Explaining Women's Success: Technological Change and the Skill Content of Women's Work

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Abstract

Although it is clear that women have fared well relative to men with respect to their labor market outcomes in recent decades, it is less clear what the sources are for this favorable development. In this paper, we adopt a task-based view of technological change and examine how the proliferation of computers in the 1980s and 1990s has affected women's tasks relative to those of men. Using data from West Germany, we find that women have witnessed large relative increases in non-routine analytic tasks and non-routine interactive tasks between 1979 and 1999. The most notable difference between the genders is, however, the pronounced decline in routine task inputs among women with almost no change in routine task input for men. Consistent with the skill-biased technological change hypothesis, task changes were most pronounced *within* occupations, whereas only minor parts of the aggregate trends are attributable to women moving towards more skill intensive occupations. In addition, the task changes are occurring most rapidly in occupations in which computers have made major headway. Overall – and in contrast to recent literature that puts a strong emphasis on only one dimension of activities on the job, namely interactive tasks – we show that changes in job content has evolved differently for men and women on several dimensions.

I. Introduction

Although it is clear that women have fared well relative to men with respect to their labor market outcomes in recent decades, it is less clear what the sources are for this favorable development. While there is much recent research on the role of changing characteristics, such as education and experience, a substantial portion of the improvement in women's labor market opportunities remained unexplained.[1] One reason for this lack of knowledge is that empirical research has been limited in its ability to directly compare women's work to that of men.

In this study, we use direct measures of job tasks to give a comprehensive characterization of how work for men and women has changed in recent decades and how these changes in skill requirements are related to the introduction of computers in the workplace – one of the potential sources of these changes. The empirical methodology is based on the task-based framework introduced by Autor, Levy and Murnane (2003), which provides an intuitive model of the relationship between computerization and workers' tasks. In this model, the work performed in an occupation is broken down into a series of tasks, each of which can be characterized based on its substitutability or complementarity with computers. Within this framework, it becomes predictable how each occupation is likely to be affected by the introduction of computers.

Using a unique, survey-based data set from West Germany, we are able to measure skill requirements directly by using the task composition of occupations; that is, survey participants indicated the activities they perform on the job. Occupational skill requirements are characterized by five categories of tasks: non-routine analytic, non-routine interactive, routine cognitive, routine manual and non-routine manual.

[1] For a comprehensive review, see work by Blau and Kahn (1997, 2003, 2004).

We find that women have witnessed large increases in non-routine analytical and non-routine interactive task inputs relative to men. The most notable difference between the genders in task changes is, however, the strong decline in routine tasks experience by women and almost not at all by men. Consistent with the skill-biased technological change hypothesis, task changes were most pronounced *within* occupations, whereas only minor parts of the aggregate trends are attributable to women moving towards more skill intensive occupations. In addition, the task changes occurred most rapidly in occupations in which computers have made major headway. Overall – and in contrast to recent literature that puts a strong emphasis on only one dimension of activities on the job, namely interactive tasks – we show that changes in job content has evolved differently for men and women along several dimensions.[2] The extent of changes at each task category has been much larger for women than for men.

Another prediction of the task framework is that we should observe a "polarization" of employment as a result of computerization. In this framework, computers are a complement to the analytical and interactive tasks that are most often used by high skilled workers, computers are substitutes for routine tasks that are most often performed by medium educated workers, and they have no predictable effect for non-routine manual skills most often used by the lowest skilled workers. As a result, we should see the largest effect on middle-education workers who are most likely to be engaged in routine manual and routine cognitive skills. We find evidence of this polarization for both women and men. Interestingly and in line with the task changes that we observe for the two genders, the polarization tendency in the labor market has been larger for women than for men.

[2] See, for example, Borghans, ter Weel and Weinberg, 2006, and Weinberg, 2000.

The paper unfolds as follows. Section 2 reviews the relevant literature, Section 3 presents the data set, and Section 4 presents descriptive statistics and decomposes the changes over time. Section 5 related the changes we observe to changes in technology. Section 6 compares our results to those in the literature, and Section 7 concludes.

II. Related Literature

In an effort to better understand the link between technological changes and labor demand, the recent literature has adopted a task-based view of technological change (see Autor, Levy and Murnane, hereafter ALM, 2003).[3] The major feature of this framework is that it conceptualizes work as a series of tasks and classifies tasks into *routine* and *non-routine* activities, with the terms *routine* and *non-routine* characterizing the relationship between the respective task measure and computer technology. Both manual and cognitive routine tasks are well-defined in the sense that they are easily programmable and can be performed by computers at economically feasible costs – a feature that makes routine tasks amenable to substitution by computer capital (Levy and Murnane, 1996). Non-routine tasks, in contrast, are not well defined and programmable and, as things currently stand, cannot be easily accomplished by computers. However, computer capital is complementary to both analytical and interactive non-routine cognitive tasks in the sense that computer technology increases the productivity of employees performing these tasks.

This task-framework is applied in ALM and in recent work by Spitz-Oener (2006), both of whom document the relationship between computer adoption and changing tasks on the aggregate level and, in the case of ALM, within industry using U.S. data

[3] For a review of earlier studies in this body of the literature see Chennells and Van Reenen (1999), Katz and Autor (1999), and Acemoglu (2002).

and, in the case of Spitz-Oener, within occupations using West German data. As predicted, the evidence suggests that tasks have shifted from routine manual and routine cognitive tasks towards analytic and interactive non-routine tasks at all levels of aggregation in recent decades. However, to date, the task-based framework has never been used to analyze how job content has changed for women relative to men.

Nevertheless, there are a number of recent studies that examine the relationship between computer adoption and gender. Weinberg (2000), for example, shows how computerization, by de-emphasizing physical skills, has benefited women's employment relative to that of men. He does so by relating the change in women's share of hours worked to the change in computer use at the occupation and industry level. However, he is not able to describe how work has actually changed due to the absence of direct task measures.

Bacolod and Blum (2006) use data from the United States to examine gender differences in task inputs and to estimate task prices using direct task measures. However, owing to the choice of task categories, a key limitation of this work is its inability to relate the changes in task prices to computerization.[4] In addition, data limitations prevent them from looking at changes in tasks within occupations, which we find to be the primary factor in explaining changes in the tasks performed by women relative to men.[5]

[4] In particular, their choice of cognitive skills comprises both routine and non-routine cognitive tasks. Given that, based on the task framework, computers are predicted to have a negative impact on prices of routine cognitive tasks and a positive impact on non-routine cognitive tasks, it is not clear what kind of price changes one should expect for the composite classification.

[5] Bacolod and Blum use the Dictionary of Occupational Titles (DOT) dataset for their analysis. See Spenner (1983) and references cited there for a detailed criticism of the DOT. In the context of this study, the most important points are that the process in which experts evaluate occupations encourages them to underestimate the true changes in job content, and that occupational titles in the DOT are not consistent over time.

Finally, the most closely related paper to our own is recent work by Borghans, ter Weel, and Weinberg (2006), that focuses on interactive, or people skills. Using data from Britain, West Germany and the United States, they find that people skills have become more important in recent decades; in addition, the relative employment of women is high in occupations in which people tasks are more important.[6] Their results suggest that the increased importance of people skills is related to changes in computerization and work-place organization and might help to explain the closing of the gender gap in recent decades. However, by limiting the focus to interpersonal skills, the authors are, in some sense, missing the bigger picture. We focus on a broader spectrum of tasks, including analytic, interpersonal, routine cognitive, routine manual, and non-routine manual. Importantly, we find that, for women relative to men, the increase in the use of interpersonal skills is not nearly as large as the decline in cognitive and manual routine skills.

