noncognitive behaviors measures at age 7, 11 and 16. The gender difference is obtained by regressing the variable of interest on an indicator variable, which equals to one if the observation is a boy and zero if it is a girl. Mothers born before 1933 were affected by the 1947 reform that raised the minimum compulsory school leaving age from 14 to 15. Robust standard errors are in paranthses.

The dependent variables are noncognitive behaviors measures. A rich variety of psychosocial maladjustment measures are assessed in the Bristol Social Adjustment Guide (BSAG) study when individuals were at age 7 and 11, which contains 12 measures for each age. The Rutter study, a similar study to BSAG, includes 18 similar measures for age 16.[38] The measures reflect child's attitude towards adults, other children, anxiety or depression symptoms, etc, rated by the child's teacher with values ranging from 0 to 15,

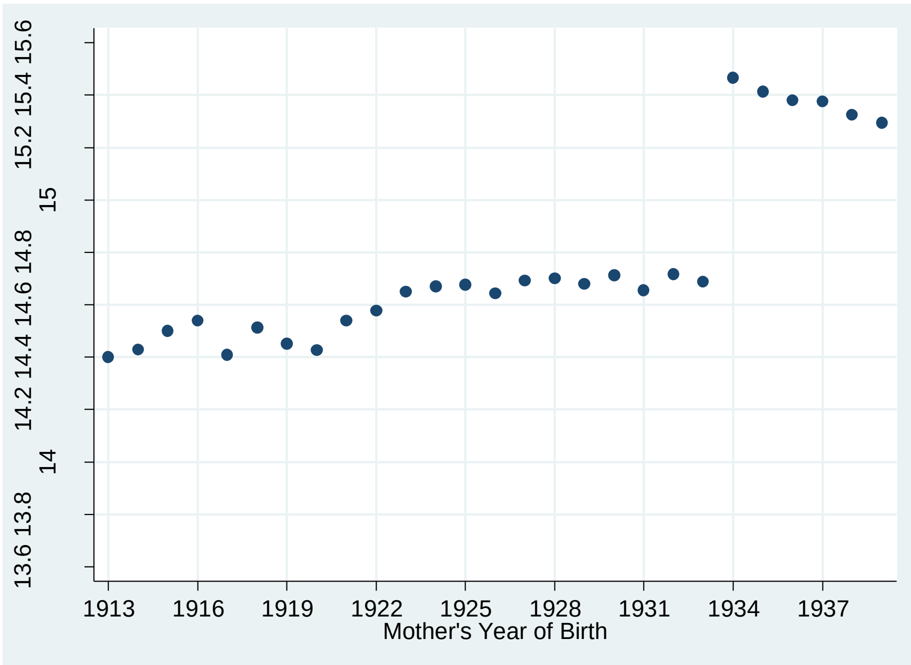
38 For age 7 and 11, the externalizing behaviors under broad definition include *hostility towards adults, writing off adults and standards, restless and hostility towards other children*. The narrow definition includes the first two behaviors for age 7 and the first one for age 11. The internalizing behaviors under broad definition include *unforthcomingness, withdrawal, depression, anxiety, inconsequential behaviors, miscellaneous symptoms and miscellaneous nervous symptoms*. The narrow definition includes *depression, withdrawal and anxiety* for both ages. For each age, the aggregate measure is the total score of all the externalizing and internalizing behaviors under broad definition. For age 16, the externalizing behaviors include *often destroys other property, frequently fights, flies off the handle, twitches face or body, frequently sucks/bites thumb or fingers, disobedient and bullies other children*. The internalizing behaviors include *restless, squirmy, not much liked by other children, often worries about things, does things on one's own, appears unhappy, miserable or tearful, and fearful*.

with higher value indicating higher maladjustment (more behavioral or emotional disorders). The total score of all measures is used to capture the aggregate noncognitive behaviors at each age. Externalizing and internalizing behaviors are also separately constructed to measure behaviors that direct problematic energy outward/towards the self. All the measures are standardized into mean zero and standard deviation of one, and the signs are reversed so that the higher value now represents higher noncognitive skills. The summary statistics of the noncognitive measures for all the children, boys and girls separately and the gender gap (the mean of boys subtracting that of girls) are shown in Table 1. Boys on average are scored lower in all the measures than girls, with a significant gender gap of around 0.3 of one standard deviation. This indicates boys have lower noncognitive skills during childhood, especially the early period of childhood (age 7 and 11). The only exception is the aggregate measure at age 16, which indicates no discernible gender gap. Also it is interesting to note that while girls are still better than boys in terms of externalizing behaviors at 16, they tend to have more problems with internalizing behaviors.

The primary explanatory variable is mother's schooling. The age at which mother left full-time education is used to measure mother's years of schooling.[39] The summary statistics in Table 1 shows that the average school leaving age for mothers is approximately 14.8. Mother's education level does not differ by child's gender, which is consistent with the expectation that gender is essentially randomly assigned across families. Mother's year of birth can be constructed by the age of mother at the initial survey in 1958. This variable is linked directly with the education reform of minimum school leaving age.

[39] The actual years of schooling should be the age left full-time education minus the age entered full-time education. But based on the law requirement for the primary starting age of 4, mothers should be expected to enter school at age of 4. So it is reasonable to use the age left full-time education to measure mother's years of schooling.

Figure 3.1: Average School Leaving Age by Birth Year for Mothers



In April 1947, as a result of the 1944 Education Act there was a major change in compulsory schooling laws in Britain: the minimum school leaving age increased from 14 to 15. The effect of the law change was such that persons born before 1933 faced a minimum school leaving age of 14, and persons born after 1933 (younger than 25 in the initial survey year 1958) faced a minimum age of 15. As shown in Table 3.1, approximately one third of mothers were affected by the reform. The fractions of mothers affected by the reform do not differ by children's gender either. The 1947 education reform that increased minimum school leaving age from 14 to 15 induces a discontinuity between mother's year of birth and schooling. Figure 3.1 plots the average school leaving age by year of birth for mothers and shows a significant break in 1934.[40] As shown in the lower part of Table 3.1, mothers' average school leaving age was around 14.6 before the reform, and increased to 15.1 after the reform. Other characteristics, such as mothers' socio-economic status, work and financial status, are smoothly distributed around the birth year 1934, suggesting that the attributes of mothers not affected by the reform are of no significant difference from those affected by the reform.

3.5 Identification Strategy

The source of exogenous variation in mother's education is the 1947 education reform in UK that raised minimum school leaving age from 14 to 15 years. I then observe the children of this generation born in 1958. The empirical model is summarized by the following equation:

$$\mathrm{NC_i} = \beta_0 + \beta_1 \mathrm{S_i^m} + \beta_2 \mathrm{Girl_i} + \beta_3 \mathrm{S_i^m} * \mathrm{Girl_i} + \mathrm{Parity_i} + \mathrm{g\{Age_i^m\}} + \varepsilon_\mathrm{i} \tag{3.1}$$

where $\mathrm{NC_i}$ is a particular measure of a child i's noncognitive behaviors. The superscript m denotes mother and $\mathrm{S_i^m}$ is the years of schooling of the child i's mother. Girl is a gender dummy, equal to one if the child is a female. Parity of child i at birth year 1958 is included to control for birth order effect. $\mathrm{g\{Age_i^m\}}$ is a quadratic function of mother's age at child i's birth year 1958. Since mother's age at the time of child's birth is equivalent to mother's year of birth (=1958-$\mathrm{Age_i^m}$), it is used to control for mother cohort effect.[41] The

[40] In addition to the discontinuity in 1934, Figure 1 shows a decrease in the average school leaving age after the initial spike in 1934. Since these are the mothers who had a child at 1958 (i.e. had a child in their early 20s), it is consistent with an earlier age of childbearing being associated with a lower number of years of education. This may bias downwards the coefficient on schooling derived from the reform if it captures the effect of human capital differences correlated with birth cohort. This suggests the importance of controlling for mothers' birth cohort.

[41] The results are not sensitive to how I specify the highest power of mother's age.

error term ε_i represents the effects of other determinants of NC_i, including unobservable attributes of the child. β_1 measures the average effect of mother's education on boys' noncognitive behaviors. β_1 is expected to be positive if mother's education improves boys' noncognitive behaviors. β_2 measures the gender gap in noncognitive behaviors between girls and boys if mother's education were zero. The estimated gender gap equals to $\widehat{\beta_2} + 14 * \widehat{\beta_3}$ If mother had 14 years of schooling. β_3 measures the differential effect of mother's education on girls' noncognitive behaviors relative to boys. If more years of mother's schooling have a greater effect in improving boys' noncognitive behaviors relative to girls', then β_3 is expected to have a negative sign.

The problem is that mother's education may be correlated with other variables that may affect children's noncognitive behaviors, such as socioeconomic status, occupation, family income, or simply that well-educated parents are better parents. To account for the endogeneity, the 1947 education reform is used to instrument for mother's education. Then a natural instrument variable for the interaction term of mother's schooling and child's gender dummy $S_i^m * \mathrm{Girl}_i$ is $\mathrm{Reform}_i^m * \mathrm{Girl}_i$. Both instruments are included in the regressions of the two endogenous terms. Specifically,

$$S_i^m = \alpha_0 + \alpha_1 \mathrm{Reform}_i^m + \alpha_2 \mathrm{Reform}_i^m * \mathrm{Girl}_i + \alpha_3 \mathrm{Girl}_i + \mathrm{Parity}_i + g\{\mathrm{Age}_i^m\} + \nu_i \tag{3.2}$$

$$S_i^m * \mathrm{Girl}_i = \varphi_0 + \varphi_1 \mathrm{Reform}_i^m + \varphi_2 \mathrm{Reform}_i^m * \mathrm{Girl}_i + \varphi_3 \mathrm{Girl}_i + \mathrm{Parity}_i + g\{\mathrm{Age}_i^m\} + \epsilon_i \tag{3.3}$$

where Reform_i^m is an indicator for whether the mother of child i is affected by the education reform. Child's gender and parity, which are exogenous to mother's schooling decisions, are included as controls. Mothers who were born after April 1st in 1933 were affected by the reform and about 3/4 of the 1933 mother cohort was impacted by the reform. With only mother's year of birth data available rather than exact birth month, I define the reform dummy equal to one if mothers were born after 1933, i.e. younger than 25 when the sample children were born. Since the education reform began to implement nationwide in 1947, the identifying variation in mother's education is restricted to the once-off change in the law and time trends. Since there were some individuals who stayed on past the minimum leaving age before the reform and some who still left school earlier than legally permitted after the reform, whether they are eligible for the new minimum schooling law is used to predict their actual treatment status – schooling. One maintained identification assumption is that attributes and circumstances of mothers, with respect to their impact on the unobserved characteristics of children's noncognitive skills, prior to the reform are identical to those affected by the reform. As discussed in the previous section, the distributions of mothers' socio-economic status, work and financial status by mothers' year of birth are smooth around 1934, suggesting that this assumption is likely to be satisfied. The quadratic function of mother's age in 1958 controls for mother's birth cohort effect, allowing for smooth changes in mother's education over time, and that despite the lower educational attainment of older mothers, their children are more likely to remain in education than those with younger mothers.

Two stage least square estimation using Equation (3.1)-(3.3) is performed to produce the IV estimates, which measure the causal effect of mother's schooling, net of changes in endowments and other factors. One issue of the instrumental variable method is that it identifies the local average treatment effect from mothers at the lower part of education distribution and may not reflect the general social returns of maternal education. However, since policies are more likely to target children from less advantaged family background, the estimates are of interest and carry important policy implications. To look at the LATE of the reform, I restrict the main sample to mothers born five year before and after 1933 (discontinuity sample), and mothers who left school before age 16 (less educated sample). The discontinuity sample focuses on a tighter time span of the reform, which will produce cleaner estimates from possible time trend effects. The less educated sample focuses on mothers that are most likely to be affected by the reform. Some of the past studies analyze the joint effect of both parents' education on children's outcomes. Due to the complication of linking birth father with the child, I focus on only mother's education for the main analysis. Due to positive sorting in the marriage market the estimated coefficient for mother's education may reflect any benefits to the child from more educated father. This issue will be addressed in Section 3.7.

3.6 Results

The first-stage results are shown in Table 3.2.[42] Consistent with previous findings, the average educational attainment is increased by 0.521 of a year for mothers and about one third of the mothers were affected by the reform, as shown in column 1.[43] According to Staiger and Stock (1997), a t-statistic of less than 5 would raise the concerns of weak instrument. The t-statistic for the significance of the excluded instrument is approximately 14, which is well above the general cut-off value. Since the reform induced a discontinuity in mothers' years of schooling between those born before and after 1933, the effect of the reform should be stronger for mothers born close to the point of discontinuity. As expected, the estimate shown in column 2 is larger in magnitude and slightly noisier. Since the compulsory education law in UK imposes no

42 The reported first stage estimates are obtained following $S_i^m = \alpha_0 + \alpha_1 Reform_i^m + Girl_i + Parity_i + g\{Age_i^m\} + \nu_i$.

43 Halmon, Colm and Waker (1995) find an average increase of 0.541 years for both male and female cohorts affected by the 1947 reform. The estimates from Silles(2011) are larger than most of the past work: 0.57 of a year for fathers and 0.71 for mothers.

restriction on education attainment past age 15, the education reform would mainly affect those at the lower part of the education distribution. As shown in column 3, the effect of reform on mother cohort who left school before or at age 16 increases to 0.949 with t-statistic of 30.

Table 3.2: First Stage Results: The Effect of Reform on Mothers' Education

Dependent Variable: Mother's School Leaving Age	**Full Sample**	**Discontinuity Sample** (5 Years +/- the Reform)	**Less Educated Sample** (<=16 School Leaving Age)
Reform	0.521***	0.730***	0.949***
	(0.042)	(0.066)	(0.031)
Observations	7,634	4,777	6,127
Percent Affected	0.330	0.456	0.534

Notes: Huber-White's robust standard errors are in parentheses. First stage also includes a quartic in mothers' year of birth, parity in 1958 and child's gender. ***Signifinicant at 1% level, ** 5% *10%. The discontinuity sample includes observations whose mothers were born five years before and after 1933 (i.e. five years younger and older than 14 in 1947). The less educated sample includes observations whose mothers left school before or at age 16.

3.6.1 The Gender Gap

The primary analysis for the effect of mother's education on the gender gap in children's noncognitive behaviors will use the main sample. Separate regressions are estimated for different measures of noncognitive behaviors. The results of Eq. (3.1) for noncognitive measures at age 7 are shown in Table 3.3. The OLS estimates in column 1-3 are obtained using mother's actual years of schooling and its interaction with child's gender as the main explanatory variables. Across all noncognitive measures, the estimates suggest a positive effect of mother's education on the level of boys' noncognitive behaviors and there is no significant difference in the effect for girls. For example, the gender gap in aggregate noncognitive behaviors at age 7 is 0.333 of one

Table 3.3: Mothers' Education and Children's Noncognitive Behaviors at Age 7

	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
	Aggregate	Externalizing	Internalizing	Aggregate	Externalizing	Internalizing
Mothers' Schooling	0.061***	0.046***	0.060***	0.016	0.008	0.018
	(0.017)	(0.017)	(0.017)	(0.097)	(0.102)	(0.096)
Mothers' Schooling*Girl	-0.006	-0.013	-0.002	-0.138*	-0.095	-0.119
	(0.021)	(0.020)	(0.021)	(0.084)	(0.089)	(0.086)
Girl	0.417	0.481	0.331	2.365*	1.709	2.063*
	(0.312)	(0.298)	(0.317)	(1.280)	(1.318)	(1.253)
Observations	7,634	7,634	7,634	7,634	7,634	7,634

Notes: Sample includes chidlren born between the 3rd and 9th of March in 1958, with natural mothers and no missing data for key variables (mothers' age at child birth, schooling, child's gender, parity and measures for noncognitive behaviors at age 7, 11 and 16). Each column corresponds to a seperate regression. Aggregated behavior is measured by the total score of 12 noncognitive behaviors in the Bristol Social Adjustment Guide (BSAG) at age 7. Externalizing/internalizing behaviors includes behaviors that direct problematic energy outward/towards the self. Girl is a gender dummy, equal to one if the observation is a girl and zero if it is a boy. Mothers' schooling is the age mother left school. An indicator of whether mother was affected by the 1947 education reform is used as an instrument for mothers' education in the IV regressions. Control variables used for both OLS and IV estimation includes parity in 1958, a quadratic function of mothers' age at child birth in 1958. Robust standard errors are reported in the parantathesis. ***Signifinicant at 1% level, ** 5% *10%.

standard deviation if mother's average years of schooling were held at 14 years, and a one-year increase in mother's education improves the level of boys' behaviors by 0.061 while reduces the gap by 0.006, which is only 2% (=0.006/0.333) of the gap.[44] Since the OLS estimates are likely to suffer from endogeneity, they are biased and at most suggestive. Using the reform to instrument for mother's education, the IV estimates in column 4-6 are of main interest for this analysis. The positive estimates for the coefficient of the gender dummy Girl indicate that girls on average perform better at (both externalizing and internalizing) noncognitive behaviors than boys at age 7. The estimated effect of mothers' education on boys' noncognitive behaviors, as captured by the coefficient of mothers' schooling, is not very precisely estimated and statistically insignificant. But there is weak evidence for a difference in the effect for boys and girls.

44 As explained in the Identification part, the estimated gender gap equals to $\widehat{\beta_2} + 14 * \widehat{\beta_3}$ if mother had 14 years of schooling. Therefore, the gender gap in aggregate noncognitive behaviors of age 7 equals to 0.417+14*(-0.006) =0.333.