III. Data

The data we use are based on the "Qualification and Career Survey", an employee survey carried out by the German Federal Institute for Vocational Training (``Bundesinstitut fur Berufsbildung, BIBB") and the Research Institute of the Federal Employment Service (``Institut fur Arbeitsmarkt- und Berufsforschung, IAB"). It includes four cross-sections launched in 1979, 1986, 1992 and 1999, each covering about 30,000 individuals, both men and women.[7]

This data set is particularly well-suited to analyze changes in skill requirements within occupations for a number of reasons. Unlike the Dictionary of Occupational Titles (DOT) data set for the United States — the data set often used by researchers for ques-

[6] For the analyses concerning West Germany, they use the same data as this study.
[7] For details on the data set see Spitz-Oener (2006). We drop occupations that do not exist in all years, which accounts for .0025, or ¼ of 1 percent, of the sample.

tions related to skills — these data are categorized using a consistent set of occupational classifications; the constant occupational titles thus provide the reference point for the analysis. Another major improvement over previous data is that survey respondents indicated themselves what kind of activities they perform on the job. It is very unlikely that this causes an underestimation of true changes in job content. In the DOT, experts assign scores to different indicators characterizing the occupations. It is well known that this process encourages analysts to underestimate the true changes in job content. Moreover, occupational titles in the DOT are not consistent over time (for detailed criticisms see Spenner, 1983, and references cited therein).[8]

Occupational skill requirements are based on the activities that employees have to perform at the workplace. We pool these activities into five task categories. They are: non-routine analytical tasks, non-routine interactive tasks, routine cognitive tasks, routine manual tasks, and non-routine manual tasks. Table 1 illustrates the assignment of activities to the five categories.[9]

For individual i, the task measures (T_{ijt}) are defined as:

$$T_{ijt} = \frac{\text{number of activities in category j performed by individual i in time t}}{\text{total number of activities in category j in time t}} \text{ x } 100,$$

where t=1979, 1986, 1992 and 1999; and j represents the task group, including non-routine analytic tasks, non-routine interactive tasks, routine cognitive tasks, routine manual tasks, and non-routine manual tasks. For example, if individual i indicates that she

[8] The credibility of the analysis in the present study would be impaired if the answers provided by male and female survey participants were systematically biased toward certain categories of tasks. This is unlikely as survey participants only indicate whether they perform certain activities or not and do not assign scores to the different measures. In addition, most of the analysis is performed in first-differences; the reporting bias therefore would only pose a problem if it changed over time.

[9] The data set does not include information about the time spent on different activities. In addition, while most questions remained the same over time, there were some changes in questions concerning the activities employees perform at the workplace. For consistency, we reduced the activities in each category to those that are comparable over time.

performs two interactive tasks and the category includes four tasks in total, then her interactive task measure is 50.

The data set also includes detailed information on the tools and machines used by the employees at the workplace. Our measure of computer use is a variable indicating whether the employees uses any of the following on the job: computers, terminals, and electronic data processing machines.

Employees are classified based on their vocational education:[10] (1) People with low levels of education, that is, people with no occupational training; (2) people with a medium level of education, that is, people with a vocational qualification who might have either completed an apprenticeship or graduated from a vocational college and (3) people with a high level of education, that is, people holding a degree from a university or technical college.

While we are using data from West Germany, there is no reason to believe that technology adoption was different in West Germany relative to other countries. However, to examine this, we also present a number of specifications that will allow us to compare our results to those of earlier work using United States data. These comparisons suggest that the patterns we observe in West Germany are not unique to that country.

IV. Patterns over Time

The labor markets of industrialized countries have experienced a considerable educational upgrading in recent decades. Recently, researchers have noticed that the educational upgrading has gone hand in hand with a considerable increase in occupational skill

[10] School qualifications are not considered, that is, it is not important which of the three different school streams (Hauptschule, Realschule or Gymnasium) an individual attended.

requirements (see ALM, 2003, and Spitz-Oener, 2006).[11] Figure 1 shows the aggregate evolution of task inputs over 1979-1999, for both men and women in West Germany.[12] The analytical task measure grew, on average, by 0.5 percentage points between 1979 and 1999, and the interactive task measure by 1.3 percentage points. In contrast, the requirements for routine cognitive and routine manual skills decreased during that period, with an average annual decline of 0.7 percentage points each. The trend in the requirements for non-routine manual skills is less clear. The overall period, however, suggests an increase of around 0.6 percentage points annually.

Pooling the information for both genders masks considerable differences between men and women, however. Table 2 compares the tasks performed by men and women in 1979 and 1999 and shows how differently they have evolved. It is striking that all the changes in task inputs have been larger for women than for men. In the earliest period, men's analytical task inputs were more than twice as high as those for women, while women had higher routine cognitive and routine manual task inputs (see Table 1, Columns 1 and 3).[13] However, by 1999, many of these patterns have reversed. Women appear to be catching up to men in terms of analytic skills and have surpassed them in the use of interactive skills. For routine cognitive and routine manual skills, where women had dominated 20 years earlier, men have taken over. In contrast, non-routine manual skills, which were used primarily by men in 1979, have a larger importance in women's work relative to that of men in 1999.

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[11] We will use the terms skill/task inputs and skill/task requirements interchangeably throughout the article, although strictly speaking, the correct term is skill/task inputs. In order to speak of skill requirements or demand, we would need information about task prices.
[12] This figure is from Spitz-Oener (2006, p.246). For a similar figure for the United States, see ALM (2003, p.1296).
[13] Results are presented for full-time workers only. See Appendix Table 1 for a similar breakdown for all workers.

The proliferation of computers has also evolved differently for men and women. They were both equally likely to use computers in 1979, with diffusion of about 6 percent. By 1999, women (60 percent) were slightly more likely to use a computer on the job than men (56 percent).

These patterns are very similar across education groups. Table 3 shows the results for each education group separately. Within each group, women have experienced large relative increases in analytical task inputs. For low- and medium-educated employees the differences in analytical skill requirements between the genders has more or less completely disappeared by 1999. Similar to the aggregate picture, low- and medium-educated women have overtaken low- and medium-educated men in terms of interactive task inputs by 1999, while for high-educated employees the difference in interactive task inputs is quite small. Women have witnessed large relative decreases in routine tasks — both cognitive and manual — at all education levels, and large relative increases in non-routine manual task inputs.

One concern about looking at these figures is unobserved heterogeneity; we know, for example, that in more recent cohorts girls performed better than boys in school, and it could be that the patterns we are observing are due to cohort effects. To examine this, we look at the evolution of tasks within cohorts (see Appendix Tables 2 and 3). Interestingly, cohort effects do not appear to play a role in explaining task changes within each gender nor in explaining task changes for women relative to men.

Workplace computerization has evolved differently across education groups. For employees with low and medium levels of education, computer use rates among men and women were quite similar in 1979. By 1999, however, women were more likely to use computers on the job. This pattern was particularly pronounced for employees with a medium level of education. Among highly-educated employees, men were always more likely to work with computers.[14] The difference in computer use rates was even larger in 1999 than in 1979.

These gender-specific changes in tasks over time can be broken into two components: (1), changes in the occupational distribution of men and women and, (2), changes in the task composition of occupations. In an effort to understand the causes of the patterns we observe, we decompose the changes in the difference between men and women into those that are due to changes in the employment of men and women between occupations (how much of the difference can be explained by differential shifts in employment across occupations) and those that are due to differential changes in task inputs within occupations (how much of the difference can be explained by the fact that woman and men experience different task changes within occupations).

Formally, the change in the gender gap in tasks can be decomposed as follows:

$$\underbrace{(\bar{Y}_M - \bar{Y}_F)_{99} - (\bar{Y}_M - \bar{Y}_F)_{79}}_{(1)} = \underbrace{\sum_j \alpha_{M99j}(\bar{Y}_{M99j} - \bar{Y}_{M79j})}_{(2)} - \underbrace{\sum_j \alpha_{F99j}(\bar{Y}_{F99j} - \bar{Y}_{F79j})}_{(3)}$$
$$+ \underbrace{\sum_j \bar{Y}_{M79j}(\alpha_{M99j} - \alpha_{M79j})}_{(4)} - \underbrace{\sum_j \bar{Y}_{F79j}(\alpha_{F99j} - \alpha_{F79j})}_{(5)}$$

where $\bar{Y}_{gtj}$ is the average value of the skills for gender g at time t in occupation j and α_{gtj} is the proportion of gender g employed in occupation j at time t. Terms (2) and (3) represent the fraction of the total change in the gender gap in a particular task that can be attributed to changes within occupations, with the first and second terms representing

[14] One observes the same pattern in the United States.

within occupation task changes for men and women respectively – holding gender-specific occupational employment shares constant at 1999 levels. The fourth and fifth term represent the fraction of the total change in the differences that can be attributed to changes in the gender-specific employment composition of occupations – holding gender-specific task inputs constant at 1979 levels. The fourth term captures the portion that can be attributed to the changing occupational employment share of men and the final term refers to the portion that can be attributed to the changing occupational employment share of women.

Table 4 presents the results of this decomposition. Column 1 shows the total change in the difference in task inputs of men and women. Columns (2) and (3) show the within occupation task changes by gender, and columns (4) and (5) show the changes in task inputs for men and women that are due to changes in the occupational distribution of employment. For each task category, the first row presents the results for all education groups together, and the next three rows show the results for each of the three education groups separately. From looking down the columns, it is clear that the largest portions of the changes are coming from within occupation task changes, which is consistent with the idea of biased technological change altering the task composition of jobs. Interestingly, for all task categories and all education groups, within occupational task changes have been larger for women than for men.

The total change in the difference in analytical tasks inputs is not particularly large, partly because the differences weren't large to begin with. There have been large increases in the use of analytic skills for both men and women between 1979 and 1999, with very little change due to changing occupational structure. The small decline in the gender gap in analytical tasks is due to the fact that within occupational changes in analytical tasks have been larger for women than for men. This overall pattern also applies to each education group separately. It is interesting to note, however, that we observe the largest reductions in the gender gap in analytical tasks for employees with medium and low levels of education.

The same is true for interactive skills, although the magnitude of the decline in the gender gap in interactive tasks is larger than for the analytical task category. Again, the primary source of the overall increase in the task measure is the large increases in the use of interpersonal tasks within occupations for both men and women; and again, the decline in the gender task gap is due to the large relative within occupational increases in interactive tasks for low and medium educated women.

Once we turn to the routine tasks, a different pattern emerges. For both cognitive and manual routine tasks, the gender task gap has increased considerably, although the use of these tasks has in fact declined for both genders. Similar to the non-routine cognitive task categories, the changes have been most pronounced within occupations and the changes have been much larger for women than for men. The large increase in the task difference results from the fact that women had larger values of routine tasks in 1979, whereas by 1999 this pattern had reversed and it was the men who had the highest values in the routine tasks. The only exception is the routine cognitive tasks category for highly educated workers; highly educated men had higher routine cognitive task inputs than women in both 1979 and 1999. For this group, the gender gap in routine cognitive tasks declined slightly over the time period.

The gender gap in the non-routine manual task category experienced the largest decline between 1979 and 1999. Again, task changes within occupations account for the largest part of the change. The decline in the gap is a result of a considerable increase in non-routine manual activities within occupations for women, with a corresponding decline in this task category for men. This pattern has occurred particularly for employees with medium levels of education. For highly educated employees, non-routine manual task inputs have increased within occupations for both genders; whereas for low educated employees, non-routine manual task inputs have decreased for both genders.

Overall, this decomposition suggests that task changes have occurred primarily within occupations, which is consistent with the idea that technological developments are a major cause for the changing skill patterns we observe. In addition, it is often the case that women are experiencing large changes relative to men.

V. Technological Change

The task framework makes two specific predictions about which occupations will adopt computers most rapidly as computer prices declined: (1) occupations intensive in cognitive and manual routine tasks, for which computers are direct substitutes; (2) occupation intensive in non-routine cognitive tasks, for which computers are relative complements to labor. As men and women had very different occupational skill requirements in 1979, these predictions are important in the context of this study. In order to test these predictions, we fit the following model:

$$\Delta C_{j,1979-1986} = \alpha + \beta T_{j,1979} + \varepsilon_j \ ,$$

where $\Delta C_{j,1979-1986}$ is the percentage point change in the share of employees using a computer in occupation j between 1979 and 1986, $T_{j,1979}$ is the measure of task intensity in occupation j in 1979 and ε_j is an error term.

Table 5 shows the results. The more intensive an occupation was in terms of cognitive and manual routine task in 1979, the faster was the growth in computerization between 1979 and 1986. This was also the case for non-routine cognitive tasks. In contrast, occupations intensive in non-routine manual tasks computerized significantly less than others. Thus, given the different task contents of jobs of men and women in the late-1970s, we would expect computers to alter women's work relatively more than that of men – an idea that we can test directly. So we next turn to examine the effect of computer adoption on task inputs, allowing the effect to vary by gender. In this case, we estimate the following specification:

$$\begin{aligned} T_{ijt} &= \beta_0 + \beta_1 C_{ijt} + \beta_2 F_i + \beta_3 Y_{1999} + \beta_4 (C_{ijt} * F_i) + \beta_5 (C_{ijt} * Y_{1999}) \\ &\quad + \beta_6 (F_i * Y_{1999}) + \beta_7 (C_{ijt} * F_i * Y_{1999}) + \beta_8 X_{ijt} + \varepsilon_j \end{aligned}$$

where, again, T_{ijt} is the task measure for individual i in occupation j at time t, C_{ijt} is an indicator of computer use by individual i in occupation j at time t, F_i indicates whether the individual is female, Y_{1999} is an indicator if the year is 1999, and X_{ijt} is a vector of other controls, including education, industry, and occupation. β_5 describes how the relationship between computers and the task measure has changed between 1979 and 1999, and β_7 describes whether this relationship has changed differently for women relative to men. The task framework suggests that we should see a positive relationship between computerization and non-routine cognitive skills (analytic and interactive) but a negative relationship between computerization and routine skills (manual and cognitive). The specifications that include occupation dummies test the relationship between changes in computer use and changes in task inputs within occupations.

Tables 6A-6E show the results for each task category separately. As before, we restrict the analysis to the overall period, 1979-1999, so the regressions are based on the pooled 1979- and 1999-waves. The dependent variables are the respective task measures in 1979 and 1999.