For the aggregate noncognitive measure, mothers' schooling has a marginally significantly smaller effect on girls' noncognitive behaviors relative to boys. A back-of-the-envelope calculation shows that the gender gap in aggregate noncognitive behaviors at age 7 is 0.433 of one standard deviation (column 4). A one-year increase in mother's years of schooling reduces the gender gap in aggregate behaviors by 0.138, or 32% of the gap. The effect is only marginally significant for aggregate noncognitive behavior, and not for specific externalizing and internalizing measures. Overall, the results provide evidence that the gender gap in children's noncognitive behaviors at age 7 is reduced with better educated mothers.

Table 3.4 shows the results of Eq. (3.1) for noncognitive measures at age 11. The OLS estimates suggest a positive effect of mother's schooling on the level of boys' noncognitive behaviors at age 11, with no significant difference for boys and girls except for externalizing behaviors. The magnitude of the effect is similar across all measures, and larger than that of age 7 measures. The results shown in column 6-10 from IV estimation are similar to OLS estimates with larger magnitude. Specifically, a one-year increase in mother's schooling significantly improves the aggregate behaviors of boys and girls by 0.174 of a standard deviation, and 0.183 and 0.163 for externalizing behaviors and internalizing behaviors respectively. In general, for children at age 11, an increase in mother's education leads to a significant improvement in boys' and girls' noncognitive behaviors. There is little evidence for a differential effect by gender.

Table 3.4: Mothers' Education and Children's Noncognitive Behaviors at Age 11

	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
	Aggregate	Externalizing	Internalizing	Aggregate	Externalizing	Internalizing
Mothers' Schooling	0.104***	0.086***	0.098***	0.174*	0.183*	0.163*
	(0.016)	(0.016)	(0.016)	(0.101)	(0.104)	(0.098)
Mothers' Schooling*Girl	-0.024	-0.038*	-0.013	-0.046	-0.001	-0.068
	(0.020)	(0.020)	(0.020)	(0.084)	(0.085)	(0.084)
Girl	0.684***	0.882***	0.509*	0.995	0.257	1.310
	(0.304)	(0.297)	(0.309)	(1.244)	(1.260)	(1.241)
Observations	7,634	7,634	7,634	7,634	7,634	7,634

Notes: Sample includes chidlren born between the 3rd and 9th of March in 1958, with natural mothers and no missing data for key variables (mothers' age at child birth, years of schooling, child's gender, parity and measures for noncognitive behaviors at age 7, 11 and 16). Each column corresponds to a seperate regression. Aggregated behavior is measured by the total score of 12 noncognitive behaviors in the Bristol Social Adjustment Guide (BSAG) at age 11. Externalizing/internalizing behaviors includes behaviors that direct problematic energy outward/towards the self. Girl is a gender dummy, equal to one if the observation is a girl and zero if it is a boy. Mothers' schooling is the age mother left school. An indicator of whether mother was affected by the 1947 education reform is used as an instrument for mothers' education in the IV regressions. Control variables used for both OLS and IV estimation includes parity in 1958, a quadratic function of mothers' age at child birth in 1958. Robust stardard errors are reported in the parantathesis. ***Signifinicant at 1% level, ** 5% *10%.

Table 3.5: Mothers' Education and Children's Noncognitive Behaviors at Age 16

	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
	Aggregate	Externalizing	Internalizing	Aggregate	Externalizing	Internalizing
Mothers' Schooling	0.068***	0.071***	0.044***	0.109	0.083	0.101
	(0.016)	(0.016)	(0.016)	(0.097)	(0.099)	(0.093)
Mothers' Schooling*Girl	0.016	0.013	0.015	-0.072	-0.034	-0.091
	(0.022)	(0.021)	(0.023)	(0.088)	(0.087)	(0.087)
Girl	-0.025	-0.122	-0.310	1.052	0.576	1.243
	(0.327)	(0.315)	(0.341)	(1.293)	(1.289)	(1.281)
Observations	7,634	7,634	7,634	7,634	7,634	7,634

Notes: Sample includes chidlren born between the 3rd and 9th of March in 1958, with natural mothers and no missing data for key variables (mothers' age at child birth, years of schooling, child's gender, parity and measures for noncognitive behaviors at age 7, 11 and 16). Each column corresponds to a seperate regression. Aggregated behavior is measured by the total score of 12 noncognitive behaviors in the Bristol Social Adjustment Guide (BSAG) at age 16. Externalizing/internalizing behaviors includes behaviors that direct problematic energy outward/towards the self. Girl is a gender dummy, equal to one if the observation is a girl and zero if it is a boy. Mothers' schooling is the age mother left school. An indicator of whether mother was affected by the 1947 education reform is used as an instrument for mothers' education in the IV regressions. Control variables used for both OLS and IV estimation includes parity in 1958, a quadratic function of mothers' age at child birth in 1958. Robust stardard errors are reported in the parantathesis. ***Signifinicant at 1% level, ** 5% *10%.

At later stage of childhood, boys tend to develop faster in noncognitive skills and catch up with girls, resulting in a smaller or even indiscernible gender gap. In Table 3.5, both OLS and IV estimates across noncognitive measures indicate the gender gap in the effect of mothers' education is not significantly different from zero. While OLS estimates suggest a positive effect of mother's schooling on boys and no difference in the effect by gender, IV estimates are too noisy to identify an effect. There is little evidence for a significant effect on the gender gap, which is consistent with our expectation that mother's education mainly affects children during their early stage of childhood (age7) and has little effect on their noncognitive behaviors in their later stage of childhood (age 11 and 16).

3.6.2 Results for the Restricted Sample

The identification strategy for IV estimation assumes that mothers increased their schooling when affected by the change in minimum school leaving age reform in 1947. Based on this assumption, the effect of reform would be stronger for those mothers who born in close vicinity of the reform (5 years) and those who were at the lower part of the education distribution. As shown in Table 2 both restricted subsamples have stronger first stage effect. The results for these two restricted samples are shown in Table 3.6. The dependent variables include only the aggregate measures at age 7, 11 and 16. For the discontinuity sample shown in Panel A, the OLS estimates are similar to those obtained for the full sample, but smaller in magnitude. The estimated effects of mother's education using reform as an instrument are larger than those for the full sample. At age 7, the estimated effect on the gender gap is 0.178, or 50% of the gender gap, which is larger than 32% for the full sample (Column 6, Table 3.3). At age 11, the effect on the level of boys' noncognitive behaviors is 0.217, slightly larger than 0.174 for the full sample (Column 6, Table4). For age 16 there is no discernible effect on either the level or the gender gap in noncognitive behaviors. Due to smaller sample size, the variation of estimates for the discontinuity sample is larger than that for the full sample. Since the less educated sample in Panel B accounts for a large portion of the full sample, the results are similar to those obtained with the full sample. These results support the validity of the identification strategy and suggest that only a subgroup of the population complied with the reform and changed their education, thus the IV estimates can only be interpreted as a LATE.

Table 3.6: Mothers' Education and Children's Noncognitive Behaviors: Restricted Sample

	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
	Age 7	Age 11	Age 16	Age 7	Age 11	Age 16
Panel A: Discontinuity Sample, N=4,777						
Mothers' Schooling	0.041***	0.080***	0.057***	-0.033	0.217***	0.100
	(0.021)	(0.021)	(0.019)	(0.124)	(0.128)	(0.122)
Mothers' Schooling*Girl	0.011	0.010	0.044	-0.178*	0.049	-0.034
	(0.027)	(0.027)	(0.027)	(0.107)	(0.106)	(0.108)
Girl	0.144	0.168	-0.691*	2.845***	-0.426	0.461
	(0.401)	(0.401)	(0.404)	(1.584)	(1.573)	(1.607)
Panel B: Less Educated Sample, N=6,127						
Mothers' Schooling	0.092***	0.133***	0.108***	-0.025	0.168*	0.070
	(0.023)	(0.024)	(0.022)	(0.093)	(0.097)	(0.095)
Mothers' Schooling*Girl	-0.041	-0.050*	-0.018	-0.128*	-0.049	-0.026
	(0.031)	(0.030)	(0.031)	(0.075)	(0.076)	(0.080)
Girl	0.918**	1.048***	0.249	1.855***	1.028	0.362
	(0.452)	(0.440)	(0.460)	(1.113)	(1.114)	(1.161)

Notes: Discontinuity sample in Panel A includes observations whose mother was born five years before and after 1933. Less educated sample in Panel B inlcudes observations whose mother had less than or equal to 16 years of schooling. Only the aggregate measures of noncognitive behaviors at each age are reported here. Girl is a gender dummy, equal to one if the observation is a girl and zero if it is a boy. Mothers' schooling is the age mother left school. An indicator of whether mother was affected by the 1947 education reform is used as an instrument for mothers' education in the IV regressions. Control variables used for both OLS and IV estimation includes parity in 1958, a quadratic function of mothers' age at child birth in 1958. Robust stardard errors are reported in the parantathesis. ***Signifinicant at 1% level, ** 5% *10%.

3.7 Effect of Father's Education

Since the education reform increased the years of schooling of male would-be-dropouts at the same time, and also because of the positive sorting in the marriage market, better educated mothers are more likely to have a better educated husband. Therefore, a potential bias may come from father's education. The estimates for mother's education may reflect any benefits to the child from more educated fathers. To separate out the direct effect of parental education from the indirect effects from marriage market, I add father's education into Equation (3.1), i.e.

$$\mathrm{NC_i} = \beta_0 + \beta_1 \mathrm{S_i^m} + \beta_2 \mathrm{S_i^f} + \beta_3 \mathrm{Girl_i} + \beta_4 \mathrm{S_i^m} * \mathrm{Girl_i} + \beta_5 \mathrm{S_i^f} * \mathrm{Girl_i} + \mathrm{Parity_i} + \mathrm{g}\{\mathrm{Age_i^m}\} + \mathrm{g}\{\mathrm{Age_i^f}\} + \varepsilon_\mathrm{i} \quad (3.4)$$

where the superscript f represents father and all the other notations are defined the same as in Section IV. The instrumental variables for father's years of schooling and the interaction term of father's schooling and child gender dummy are constructed in the same way as those for mothers. Since fathers are generally older than mothers, it is possible to construct the reform indicator for fathers, which is not perfect collinear with the reform indicator for mothers. In order to implement the estimation, I further restrict the main sample to observations with no missing data for father's age, years of schooling and relationship with child, and the sample size reduces from 7,634 to 6,753.

The results are presented in Table 3.7 and Table 3.8. The first stage results in Table 3.7 indicate the jump in educational attainment is 0.53 of a year for mothers and 0.49 of a year for fathers, and these are both strongly statistically significant.[45] For

45 Table 8a reports the first stage results following equation $S_i^f = \alpha_0^f + \alpha_1^f Reform_i^m + \alpha_2^f Reform_i^f + \alpha_3^f Girl_i + Parity_i + g\{Age_i^m\} + g\{Age_i^f\} + \nu_i$ for father's schooling and $S_i^m = \alpha_0^m + \alpha_1^m Reform_i^m + \alpha_2^m Reform_i^f + \alpha_3^m Girl_i + Parity_i + g\{Age_i^m\} + g\{Age_i^f\} + \mu_i$ for mother's schooling. To implement 2SLS estimation and obtain results in Table 8b, the vector of IVs ($Reform_i^m$, $Reform_i^f$, $Reform_i^m * Girl_i$, $Reform_i^f * Girl_i$) are used in the first stage to predict S_i^f and S_i^m.

children's noncognitive behaviors at age 7, the IV estimates in columns 1-5 of Table 3.8 show that father's education has a statistically negative effect on the level of boys' noncognitive behaviors. Though the effect of father's education on the gender gap is not significant, the sign is positive, indicating that an increase in father's education may enlarge the gender gap in children's noncognitive skills. On the other hand, the estimated effect of mother's education is similar to the baseline results. The estimates for the interaction term of mother's schooling and child's gender dummy in the fourth row are negative and slightly larger in magnitude than those in Table 3.3, but they are not precisely estimated and thus not statistically significant.. For noncognitive measures at age 11 in columns 6-10, father's education has no discernible effect on either the level or the gender gap in all the measures. The estimates of mother's education are also similar to the baseline results and larger in magnitude, indicating a significantly positive effect on the level of boys' noncognitive behaviors across all measures and less significant effect on reducing the gender gap. Neither parent's education has significant effect on the noncognitive behaviors at age 16. Overall, father's education has very little or negative effect on children's noncognitive behaviors, which may be explained by the fact that fathers affected by the reform had higher probability of being employed or worked more hours with increased years of schooling, thus cared less about their children's development. It should be noted that the match between father's information and child is imprecisely coded due to changes in mother's marital status, and the results in this section should be interpreted with caution. But we can conclude from the results that the effect of mother's education on children's noncognitive behaviors is unlikely to be driven by the effect of father's education.

Table 3.7: The Effect of Reform on Mothers and Fathers' Education

	Mother's Schooling Leaving Age	Father's Schooling Leaving Age
Mother Affected by Reform	0.534***	0.028
	(0.045)	(0.049)
Father Affected by Reform	-0.014	0.492***
	(0.049)	(0.052)
Observations	6,753	6,753

Notes: Both parents' school leaving ages are instrumented using indicators of whether they were affected by the 1947 education reform. Additional control variables include a quartic in parents' year of birth, parity in 1958 and child's gender. Huber-White's robust standard errors are in parentheses. ***Signifinicant at 1% level, ** 5% *10%.

Table 3.8: Both Parents' Education and Children's Noncognitive Behaviors: IV Estimates

	Age 7			Age 11			Age 16		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Aggre.	Exter.	Inter.	Aggre.	Exter.	Inter.	Aggre.	Exter.	Inter.
Mothers' Schooling	0.034	0.055	0.018	0.212**	0.239**	0.177*	0.131	0.110	0.113
	(0.105)	(0.111)	(0.103)	(0.107)	(0.110)	(0.104)	(0.099)	(0.103)	(0.097)
Fathers' Schooling	-0.294**	-0.347**	-0.230*	-0.112	-0.186	-0.055	-0.004	-0.077	-0.085
	(0.141)	(0.155)	(0.135)	(0.136)	(0.143)	(0.131)	(0.129)	(0.136)	(0.123)
Mothers' Schooling*Girl	-0.152†	-0.072	-0.133	-0.012	0.02	-0.027	-0.012	-0.017	-0.002
	(0.102)	(0.104)	(0.102)	(0.096)	(0.098)	(0.097)	(0.102)	(0.104)	(0.102)
Fathers' Schooling*Girl	0.182	0.182	0.157	-0.027	-0.002	-0.037	-0.163	-0.041	-0.254
	(0.161)	(0.173)	(0.156)	(0.153)	(0.160)	(0.149)	(0.161)	(0.173)	(0.156)
Girl	0.831	1.308	0.464	0.895	0.003	1.262	-2.540	-0.093	-3.618*
	(2.232)	(2.379)	(2.161)	(2.114)	(2.194)	(2.044)	(1.980)	(2.176)	(2.083)
Observations	6,753	6,753	6,753	6,753	6,753	6,753	6,753	6,753	6,753

Notes: Sample includes chidlren born between the 3rd and 9th of March in 1958, with natural mothers and no missing data for key variables (mothers' age at child birth, years of schooling, child's gender, parity and measures for noncognitive behaviors at age 7, 11 and 16). Each column corresponds to a seperate regression. Aggregated behavior is measured by the total score of 12 noncognitive behaviors in the Bristol Social Adjustment Guide (BSAG) at age 16. Externalizing/internalizing behaviors includes behaviors that direct problematic energy outward/towards the self. Girl is a gender dummy, equal to one if the observation is a girl and zero if it is a boy. Both parents' schooling are the age parent left school. Both parents' education are instrumented by an indicator of whether the parent was affected by the 1947 education reform. Control variables used for both OLS and IV estimation includes parity in 1958, a quadratic function of mothers' age at child birth in 1958. Robust standard errors are reported in the parantathesis. ***Signifinicant at 1% level, ** 5% *10% †15%.

3.8 Interpretation of the Results

The results presented in Section 6 show strong evidence of a causal effect of mother's education on the gender gap in children's noncognitive behaviors. In this section, I explore the link between mothers' education and the gender differential development of noncognitive behaviors caused by mothers' education. More specifically, why do we expect mothers' education to have a differential effect by gender on children's noncognitive development? As discussed in the theoretical framework, mothers with higher education spend more time with children and they spend their time engaging in different activities for boys and girls. These different types of maternal inputs may have differential effect on the noncognitive development of boys and girls.

Table 3.9 shows the relationship between mothers' education level and the amount of time inputs for children. The input variables used for age 7 include how frequently spend time reading to child, and how frequently go outing with child. For age 11, the measures are how frequently take a walk with child and how much interest shown in child's education. The OLS estimations of mothers' time inputs on mothers' years of schooling suggest a positive correlation between these two factors. Mothers with more years of schooling are likely to spend more time on children. The IV estimates obtained using the minimum schooling law reform as instrument for mothers' years of schooling in column 3 and 4 are not precisely estimated. However, the signs of the estimates are positive, which is consistent with what the OLS estimates suggest. Altogether this table provides evidence that better educated mothers spend more time on children.

Table 3.9: Mothers' Education and Time Inputs for Children

	OLS		IV	
	(1)	(2)	(3)	(4)
Panel A: Dependent variable = Input activity when child was at age 7				
	Reading	Outing	Reading	Outing
Mothers' Schooling	0.012***	0.002**	0.014	0.004
	(0.003)	(0.001)	(0.018)	(0.006)
Panel B: Dependent variable = Input activity when child was at age 11				
	Walking	Interest in Educ	Walking	Interest in Educ
Mothers' Schooling	0.011***	0.010***	0.007	0.003
	(0.002)	(0.002)	(0.012)	(0.013)
Observations	7,634	7,634	7,634	7,634

Notes: Sample includes chidlren born between the 3rd and 9th of March in 1958, with natural mothers and no missing data for key variables (mothers' age at child birth, years of schooling, child's gender, parity and measures for noncognitive behaviors at age 7, 11 and 16). In Panel A, the depent variables are respectivly whether mother reads to children (1 if yes and 0 if no), and whether mother goes outings with child (1 if yes and 0 if no) when child was age 7. In Panel B, the depent variables are respectivly whether mother walks with children (1 if yes and 0 if no), and whether mother is interested in child's education (1 if yes and 0 if no) when child was age 11. Mothers' schooling is the age mother left school. An indicator of whether mother was affected by the 1947 education reform is used as an instrument for mothers' education in the IV regressions. Control variables used for both OLS and IV estimation includes parity in 1958, a quadratic function of mothers' age at child birth in 1958. Robust stardard errors are reported in the parantathesis. ***Signifinicant at 1% level, ** 5% *10%.