Table 6A presents the results for analytic skills. Column 1 presents the most basic specification, with only the controls listed in the table. We can see from the interaction of PC and 1999 that increasing computer use is associated with an increase in analytical tasks. This patterns is true with no controls (column 1), with education controls (column 2), with education and occupation controls (column 3), and with gender-specific education and occupation controls (column 4). In addition, we can see from the coefficient on PC*1999*Female that the computerization effect is stronger for women than men (the coefficient represents the *difference* in the effect for women relative to men). This is true even with the occupational controls. A possible explanation for this larger effect of computer use on women's tasks even within occupations is that women started out with higher levels ex ante and so, even within occupations, there is more room for computers to affect skills.[15]

Columns (5)-(7) of Table 6A then present the results separately by education group. In this case, we see little effect of computerization on analytic skills of low-educated males but a significantly positive effect for low-educated women. We see posi-

[15] In order to examine this further, we break our occupations into 10 deciles based on the distribution individual tasks (we do this each for analytical, interactive, routine-manual, routine-cognitive, and non-routine manual). When we allow the effects to vary by decile of this distribution, we find that the effects of computerization are the same for men and women, suggesting that it is the relative starting point that allows for differential effects for men and women.

tive effects of computerization among middle educated men and women, though the effect is larger for women, and we see a negative relationship between analytical skills and computerization among high educated males (which is not statistically different from the effect for women). Overall, however, the results are in line with the hypothesis that computers are relative complements to non-routine analytic task inputs.

The results for the interactive task category are shown in Table 6B. As with the analytical task category, computer adoption is associated with an increase in interactive skills. Importantly, the effect is much stronger for men relative to women. This is the case for all specifications. This is an interesting finding, given the recent literature focusing on interactive skills as an explanation for the recent declines in the gender wage gap. The overall results suggest that computers are relative complements to non-routine interactive task inputs, particularly among men.

In the case of routine skills, we predict a negative change between computerization and task inputs. Table 6C shows the results for the routine cognitive task category. Female computer users and male computer users have experienced similar declines in routine cognitive task inputs, though women have slightly smaller declines (marginally statistically significant). Again, the results are robust to the inclusion of the additional controls in column (2)-(4). It is interesting to note, however, that relative decreases in routine cognitive task inputs for female computer users were large among low educated employees (column 5). The results do suggest that there is a substitutive relationship between computers and routine cognitive activities.

Table 6D shows the results for the routine manual task category. As expected computer adoption is associated with a decline in the use of routine manual skills, and this relationship is similar for men and women. This result again is robust to the successive inclusion of education dummies (column 2), of occupation dummies (column 3) and of interactions of the education and occupation dummies with the female dummy. When looking at the different education group, it is interesting to note that, among low-educated individuals, there is no relationship between computer adoption and routine manual skills for men but a very large and significant effect for women. Among the highly educated, in contrast, we see a positive relationship between routine manual skills and computer adoption, and this is the same for both men and women. Overall, the results confirm the hypothesis that computers and routine manual task inputs are substitutes.

Based on the task framework, we do not have testable hypotheses about the relationship between computers and non-routine manual activities. However, as the relationship might still be interesting, Table 6E presents the results for this task category. We see that computer adoption is associated with significantly more non-routine manual tasks among men; however, this effect is much smaller among women. This holds true even with gender-specific education and occupation dummies. It is interesting to note that, among low-educated workers, the effect of computerization is large and positive for both men and women; it is among the middle-educated workers that we observe the significant differences for men and women.

VI. Polarization

There is one dimension in which the task-based framework diverges from the traditional skill-biased technological change hypothesis: in its prediction about who is most affected by technological change. The traditional skill-biased technological change hypothesis predicts an increased demand for skilled jobs relative to unskilled jobs. The task-based framework presents a more nuanced view of this (see Goos and Manning, 2006, and Spitz-Oener, 2006). The argument is that it is jobs that employ middle education workers that are going to be most affected by computerization, which will lead to a hollowing-out of the distribution of jobs by skill. Computerization substitutes for routine cognitive tasks, which affects mainly employees with medium levels of education such as book-keepers and bank clerks. Non-routine manual tasks, in contrast, that at present cannot be accomplished by computers, are often found in occupations held by employees with low levels of education, such as waiters are cleaning staff. As a result, one would expect to see a polarization of employment into tasks originally performed by the lowest and highest skilled workers as a result of computerization.

Given the large relative decreases in routine tasks inputs and the large relative increases in non-routine manual activities experienced by women, we suspect that the polarization pressure in the labor market was larger for women than for men in the last three decades. We explore this by first constructing a scalar index of occupational education requirements; occupations are then classified based on their demand for education in the initial period. In order to calculate this skill index, we run the following regression:

$$E_c = \alpha_0 + \sum_{j=1}^{5} S_{jc}\alpha_j + v_c,$$

with c indicating the occupation, E_c being the fraction of highly educated in occupation c, and j indicating the task categories (j=1: non-routine analytic; j=2: non-routine interactive; j=3: routine cognitive; j=4: routine manual; j=5: non-routine manual) . The term S_{jc} is the measure of task j in occupation c. The estimated α_j coefficients represent an estimate of the relative employment of high education workers as a function of task inputs.

We use these estimated α_j's to construct the skill index which is the predicted value of the previous regression specification:[16]

$$\hat{E}_c = \hat{\alpha}_0 + \sum_{j=1}^{5} S_{jc}\hat{\alpha}_j$$

The skill index is estimated using only the data for 1979, the year that is closest to the pre-computer era. Based on the 1979 value of this skill index, we then classify occupations into 10 groups. The occupations in the first group are in the lowest decile of the skill index and the occupations in the 10th group have a value in the largest decile of the skill index. This classification serves as the baseline occupational distribution.

The question of polarization concerns the evolution of employment across these different occupation groups. Figure 2 shows the employment changes between 1979 and 1999 by occupational skill deciles for men and women separately. The graphs for men and women look quite different; with the "hollowing out" tendency of the labor market being more pronounced for women than for men. While employment of men has grown by 2.9 percentage points and that of women by 2.6 percentage points in the tenth decile of the skill index between 1979 and 1999, the employment growth was much larger for women (5.5 percentage points) than for men (1.3 percentage points) in the ninth decile. The employment growth has also been larger for women than for men in the first decile (0.5 versus 0.2 percentage points). In addition, employment declines in the "middle" occupations has been more pronounced for women, with the largest difference being in the fifth decile in which employment has shrunk for women by 5.5 percentage points and for men by 2.8 percentage points.

[16] Also see ALM, 2003, and Spitz-Oener, 2006, for a detailed discussion of this procedure.

VII. Conclusion

Since the 1970s, women have experienced great improvements in terms of labor market success. However, until recently, the literature has been limited in its ability to determine the role of technological change in this success due to an absence of data on the actual tasks women and men perform at work.

Using survey-based data from West Germany, we are able to measure skill requirements by using the task composition of occupations directly. We then apply the task framework used in Autor, Levy, and Murnane (2003) and Spitz-Oener (2006) to examine the role of computerization on women relative to men. We find that women's jobs are relatively more affected by the introduction of computers. This is not surprising in light of the task framework; women started out using more routine cognitive and routine manual tasks in their jobs, and these are exactly the tasks that are most substitutable for by computers. The largest part of the task changes are occurring within occupations, which again is consistent with the idea of skill-biased technological change.

We also contribute to the recent discussion on polarization that has been triggered by the introduction of the task framework. In line with our observed patterns of relative task changes for women, the findings suggest that the polarization in the labor market has been more pronounced for women than for men.

Our results are particularly interesting in light of recent work focusing solely on interactive, or "people" skills. We show that, although women experienced large relative increases in non-routine interactive tasks and also in non-routine analytic tasks, the most strikingly difference between the genders in changes at the workplace in recent decades is the marked decline in routine tasks experienced by women and almost not at all by men.