Table 3.10 provides a piece of suggestive evidence by performing an OLS estimation of Equation (3.1) including mother's input variables as additional controls, and comparing the results with those from the baseline specification to see if mothers' inputs work as a mechanism between mothers' schooling and children's noncognitive behaviors.[46] If inclusion of these input variables leads to a decline in the coefficients of mother's schooling or the interaction term (Schooling*Girl) and an increase in the R-squared, it would suggest that mother's inputs represent a pathway toward children's noncognitive behaviors. Similar to the baseline OLS results in Table 3, 4 and 5, the estimates obtained without using mother's inputs as controls (column 1-3) show significantly positive effect of mother's education on the level of children's noncognitive

[46] However, it should be noted that these regression results are at most suggestive, as they are open to potential concerns about omitted variables, measurement error, and reverse causality.

Table 3.10: The Effect of Mothers Education on Children's Noncognitive Behaviors as Mediated by Mother's Inputs

	Without Controls			With Mother's Inputs As Controls		
	Aggregate Behavior at Age 7	Aggregate Behavior at Age 11	Aggregate Behavior at Age 16	Aggregate Behavior at Age 7	Aggregate Behavior at Age 11	Aggregate Behavior at Age 16
	(1)	(2)	(3)	(4)	(5)	(6)
Mothers' Schooling	0.061***	0.104***	0.068***	0.031*	0.065***	0.056***
	(0.017)	(0.016)	(0.016)	(0.017)	(0.017)	(0.017)
Girl	0.417	0.684***	-0.250	0.355	0.652**	-0.409
	(0.312)	(0.304)	(0.327)	(0.315)	(0.312)	(0.349)
Mother's Schooling*Girl	-0.006	-0.024	0.016	-0.003	-0.024	0.026
	(0.021)	(0.020)	(0.022)	(0.021)	(0.021)	(0.023)
Observations	7,634	7,634	7,634	7,358	7,074	5,928
R-Squared	0.051	0.059	0.015	0.074	0.079	0.022

Notes: Column 1 to 3 display results without adding mothers' time inputs as control variables, with the sample used being the main sample of 7,634 observations. Column 4 to 6 show results with mothers' inputs as control variables, and each column has a different sample that excludes from the main sample observations with missing data for the input variables. Robust standard errors are in parentheses. ***Significant at 1% level, **5% *10%.

skills. Inclusion of mother's inputs lowers the estimates of coefficients for mother's schooling (column 4-6). For example, without inputs as controls, a one-year increase in mother's education improves boys' noncognitive behaviors by 0.06 of one standard deviation, compared to 0.03 when mother's inputs are included as controls. The estimates for the effect on the gender gap are also slightly smaller with controls. For example, the gender gap at age 7 without controls is 0.333 and an increase in mother's schooling from 14 to 15 years reduces the gap by 1.8% (=0.006/0.333). With inputs as controls, the gender gap equals 0.313 and an increase in mother's schooling reduced the gap by 0.96% (=0.003/0.313), which is only slightly smaller than that without controls. The R-squared is larger for the regression with inputs as controls. Although roughly in line with the theoretical conjecture, the results from OLS regressions should be interpreted with caution due to potential biases and small magnitude. The results suggest that mother's inputs into children are pathways for the effect of mother's education on the gender gap in children's noncognitive behaviors.

Table 3.11: Mother's Time Inputs for Boys and Girls

	Total	Boys	Girls	Diff(B-G)
Panel A: Mothers' Time Inputs at Age 7				
Reading to Child	0.843	.827	0.848	-0.21***
	(0.364)	(0.369)	(0.359)	(0.008)
Go Outings with Child	0.986	0.988	0.984	0.004***
	(0.119)	(0.109)	(0.127)	(0.002)
Panel B: Mothers' Time Inputs at Age 11				
Walking with Child	.943	0.958	0.930	0.028***
	(0.231)	(0.202)	(0.255)	(0.005)
Interested in Child's Education	0.074	0.055	0.093	-0.038***
	(0.262)	(0.228)	(0.290)	(0.006)

Notes: Sample includes chidlren born between the 3rd and 9th of March in 1958, with natural mothers and no missing data for key variables (mothers' age at child birth, years of schooling, child's gender, parity and measures for noncognitive behaviors at age 7, 11 and 16). In Panel A, the depent variables are respectivly whether mother reads to children (1 if yes and 0 if no), and whether mother goes outings with child (1 if yes and 0 if no) when child was age 7. In Panel B, the depent variables are respectivly whether mother walks with children (1 if yes and 0 if no), and whether mother is interested in child's education (1 if yes and 0 if no) when child was age 11. Robust stardard errors are reported in the parantathesis. ***Signifinicant at 1% level, ** 5% *10%.

Table 3.12: Responsiveness of Boys and Girls to Mothers' Inputs at Age 7

	Boys			Girls		
	Aggregate Behaviors	Externalizing Behaviors	Internalizing Behaviors	Aggregate Behaviors	Externalizing Behaviors	Internalizing Behaviors
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Responsiveness of noncognitive behaviors to mother's inputs when child was at age 7						
Time Spent Reading to Child	-0.000	0.025	-0.016	0.011	-0.017	0.024
	(0.022)	(0.024)	(0.022)	(0.019)	(0.018)	(0.020)
Go Outing with child	0.107**	0.112**	0.089**	0.030	-0.026	0.059
	(0.045)	(0.051)	(0.042)	(0.035)	(0.035)	(0.038)
Interested in Child's Study	0.105***	0.113***	0.086***	0.080***	0.051***	0.087***
	(0.020)	(0.021)	(0.019)	(0.017)	(0.017)	(0.017)
Observation	3,763	3,763	3,763	3,595	3,595	3,595
Panel B: Responsiveness of noncognitive behaviors to mother's inputs when child was at age 11						
Walk with child	0.141***	0.152***	0.077***	0.100***	0.125***	0.034
	(0.030)	(0.030)	(0.029)	(0.028)	(0.028)	(0.029)
Interested in Child's Study	0.037**	0.056***	0.001	0.027	0.042**	-0.001
	(0.017)	(0.017)	(0.017)	(0.018)	(0.018)	(0.017)
Observation	3,611	3,611	3,611	3,463	3,463	3,463

Notes: The estimation follows NC7= b0+b1*Inputs7+NC7+X'B+e in Panel A and NC11=b0+b1*Inputs11+NC11+X'B+e Panel B. Column1-3 use the sample of only boys and column 4-6 use the sample of only girls. Each column within a panel corresponds to a differentregression. The background covariates in X include race dummies, birthweight, number of older/younger brothers and sisters, familySES and dummies for region. Robust standard errors are reported. ***Significant at 1% level, **5% *10%.

Table 3.11 looks at mothers' time inputs for boys and girls separately. Consistent with Baker and Milligan (2011), the summary statistics shows that mothers spend significantly more time reading to girls and are more interested in girls' education. On the other hand, they spend more time going outings and walking with boys. As reading has a positive effect on children's cognitive skills and outing/walking is more likely to foster noncognitive skills (Baker and Milligan, 2011), the differential use of quality time by mothers may lead to distinct development paths of noncognitive skills for boys and girls. Next I examine the responsiveness of boys and girls to the changes in mother's inputs by looking at the relationship between mother's inputs and noncognitive behaviors for boys and girls separately. Table 3.12 shows the OLS estimates of regressing boys and girls' noncognitive behaviors on mothers' inputs variables at age 7 and 11respectively. The results suggest that boys respond more to going outing with mothers at age 7 than girls. Reading to children is not significantly related to either boys' or girls' noncognitive behaviors, while interest in child' study is positively correlated to both boys' and girls' noncognitive behaviors. This is consistent with the conjecture that the differential use of mother's time inputs has a different effect on boys and girls.

3.9 Conclusions

Previous studies have suggested boys' noncognitive maladjustment may be a key reason for their disadvantage in higher level of education and labor market outcomes. Besides nature-based influences, nurture-based influences are also important. By using the legislation change in the minimum school leaving age from 14 to 15 in Great Britain in 1947, I look at the causal effect of mother's education on the gender gap in children's non-cognitive behaviors. The findings suggest mother's education has a positive effect on the level of boys' noncognitive behaviors, and reduces the gender gap during the early stage of childhood. There is little evidence for a significant effect on children's noncognitive behaviors at age 16. I also find that mother's inputs are pathways for the causal link between mother's education and the gender gap. Better educated mothers invest more time and care to children and boys respond more to the inputs than girls, which lead to a greater improvement in boys' noncognitive skills and a smaller gap.