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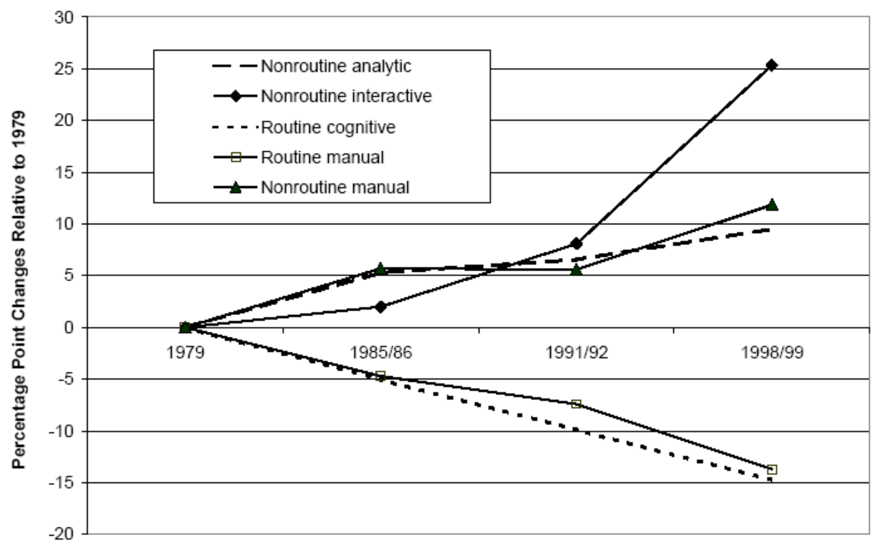

Figure 1: Trends in Aggregate Skill Inputs—West German Men and Women.

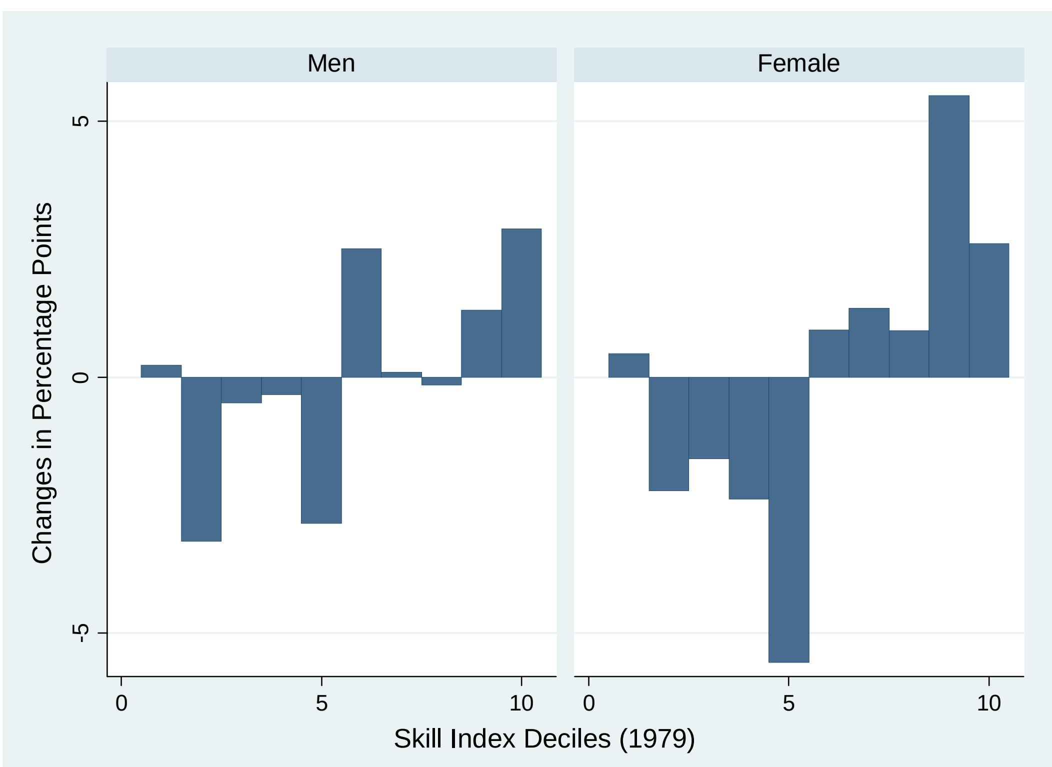

Figure 2: Changes in Employment Shares by Occupational Skill Index Deciles

Table 1: Assignment of Activities

Classification	Tasks
Non-routine analytic	researching/analyzing/evaluating and planning, making plans/constructions/designing and sketching, working out rules/prescriptions, using and interpreting rules
Non-routine interactive	negotiating/lobbying/coordinating/organizing, teaching/training, selling/buying/advising customers/advertising, entertaining/presenting, employ/manage personnel
Routine cognitive	calculating/bookkeeping, correcting of texts/data, measuring of length/weight/temperature
Routine manual	operating/controlling machines, equipping machines
Non-routine manual	repairing/renovation of houses/apartments/machines/vehicles, restoring of art/monuments, serving or accommodating

Table 2: Summary Statistics: Full-Time Workers Only
(Standard Deviations in Parentheses)

	Analytic	Inter-active	Routine Cogni-tive	Routine Manual	Non-Routine Manual	PC Use
Male						
1979	6.9	11.0	42.0	31.4	31.2	.06
(N=15,118)	(14.8)	(14.7)	(43.6)	(40.4)	(40.3)	(.24)
1999	15.3	31.1	33.2	26.1	25.7	.56
(N=11,813)	(23.0)	(28.6)	(46.1)	(34.5)	(24.4)	(.50)
Change 1979-1999	8.4	20.1	-8.8	-5.3	-5.5	.50
Female						
1979	2.8	8.4	51.8	59.9	12.6	.06
(N=6,369)	(9.6)	(11.1)	(46.9)	(44.5)	(28.9)	(.24)
1999	12.7	33.8	12.2	10.6	28.3	.60
(N=6,009)	(20.5)	(25.4)	(31.9)	(24.2)	(23.9)	(.49)
Change 1979-1999	9.9	25.4	-39.6	-49.3	15.7	.54
Difference (Male-Female)						
1979	4.1	2.6	-9.8	-28.5	18.6	0.0
	(.2)	(.2)	(.7)	(.6)	(.5)	(.0)
1999	2.6	-2.7	21.0	15.5	-2.6	-.04
	(.4)	(.4)	(.6)	(.5)	(.4)	(.01)

Table 3: Summary Statistics by Education Group
(Standard Deviations in Parentheses)

	Analytic	Interactive	Routine Cognitive	Routine Manual	Non-Routine Manual	PC Use
			Low Education			
Male						
1979	5.2	6.8	39.1	40.0	25.7	.04
(N=2,553)	(13.2)	(11.4)	(41.7)	(40.0)	(34.4)	(.20)
1999	7.5	14.4	36.3	29.6	18.8	.27
(N=1,093)	(15.3)	(21.7)	(46.0)	(35.1)	(23.1)	(.44)
Female						
1979	2.5	6.5	40.5	50.9	20.7	.03
(N=1,921)	(8.6)	(9.6)	(44.6)	(42.2)	(33.7)	(.18)
1999	7.2	18.6	18.6	28.2	21.6	.30
(N=718)	(14.4)	(22.9)	(38.0)	(31.0)	(23.8)	(.46)
			Middle Education			
Male						
1979	5.7	10.7	41.7	31.3	35.5	.06
	(13.0)	(14.4)	(43.3)	(40.5)	(42.0)	(.23)
(N=11,247)						
1999	12.8	28.4	36.9	29.4	27.9	.51
(N=8,595)	(21.1)	(27.9)	(47.2)	(35.7)	(24.2)	(.50)
Female						
1979	2.2	8.1	58.6	68.1	9.6	.07
(N=4,033)	(8.3)	(11.1)	(46.5)	(43.0)	(26.4)	(.26)
1999	12.3	33.4	12.3	10.6	29.6	.62
(N=4,441)	(19.9)	(24.5)	(32.0)	(24.0)	(23.6)	(.49)
			High Education			
Male						
1979	20.2	21.8	49.9	15.1	4.9	.15
(N=1,318)	(23.6)	(17.0)	(48.7)	(34.9)	(20.9)	(.36)
1999	29.5	50.5	16.5	11.2	20.4	.89
(N=2,125)	(27.9)	(24.7)	(36.9)	(24.0)	(24.4)	(.31)
Female						
1979	9.4	19.1	38.8	21.3	3.5	.05
(N=415)	(18.9)	(12.2)	(48.2)	(40.2)	(17.8)	(.21)
1999	19.5	49.2	6.2	4.4	27.0	.77
(N=850)	(25.8)	(23.7)	(23.9)	(14.7)	(24.7)	(.42)