These results suggest the importance to invest in children during their childhood. According to human skill formation theory, cognitive and noncognitive skills required in one period persist into future periods (self-productivity) and augment the skills attained at later stages (complementarity). Inadequate skills at early age are difficult to remediate at later age. Therefore, the insufficient noncognitive skills of boys at age 7 and 11, if not adequately remediated with more investment, will generate a negative effect on their later outcomes. Even if they catch up in noncognitive skills at age 16, their cognitive behaviors and other skills may be persistently affected by the inadequate level of noncognitive skills in early ages.

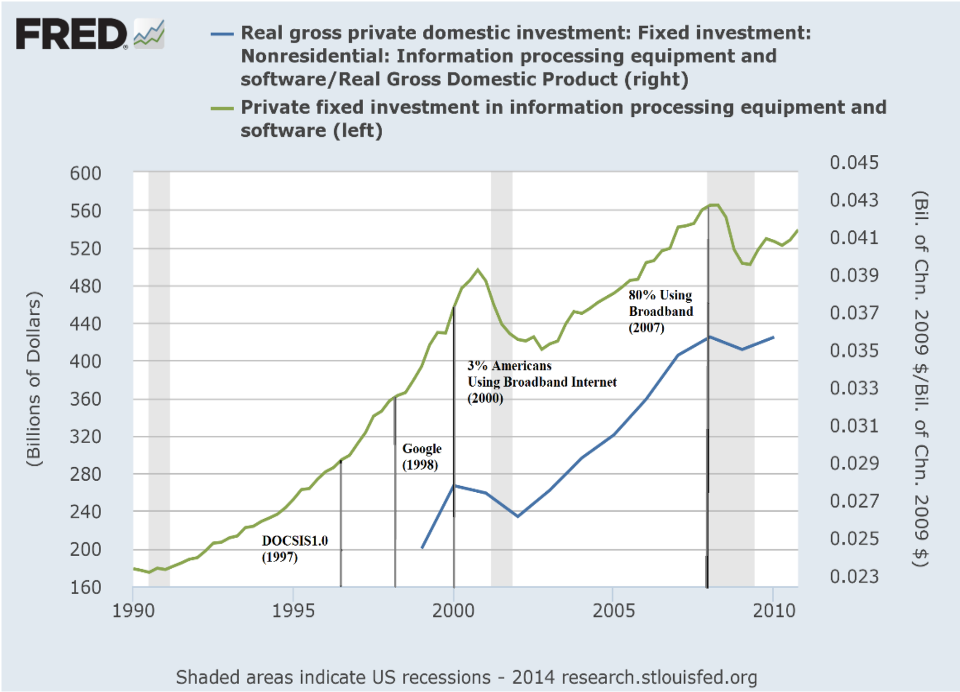
Appendices

Appendix A

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

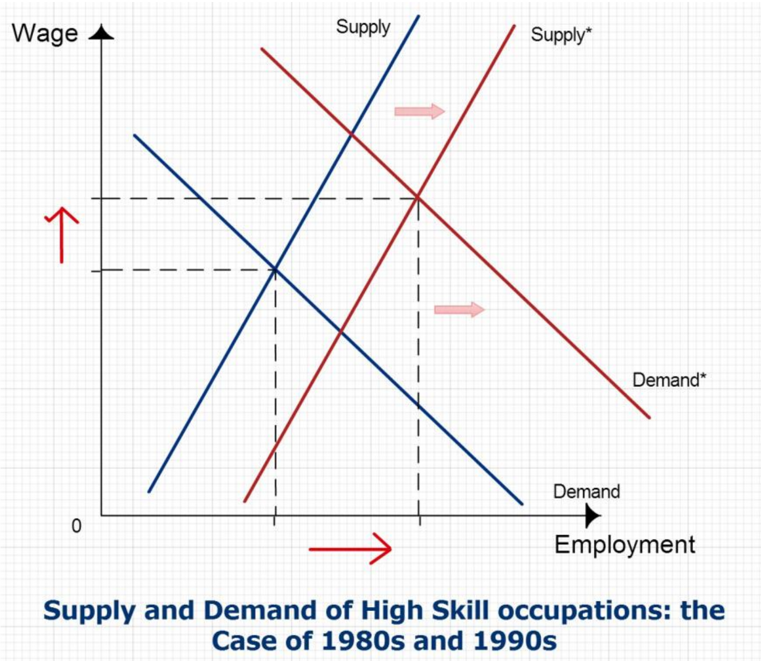
A.1 Figures and Tables

Figure A.1.2: Investment in Information Technology and Key Events Since 1990



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

Figure A.1.3: High Skill Market, Before and After 2000



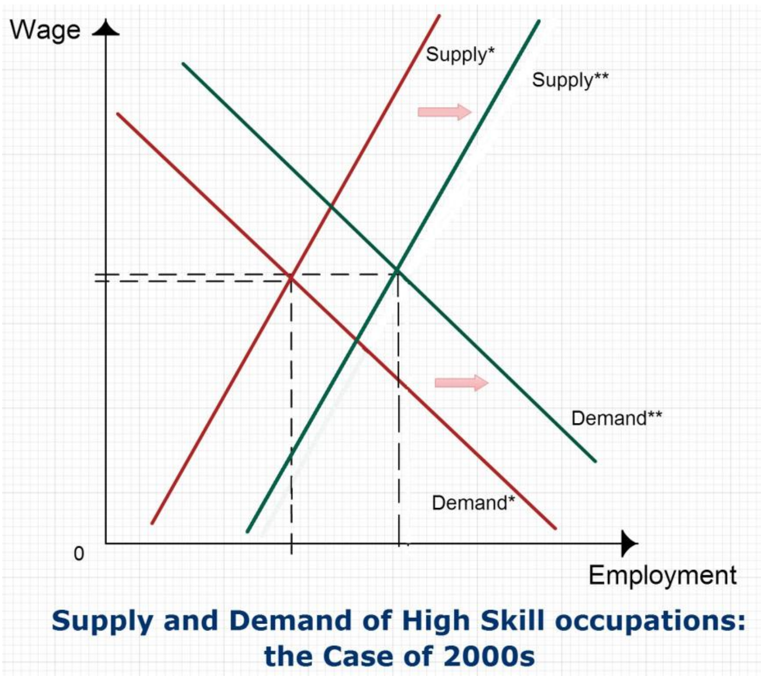


Table A.1.13: Change in Industry Task Inputs and Internet Use

Dependent Variable: 100 * Annual Log Difference in Task Inputs

Robustness Check: Do the results hold with internet use as the proxy for the post-2000 technological change?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Measures		Single Task Measures				
A. Analytical Tasks							
	Simple Average	Principle Component	Evaluate Information	Interpret Information	Problem Solving	Originility	Critical Thinking
ΔTech	0.053***	0.084***	0.049**	0.059***	0.058***	0.060***	0.042***
	(0.016)	(0.029)	(0.021)	(0.022)	(0.019)	(0.019)	(0.014)
ΔTech*1{post-2000}	-0.020	-0.025	-0.005	-0.018	-0.021	-0.023	-0.028*
	(0.017)	(0.030)	(0.022)	(0.023)	(0.020)	(0.020)	(0.015)
R-squared	0.261	0.240	0.270	0.151	0.280	0.231	0.207
B. Managerial Tasks							
	Simple Average	Principle Component	Establishing Interpersonal	Developing Strategy	Resolving Conflict	Building Team	Making Decision
ΔTech	0.046***	0.084***	0.027**	0.063***	0.057***	0.048**	0.044***
	(0.014)	(0.027)	(0.012)	(0.022)	(0.020)	(0.019)	(0.015)
ΔTech*1{post-2000}	-0.014	-0.021	-0.003	-0.010	-0.023	-0.017	-0.018
	(0.015)	(0.028)	(0.013)	(0.022)	(0.021)	(0.020)	(0.015)
R-squared	0.203	0.199	0.098	0.239	0.111	0.207	0.242
C. Cognitive Reasoning Tasks							
	Simple Average	Principle Component	Problem Sensitivity	Deductive Reasoning	Data Comparison	System Analysis	Judging Quality
ΔTech	0.050***	0.117***	0.037***	0.041***	0.064***	0.066***	0.047***
	(0.011)	(0.029)	(0.010)	(0.010)	(0.015)	(0.023)	(0.013)
ΔTech*1{post-2000}	-0.033***	-0.076**	-0.029***	-0.026**	-0.044***	-0.038	-0.030**
	(0.012)	(0.030)	(0.011)	(0.011)	(0.016)	(0.024)	(0.013)
R-squared	0.291	0.255	0.141	0.222	0.264	0.283	0.232
D. Information Transfer Tasks							
	Simple Average	Principle Component	Guiding	Coaching	Instructing	Staffing Unit	Reviewing Information
ΔTech	0.058***	0.104***	0.075***	0.055***	0.032***	0.089***	0.058***
	(0.015)	(0.027)	(0.022)	(0.019)	(0.011)	(0.027)	(0.013)
ΔTech*1{post-2000}	-0.045***	-0.079***	-0.069***	-0.036*	-0.037***	-0.067**	-0.031**
	(0.015)	(0.028)	(0.023)	(0.020)	(0.012)	(0.028)	(0.014)
R-squared	0.243	0.243	0.210	0.221	0.161	0.277	0.205
E. Routine Tasks							
	Simple Average	Principle Component	Being Structured	Following Equipment	Controlling Machine	Monitoring Operation	Controling Pace
ΔTech	-0.049*	-0.047**	-0.073***	-0.072**	-0.048	-0.007	-0.055
	(0.025)	(0.024)	(0.021)	(0.035)	(0.030)	(0.027)	(0.042)
ΔTech*1{post-2000}	0.019	0.018	0.042*	0.043	0.007	-0.002	0.012
	(0.026)	(0.025)	(0.022)	(0.036)	(0.031)	(0.028)	(0.044)
R-squared	0.141	0.141	0.145	0.162	0.152	0.143	0.155
F. Manual Tasks							
	Simple Average	Principle Component	Using Hands	Manual Dexterity	Service orientated	Assisting others	Performing for public
ΔTech	0.027**	0.061***	-0.009	0.025	0.056***	0.021	0.063**
	(0.013)	(0.021)	(0.023)	(0.034)	(0.016)	(0.019)	(0.025)
ΔTech*1{post-2000}	-0.042***	-0.057***	-0.033	-0.080**	-0.032*	-0.019	-0.067**
	(0.013)	(0.022)	(0.024)	(0.035)	(0.017)	(0.020)	(0.027)
R-squared	0.200	0.128	0.158	0.179	0.179	0.172	0.081