Table 4: Decomposition of the Change in the Difference: 1979-1999

	Total Change in Difference (1)	Within Male (2)	Within Female (3)	Between Male (4)	Between Female (5)
Analytic					
All	-1.5	7.6	9.2	.9	.7
High Education	-.9	8.0	8.2	1.0	1.7
Middle Education	-3.0	6.9	9.5	.2	.6
Low Education	-2.4	4.2	5.3	-2.0	-.6
Interactive					
All	-5.4	19.2	24.1	.8	1.4
High Education	-1.3	29.0	30.5	-.7	-.7
Middle Education	-7.5	17.5	24.2	.2	1.0
Low Education	-4.6	7.5	11.9	-.1	.1
Routine Cognitive					
All	30.8	-10.3	-41.0	1.5	1.3
High Education	-.8	-38.6	-43.5	4.7	10.8
Middle Education	41.4	-4.8	-45.0	-.0	-1.3
Low Education	19.0	3.3	-19.3	-6.2	-2.6
Routine Manual					
All	44.0	-4.2	-46.3	-1.0	-3.0
High Education	12.7	-4.0	-22.1	-.4	5.1
Middle Education	55.7	-1.8	-55.1	-.2	-2.5
Low Education	22.5	-7.4	-31.8	-3.2	-1.0
Non-Routine Manual					
All	-21.2	-4.1	16.7	-1.4	-1.0
High Education	-8.3	14.7	22.9	.3	.5
Middle Education	-27.5	-7.7	18.6	.0	1.3
Low Education	-7.8	-11.4	-2.2	4.4	3.1

Table 5: Predicting Computer Adoption
Dependent Variable: Change in PC Use (1979-1985)

1979 Value:	
Analytic	.67 (.20)
Interactive	.61 (.21)
Routine Cognitive	.41 (.03)
Routine Manual	.19 (.06)
Non-Routine Manual	-.27 (.04)
N=81	

Each cell represents the coefficient from a separate regression estimating the relationship between the 1979 level of the specified task and the change in PC use between 1979 and 1985.

Table 6A
Analytic Skills and Computerization
Dependent Variable: Analytic Skills

	(1)	**(2)**	**(3)**	**(4)**	**(5) Low Education**	**(6) Middle Education**	**(7) High Education**
PC	9.30	7.68	4.08	3.72	2.31	2.56	8.97
	(.59)	(.58)	(.56)	(.57)	(1.17)	(.65)	(1.90)
PC*Female	-7.84	-6.15	-4.75	-3.89	-1.43	-2.88	-7.61
	(1.09)	(1.07)	(1.02)	(1.04)	(1.86)	(1.15)	(6.37)
PC*1999	3.48	2.22	1.17	1.18	-1.82	2.72	-6.01
	(.67)	(.65)	(.63)	(.63)	(1.39)	(.72)	(2.60)
PC*Female*1999	4.78	4.74	5.59	5.68	7.69	4.56	8.55
	(1.23)	(1.20)	(1.15)	(1.16)	(2.19)	(1.28)	(6.85)
Female	-3.63	-3.37	-3.20	3.47	29.43	-7.13	8.35
	(.27)	(.27)	(.29)	(10.07)	(12.76)	(11.85)	(28.27)
Female*1999	2.24	1.59	.56	.63	-.40	1.16	-2.15
	(.51)	(.50)	(.48)	(.50)	(.76)	(.57)	(2.87)
Education Dummies	N	Y	Y	Y	Y	Y	Y
Occupation Dummies	N	N	Y	Y	Y	Y	Y
Education*Female	N	N	N	Y			
Occupation*Female	N	N	N	Y	Y	Y	Y
N	39,309	39,309	39,309	39,309	6,285	28,316	4,708

Note: Robust standard errors are in parentheses.

Table 6B
Interpersonal Skills and Computerization
Dependent Variable: Interpersonal Skills

	(1)	(2)	(3)	(4)	(5) Low Education	(6) Middle Education	(7) High Education
PC	6.68	4.62	1.30	.86	5.66	.55	1.75
	(.67)	(.65)	(.62)	(.62)	(1.28)	(.77)	(1.60)
PC*Female	-8.47	-6.95	-2.34	-.85	-7.04	-.45	5.42
	(1.24)	(1.20)	(1.13)	(1.15)	(2.03)	(1.36)	(5.37)
PC*1999	19.50	17.90	16.48	16.53	13.46	16.16	4.30
	(.76)	(.74)	(.69)	(.69)	(1.51)	(.85)	(2.19)
PC*Female*1999	-7.01	-6.90	-4.14	-4.62	4.27	-5.42	-5.91
	(1.39)	(1.35)	(1.26)	(1.27)	(2.39)	(1.51)	(5.78)
Female	-2.12	-1.26	-7.16	26.40	32.70	2.86	59.24
	(.30)	(.30)	(.32)	(11.05)	(13.94)	(13.98)	(23.84)
Female*1999	12.97	11.92	7.56	7.34	4.28	8.52	4.34
	(.58)	(.56)	(.53)	(.55)	(.84)	(.68)	(2.42)
Education Dummies	N	Y	Y	Y	Y	Y	Y
Occupation Dummies	N	N	Y	Y	Y	Y	Y
Education*Female	N	N	N	Y			
Occupation*Female	N	N	N	Y	Y	Y	Y
N	39,309	39,309	39,309	39,309	6,285	28,316	4,708

Note: Robust standard errors are in parentheses.

Table 6C
Routine Cognitive Skills and Computerization
Dependent Variable: Routine Cognitive Skills

	(1)	(2)	(3)	(4)	(5) Low Education	(6) Middle Education	(7) High Education
PC	25.66	26.53	16.40	16.89	8.27	18.06	6.50
	(1.45)	(1.45)	(1.42)	(1.42)	(3.93)	(1.75)	(3.00)
PC*Female	-.84	-2.65	-4.59	-7.49	3.48	-10.80	-4.28
	(2.69)	(2.69)	(2.58)	(2.63)	(6.24)	(3.07)	(10.05)
PC*1999	-34.86	-24.16	-36.47	-36.35	-27.15	-35.00	-6.54
	(1.66)	(1.65)	(1.59)	(1.59)	(4.65)	(1.93)	(4.10)
PC*Female*1999	5.81	6.09	5.36	5.23	-20.18	8.80	2.28
	(3.03)	(3.02)	(2.89)	(2.91)	(7.34)	(3.42)	(10.82)
Female	9.94	10.58	9.32	68.48	115.19	48.01	70.20
	(.66)	(.67)	(.72)	(25.32)	(42.79)	(31.71)	(44.63)
Female*1999	-33.47	-33.45	-31.62	-32.31	-18.49	-40.22	-.99
	(1.25)	(1.25)	(1.22)	(1.26)	(2.56)	(1.54)	(4.54)
Education Dummies	N	Y	Y	Y	Y	Y	Y
Occupation Dummies	N	N	Y	Y	Y	Y	Y
Education*Female	N	N	N	Y			
Occupation*Female	N	N	N	Y	Y	Y	Y
N	39,309	39,309	39,309	39,309	6,285	28,316	4,708

Note: Robust standard errors are in parentheses.