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 the change in industry **internet** use 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 deŽnitions and examples of task variables.

Table A.1.14: Change in Task Inputs and PC Use: Adding Industrial Controls

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 deŽnitions and examples of task variables.

Table A.1.15: Change in Task Inputs and PC Use: 1983-2000 vs 2000-2007

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 deŽnitions and examples of task variables.

Table A.1.16: Change in Task Inputs (Simple Difference) and PC Use

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	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 deŽnitions and examples of task variables.

Table A.1.17: Change in Task Inputs and PC Use by Education: College Only

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
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	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.

Table A.1.18: Change in Task Inputs and PC Use by Education: Non-College Only

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
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 deŽnitions and examples of task variables.

A.2 Data Appendix

A.2.1 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).

A.2.2 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.

A.2.3 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.

A.2.4 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.

A.3 DATA APPENDIX 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]. $Y = \exp[\int_0^1 \ln y(i) di]$. 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 $\hat{I}_H$.

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

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.[47]

[47] 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.

Appendix B

A Tale of Many Cities: The Effect of Computerization on the Change in Gender Wage Gap across Cities

B.1 Figures and Tables

Figure B.4.1: Change in Relative Female PC Adoption by MSA, 1980-2000

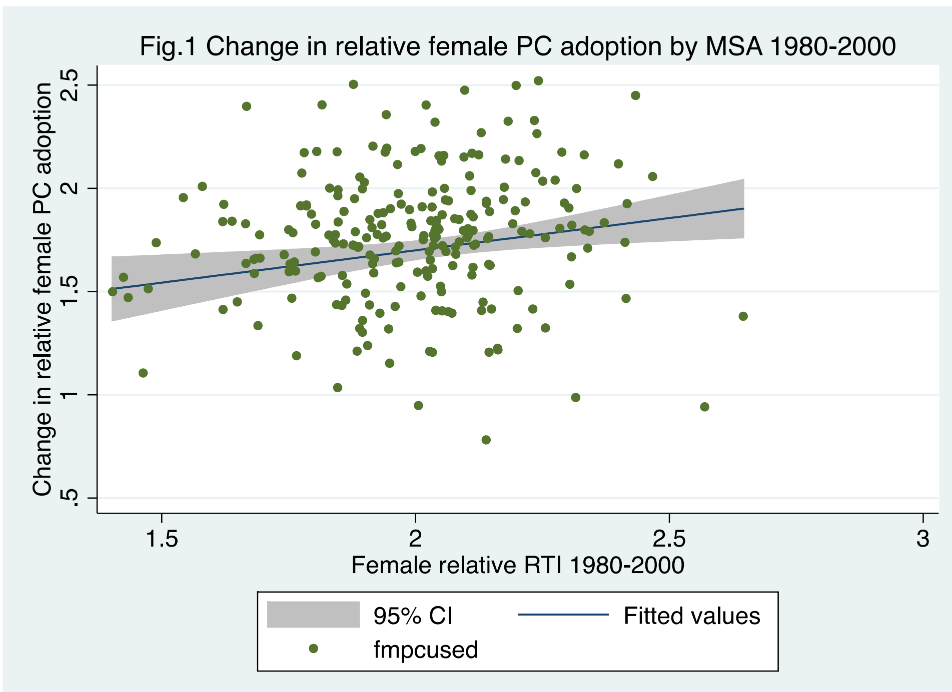


Figure B.1.5: Change in Gender Wage Gap by MSA, 1980-2000

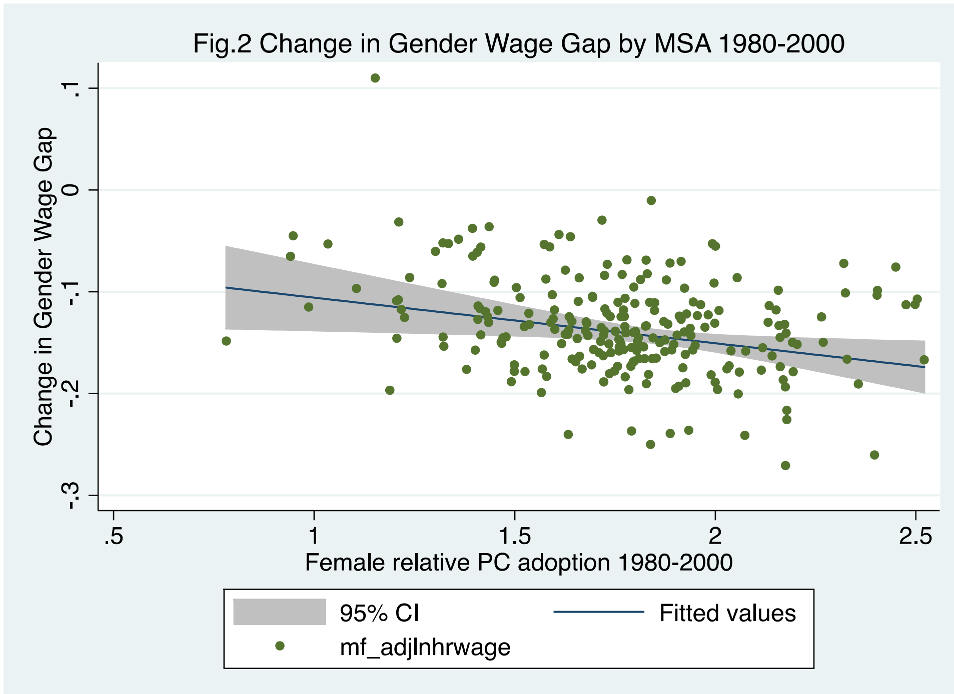


Fig.2 Change in Gender Wage Gap by MSA 1980-2000
Change in Gender Wage Gap
.1
0
-.1
-.2
-.3
.5
1
1.5
2
2.5
Female relative PC adoption 1980-2000
95% CI
Fitted values
mf_adjlnhrwage

Figure B.1.6: Change in Gender Wage Gap by MSA, 1980-2000

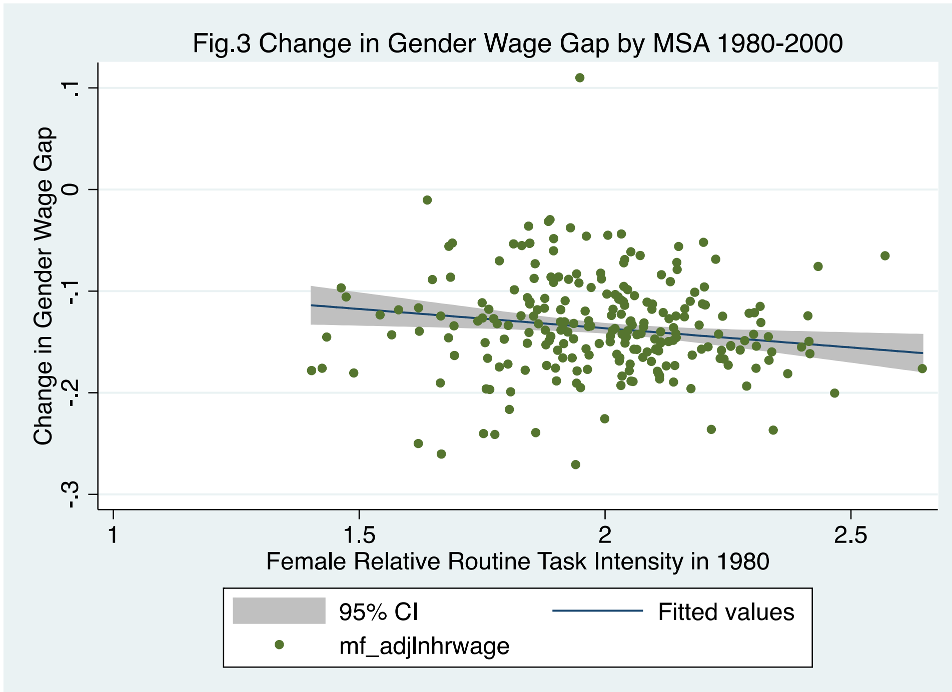


Table B.1.19: Change in Adjusted Male-Female Wage Gap vs MSA Level PC Adoption across MSAs 1980-2000