Table 6D
Routine Manual Skills and Computerization
Dependent Variable: Routine Manual Skills

	(1)	(2)	(3)	(4)	(5) Low Education	(6) Middle Education	(7) High Education
PC	-.76	1.53	2.93	3.66	.91	7.30	-7.21
	(1.25)	(1.24)	(1.20)	(1.19)	(3.59)	(1.47)	(2.12)
PC*Female	6.82	4.24	-.78	-4.02	-4.73	-8.61	-6.69
	(2.32)	(2.30)	(2.18)	(2.20)	(5.70)	(2.59)	(7.11)
PC*1999	-11.03	-9.24	-10.32	-9.37	-1.54	-14.85	11.57
	(1.43)	(1.42)	(1.37)	(1.33)	(4.24)	(1.62)	(2.90)
PC*Female*1999	-2.53	-2.41	-2.64	-4.48	-16.86	2.71	2.62
	(2.62)	(2.59)	(2.44)	(2.44)	(6.71)	(2.88)	(7.64)
Female	28.11	27.90	31.44	23.49	51.23	17.38	86.40
	(.57)	(.57)	(.61)	(21.25)	(39.08)	(26.70)	(31.55)
Female*1999	-45.64	-44.80	-42.48	-41.70	-20.77	-52.68	-10.83
	(1.08)	(1.07)	(1.03)	(1.06)	(2.34)	(1.29)	(3.21)
Education Dummies	N	Y	Y	Y	Y	Y	Y
Occupation Dummies	N	N	Y	Y	Y	Y	Y
Education*Female	N	N	N	Y			
Occupation*Female	N	N	N	Y	Y	Y	Y
N	39,309	39,309	39,309	39,309	6,285	28,316	4,708

Note: Robust standard errors are in parentheses.

Table 6E
Non-Routine Manual Skills and Computerization
Dependent Variable: Non-Routine Manual Skills

	(1)	(2)	(3)	(4)	(5) Low Education	(6) Middle Education	(7) High Education
PC	-22.45	-21.08	-7.55	-7.12	-8.07	-8.37	5.53
	(1.07)	(1.07)	(.92)	(.92)	(2.67)	(1.14)	(1.69)
PC*Female	11.85	9.65	5.84	5.50	2.30	7.88	.18
	(1.99)	(1.98)	(1.68)	(1.71)	(4.25)	(2.01)	(5.65)
PC*1999	18.06	19.14	22.60	22.72	26.96	22.59	-8.33
	(1.22)	(1.22)	(1.04)	(1.03)	(3.16)	(1.26)	(2.31)
PC*Female*1999	-14.75	-14.49	-15.38	-16.91	-4.12	-22.01	-1.60
	(2.24)	(2.22)	(1.89)	(1.89)	(5.00)	(2.23)	(6.07)
Female	-19.35	-18.90	-9.82	29.50	36.60	22.87	24.85
	(.49)	(.49)	(.73)	(16.45)	(29.15)	(20.69)	(25.07)
Female*1999	23.88	24.14	25.45	27.95	10.33	34.82	9.73
	(.93)	(.92)	(.79)	(.82)	(1.75)	(1.00)	(2.55)
Education Dummies	N	Y	Y	Y	Y	Y	Y
Occupation Dummies	N	N	Y	Y	Y	Y	Y
Education*Female	N	N	N	Y			
Occupation*Female	N	N	N	Y	Y	Y	Y
N	39,309	39,309	39,309	39,309	6,285	28,316	4,708

Note: Robust standard errors are in parentheses.

Appendix Table 1: Summary Statistics: All Workers
(Standard Deviations in Parentheses)

	Male		Female		Difference (Male-Female)	
	1979	1998	1979	1998	1979	1998
Analytic	6.9	15.2	2.4	11.5	4.5	3.7
	(14.8)	(23.0)	(9.1)	(19.5)		
Interactive	11.1	31.0	8.1	31.7	3.0	-0.7
	(14.7)	(28.5)	(10.9)	(24.7)		
Routine Cognitive	41.9	32.5	51.0	11.1	-9.1	21.4
	(43.6)	(45.8)	(47.0)	(30.6)		
Routine Manual	31.3	25.6	59.2	9.3	-27.9	16.3
	(40.4)	(34.3)	(44.9)	(22.4)		
Non-Routine Manual	31.0	25.7	13.9	28.1	17.1	-2.4
	(40.3)	(24.4)	(30.5)	(23.9)		
PC Use	.06	.55	.06	.56	0.0	-.01
	(.24)	(.50)	(.23)	(.50)		
N	15,206	12,327	8,164	9,735		

Appendix Table 2: List of Occupations

1	Agricultural Worker	48	Plasterer
2	Animal Producer and Related Worker	49	Interior decorator
3	Administration worker in agriculture	50	Wood and plastic processing worker
5	Gardener, horticultural worker	51	Painter/varnisher
6	Forestry and Hunting Worker	52	Product tester
7	Miner	53	Unskilled worker
8	Mineral processing worker	54	Machine operator
10	Stone Cutter and Carver	55	Machine installer
11	Construction Material Manufacturer	60	Engineer
12	Potter	61	Chemist, Physicist, Mathematician
13	Worker in glass production and processing	62	Technician
14	Chemistry worker	63	Technical service worker
15	Worker in plastics production	64	Technician draftsperson
16	Paper production and processing worker	65	Foremen
17	Printing and related trades worker	66	Sales person
18	Wood and textile worker	67	Wholesale and retailing worker
19	Steel and smelter worker	68	Sales representative
20	Foundry worker	69	Bank and insurance clerk
21	Metal molder	70	Other (unspecified) sales person
22	Metal machine-cutter	71	Land traffic operator
23	Precision worker in metal	72	Water and air traffic operator
24	Metal welder	73	Communication worker
25	Metal construction worker	74	Storekeeper
26	Sheet metal and construction worker	75	Management Consultant
27	Machine construction and maintenance worker	76	Member of Parliament
28	Vehicle and aircraft construction/maintenance worker	77	Computer scientist/accountant
29	Tool and mould construction worker	78	Office clerk
30	Precision mechanics worker	79	Guard/watchmen
31	Electrician	80	Security personnel
32	Assembler	81	Judicial officer
33	Weaver, spinner	82	Librarian/translator/publicist
34	Textile producer	83	Artist/performer
35	Textile processing worker	84	Physician/pharmacist
36	Textile refinement worker	85	Medical service worker
37	Leather and fur processing worker	86	Social worker
39	Baker	87	Teachers
40	Butcher	88	Scientist in humanities and natural sciences
41	Cooks	89	Clergyman
42	Beverage and foodstuff production worker	90	Hairdresser/cosmetician/personal hygiene technician
43	Worker in other nutrition industries	91	Hotel and guesthouse worker
44	Building construction worker	92	Housekeeper/dietician
46	Underground construction worker	93	Cleaning and waste disposal worker
47	Unskilled construction worker		

Year of Birth:	Analytic		Interactive		Routine Cognitive		Routine Manual		Non-Routine Manual	
	1979	1999	1979	1999	1979	1999	1979	1999	1979	1999
Males										
After 1970		10.3		23.2		33.8		28.5		28.9
1950-1969	5.9	15.9	9.1	31.8	40.7	34.6	35.5	26.9	35.4	25.5
1930-1949	7.6	17.4	12.0	34.7	42.7	28.8	29.1	22.4	30.2	24.0
Before 1930	6.4		10.8		41.9		32.4		28.0	
Average Change:										
Within Cohort	9.9		22.7		-10.0		-7.6		-8.1	
Within Age	7.9		19.3		-9.4		-6.4		-5.1	
Females										
After 1970		10.8		31.1		12.7		10.8		31.3
1950-1969	3.1	13.5	8.8	34.8	58.0	12.3	65.4	10.9	9.0	27.6
1930-1949	2.7	13.0	8.3	34.8	47.7	11.0	57.0	9.5	14.2	26.0
Before 1930	1.7		7.0		42.3		49.1		20.3	
Average Change:										
Within Cohort	10.3		26.2		-41.2		-51.0		15.2	
Within Age	9.9		25.5		-37.3		-46.8		13.8	

Year of Birth:	Analytic		Interactive		Routine Cognitive		Routine Manual		Non-Routine Manual	
	1979	1999	1979	1999	1979	1999	1979	1999	1979	1999
Low Education										
Males										
After 1970		8.4		13.2		33.6		28.3		22.5
1950-1969	6.7	7.4	5.9	14.6	40.7	38.2	45.7	30.6	18.7	18.6
1930-1949	5.1	6.7	7.3	15.1	38.2	33.6	37.3	28.1	27.5	15.9
Before 1930	4.2		6.8		39.3		40.0		28.8	
Females										
After 1970		6.7		18.7		16.1		15.2		29.6
1950-1969	3.8	7.0	8.0	18.8	51.1	20.0	54.7	19.8	13.9	20.1
1930-1949	2.1	8.0	6.0	18.0	36.5	17.9	51.6	17.6	23.0	17.1
Before 1930	1.2		5.3		31.9		44.3		26.5	
Middle Education										
Males										
After 1970		9.0		23.5		35.0		29.8		30.5
1950-1969	4.6	13.3	8.9	28.9	40.0	38.3	34.7	30.1	40.8	27.8
1930-1949	6.2	14.5	11.5	31.0	42.5	34.3	29.4	26.8	34.3	25.8
Before 1930	5.8		11.1		42.2		31.9		30.5	
Females										
After 1970		10.6		31.7		12.5		10.6		32.0
1950-1969	2.4	13.0	8.3	34.0	61.4	12.8	72.0	11.0	7.8	28.9
1930-1949	2.1	13.0	8.0	34.1	55.3	10.5	65.2	8.9	10.7	27.4
Before 1930	1.8		7.7		55.0		57.2		15.8	
High Education										
Males										
After 1970		27.2		35.9		21.7		14.3		22.3
1950-1969	19.5	29.5	18.6	50.8	50.2	18.6	21.1	12.6	8.3	19.7
1930-1949	20.6	30.1	22.9	53.1	50.4	10.8	14.1	7.2	4.6	21.4
Before 1930	19.5		20.7		47.1		12.6		2.3	
Females										
After 1970		19.8		44.0		10.4		5.2		26.2
1950-1969	9.8	19.9	18.4	48.6	40.0	5.4	22.2	4.4	5.0	26.6
1930-1949	10.1	18.0	20.1	54.5	29.8	6.3	20.2	4.1	2.9	28.8
Before 1930	5.1		17.5		30.1		22.8		0.0	

Appendix: Generalizability of results

Computer use has evolved quite similarly in the United States and West Germany (with West Germany only lagging behind in the early-1980s), and we have little reason to believe that the adoption of these new technologies would have different effects in West Germany relative to the U.S. or other countries. The results in ALM (2003) and Spitz-Oener (2006) show that aggregate task changes have followed the same pattern in both countries. As an additional test of generalizability of our study, however, we replicate some of our summary statistics using CPS data augmented by the occupational task measures from the DOT. While our data are uniquely suited to answer questions of how the task composition has changed within occupations, we can provide summary statistics of gender differences in the distribution of tasks at the aggregate and industry levels that enable us to compare the findings across countries.

In ALM (2003), the authors present task means broken down by gender. Although the numbers themselves are not comparable, we can compare the relative distribution of tasks across men and women. In their case, as in ours, men's analytic skills exceed those of women in 1980 but women make significant strides towards closing the gap by 1998/9. This is also the case for interactive skills, though women actually catch up and surpass men by 1998/9. In the case of routine cognitive and routine manual skills, in the U.S., women start out much higher than men but, by the end, women decline by substantially more than men. In the case of routine cognitive skills, women are lower than men by 1998/9, whereas for routine manual, women have narrowed the gap substantially. In West Germany, we see the same pattern except that women start higher and end lower than men in both categories. Finally, ALM find almost no change in non-routine manual skills for men and women while we have evidence of an increase in non-routine manual skills for women but a decline for men. Overall, the comparison suggests that the relative distribution of skills may be similar in the U.S. and West Germany.

ALM conduct their analyses at the industry level. For comparison's sake, we replicate their analyses on our data. The results are shown in Appendix Table 2, which is directly comparable to ALM (2002), Table 6. The two tables reveal strikingly similar patterns. More rapidly computerizing industries experienced larger increases in non-routine analytic and non-routine interactive task inputs. In both countries, the relationship was stronger for women than for men in terms of analytic tasks, while the reverse is true in terms of interactive task inputs. In addition, heavily computerizing industries witnessed larger decline in manual and cognitive routine tasks. We find the effect to be bigger for women than for men in both countries. These similar patterns of computer adoption/task input changes, combined with comparable relative means of tasks by gender, suggests the patterns we observe are likely not isolated to the West German case.

Industry Computerization and Task Inputs by Gender, 1979-1999.

Comparable to ALM (2002)

Dependent Variable: Annual Changes in Task Measure

	Nonroutine Analytic			Nonroutine Interactive			Routine Cognitive			Routine Manual			Nonroutine Manual		
	All	Male	Fem	All	Male	Fem	All	Male	Fem	All	Male	Fem	All	Male	Fem
Δ PC-Use	.132	.133	.188	.205	.247	.160	-.994	-.895	-.942	-.424	-.382	-.583	.431	.604	.055
	(.063)	(.048)	(.060)	(.038)	(.057)	(.049)	(.188)	(.286)	(.066)	(.174)	(.203)	(.170)	(.184)	(.078)	(.183)
Intercept	.073	.080	-.043	.529	.351	.790	1.405	1.792	.317	-.009	.763	-.993	-.934	-1.792	.725
	(.129)	(.092)	(.129)	(.093)	(.143)	(.157)	(.489)	(.740)	(.214)	(.518)	(.505)	(.646)	(.593)	(.213)	(.606)
R^2	0.334	0.350	0.537	0.334	0.456	0.257	0.400	0.342	0.726	0.020	0.120	0.316	0.154	0.417	0.005
N	37	37	37	37	37	37	37	37	37	37	37	37	37	37	37
Mean Δ	.421	.418	.475	1.065	.976	1.231	-1.197	-.471	-2.275	-1.119	-.204	-2.599	.195	-.263	.877

Note: Robust standard errors in parentheses. Dependent variables and PC-use variable are measures in annualized changes. Regressions are weighted by the number of observations within industries (industry/gender cell).