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A. OLS: the effect of MSA level PC adoption on change in adjusted gender wage gap, 1980-2000. (N=237)									
PC 2000	0.001	-0.003	-0.015***	-0.007*	-0.001	-0.007*	-0.003	-0.004	-0.001
	(0.003)	(0.004)	(0.005)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
R-squared	0.001	0.109	0.181	0.193	0.165	0.187	0.359	0.366	0.528
B. 2SLS: the effect of MSA level PC adoption on change in adjusted gender wage gap,1980-2000. (N=237)									
PC 2000	0.007	0.007	0.006	0.000	0.010	0.002	0.007	0.004	0.001
	(0.009)	(0.009)	(0.013)	(0.011)	(0.008)	(0.011)	(0.013)	(0.010)	(0.012)
R-squared		0.055	0.061	0.164	0.097	0.150	0.340	0.351	0.527
C. First stage: MSA level RTI in 1980 vs. PC adoption over 1980 and 2000. (N=237)									
RTI 1980	0.414***	0.335***	0.217***	0.285***	0.323***	0.291***	0.222***	0.267***	0.351***
	(0.067)	(0.088)	(0.060)	(0.093)	(0.091)	(0.093)	(0.059)	(0.057)	(0.096)
R-squared	0.186	0.424	0.726	0.464	0.436	0.464	0.793	0.774	0.647
city char	N	Y	Y	Y	Y	Y	Y	Y	Y
skills share	N	N	Y	N	N	N	Y	N	N
f empt 1980	N	N	N	Y	N	N	Y	N	N
f-m skills share	N	N	N	N	Y	N	N	Y	N
f-m empt 1980	N	N	N	N	N	Y	N	Y	N
educ share 1980	N	N	N	N	N	N	Y	Y	N
state effect	N	N	N	N	N	N	N	N	Y

*Notes:*The unit of observation is at city level. Main explanatory variable is the male-female difference in initial RTI in 1980. Dependent variable in column 1 is the male-female difference in PC adoption rate in 2000, and male-female difference in the change of abstract,routine and manual task inputs respectively in column 2,3 and 4. All regressions control for city level characterisitcs. In column 1, both PC measure and m-f diff in RTI 1980 are in logs. In column 2 to 4, all measures are standardized. *** p<0.01, ** p<0.05, * p<0.1

Table B.1.20: Change in Task Inputs vs PC Adoption in gender-MSA unit (N=474)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: Change in abstract inputs 1980-2000						
PC	0.445***	0.472***	0.521***	0.464***	0.494***	0.461***	0.536***
	(0.072)	(0.068)	(0.063)	(0.068)	(0.064)	(0.065)	(0.063)
PC*female	0.011	0.025	0.031	0.023	0.028	0.022	0.077
	(0.051)	(0.054)	(0.059)	(0.093)	(0.054)	(0.055)	(0.054)
R-squared	0.785	0.810	0.812	0.811	0.819	0.811	0.887
	Panel B: Change in routine inputs 1980-2000						
PC	-0.187***	-0.133**	-0.142**	-0.178***	-0.124*	-0.175***	-0.031
	(0.057)	(0.064)	(0.065)	(0.060)	(0.066)	(0.062)	(0.040)
PC*female	-0.348***	-0.342***	-0.344***	-0.351***	-0.341***	-0.351***	-0.359***
	(0.068)	(0.068)	(0.070)	(0.078)	(0.069)	(0.070)	(0.074)
R-squared	0.865	0.882	0.882	0.889	0.883	0.888	0.922
	Panel C: Change in manual inputs 1980-2000						
PC	-0.121***	-0.125***	-0.181***	-0.115***	-0.131***	-0.114***	-0.180***
	(0.035)	(0.034)	(0.031)	(0.034)	(0.034)	(0.034)	(0.029)
PC*female	0.192***	0.196***	0.189***	0.198***	0.195***	0.199***	0.186***
	(0.033)	(0.034)	(0.035)	(0.042)	(0.034)	(0.034)	(0.040)
R-squared	0.175	0.217	0.234	0.224	0.222	0.227	0.432
city char	N	Y	Y	Y	Y	Y	Y
skills share	N	N	Y	N	N	N	N
f empt 1980	N	N	N	Y	N	N	N
f-m skills share	N	N	N	N	Y	N	N
f-m empt 1980	N	N	N	N	N	Y	N
state dummies	N	N	N	N	N	N	Y

Note: The data sources are 1980 and 2000 Census, DOT and CPS Computer and Internet Use. See the note of Table2 and 3 for details about PCuse and task construction. The unit of observation is gender-MSA.The main explanatory variables for Panel A-C are the standardized PC use in 1997, as a proxy for the increase in PC adoption over 1980 and 2000. The dependent variables for Panel A,B and C are the change in task inputs between 1980 and 2000 for abstract, routine and manual respectively. "city char" includes MSA level employment rate, log of labor force participation, share of black, Hispanic and foreign born. "skills share"is the initial MSA level skills share, which is the log ratio of college to high school equivalent workers in 1980. "f empt 1980" is female employment rate in 1980. "f-m skills share" is the female-male difference in initial skills share in 1980 and "f-m empt 1980" is thefemale-male difference in employment rate in 1980. "state effect" includes state dummies. *** p<0.01, ** p<0.05, * p<0.1

Table B.1.21: Change in task inputs 1980-2000, vs 1980 Routine Task Intensity in gender-MSA unit (N=474)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: Change in abstract inputs 1980-2000						
RTI	0.662***	0.487**	0.476**	0.526**	0.496**	0.506**	0.144
	(0.224)	(0.226)	(0.218)	(0.231)	(0.228)	(0.228)	(0.215)
RTI*female	0.079	-0.024	-0.157	0.029	0.045	0.043	0.299*
	(0.252)	(0.232)	(0.215)	(0.267)	(0.215)	(0.210)	(0.151)
R-squared	0.676	0.715	0.753	0.730	0.718	0.731	0.799
	Panel B: Change in routine inputs 1980-2000						
RTI	-0.591***	-0.571***	-0.565***	-0.562***	-0.569***	-0.567***	-0.210
	(0.175)	(0.206)	(0.207)	(0.194)	(0.206)	(0.205)	(0.280)
RTI*female	-1.216***	-1.024***	-0.957***	-1.012***	-1.011***	-1.011***	-1.155***
	(0.213)	(0.240)	(0.247)	(0.234)	(0.235)	(0.240)	(0.319)
R-squared	0.869	0.891	0.896	0.891	0.891	0.891	0.925
	Panel C: Change in manual inputs 1980-2000						
RTI	0.449***	0.477***	0.477***	0.470***	0.477***	0.473***	0.703***
	(0.103)	(0.112)	(0.112)	(0.115)	(0.113)	(0.112)	(0.109)
RTI*female	-0.057	-0.020	-0.021	-0.029	-0.020	-0.034	-0.135
	(0.110)	(0.107)	(0.109)	(0.129)	(0.101)	(0.107)	(0.122)
R-squared	0.200	0.240	0.240	0.245	0.240	0.248	0.447
city char	N	Y	Y	Y	Y	Y	Y
skills share	N	N	Y	N	N	N	Y
f empt 1980	N	N	N	Y	N	N	Y
f-m skills share	N	N	N	N	Y	N	N
f-m empt 1980	N	N	N	N	N	Y	N
state dummies	N	N	N	N	N	N	Y

Note: The data sources are 1980 and 2000 Census, DOT and CPS Computer and Internet Use. See the note of Table2 and 3 for details about routine task intensity (RTI) and task construction. The unit of observation is gender-MSA.The main explanatory variables for Panel A-C are the standardized routine task intensity. The dependent variables for Panel A,B and C are the change in task inputs between 1980 and 2000 for abstract, routine and manual respectively. "city char" includes MSA level employment rate, log of labor force participation, share of black, Hispanic and foreign born. "skills share"is the initial MSA level skills share, which is the log ratio of college to high school equivalent workers in 1980. "f empt 1980" is female employment rate in 1980. "f-m skills share" is the female-male difference in initial skills share in 1980 and "f-m empt 1980" is thefemale-male difference in employment rate in 1980. "state effect" includes state dummies. *** p<0.01, ** p<0.05, * p<0.1

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