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

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Abstract

The closing of the gender wage gap is an ongoing phenomenon in industrialized countries. However, research has been limited in its ability to understand the causes of these changes, due in part to an inability to directly compare the work of women to that of men. In this study, we use a new approach for analyzing changes in the gender pay gap that uses direct measures of job tasks and gives a comprehensive characterization of how work for men and women has changed in recent decades. Using data from West Germany, we find that women have witnessed relative increases in non-routine analytic tasks and non-routine interactive tasks, which are associated with higher skill levels. The most notable difference between the genders is, however, the pronounced relative decline in routine task inputs among women with little change for men. These relative task changes explain a substantial fraction of the closing of the gender wage gap. Our evidence suggests that these task changes are driven, at least in part, by technological change. We also show that these task changes are related to the recent polarization of employment between low and high skilled occupations that we observed in the 1990s.

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I. Introduction

The closing of the gender wage gap is an ongoing phenomenon in industrialized countries. When investigating potential explanations, most research has focused on factors such as education and experience, for which changes have been more favorable for women than for men in recent decades. However, a substantial portion of the improvement in women's labor market opportunities still remains unexplained.[1] One reason for this is that empirical research has been limited in its ability to directly compare women's work to that of men.

In this study, we apply a new approach for analyzing changes in the gender pay gap that uses direct measures of job tasks and gives a comprehensive characterization of how work for men and women has changed in recent decades. The strategy is based on the task-based framework introduced by Autor, Levy and Murnane (2003). The advantage of this framework is that, in addition to the analysis of task changes, it also allows us to investigate one of the potential underlying causes of changes in occupational skill requirements: workplace computerization. In this framework, 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. Hence, it becomes predictable how each occupation is likely to be affected by the introduction of computers.

Using a rich, survey-based data set from West Germany covering 1979 to 1999, 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 (such as researching and analyzing), non-routine interactive (such as managing and

[1] For a comprehensive review, see work by Blau and Kahn (1997, 2003, 2006).

organizing), routine cognitive (such as calculating and bookkeeping), routine manual (such as operating machinery) and non-routine manual (such as serving and repairing).

We find that women witnessed relative increases in non-routine analytical and non-routine interactive task inputs, which are associated with higher skill levels. The most notable difference between the genders in task changes is, however, the strong decline in routine tasks experienced by women and almost not at all by men. When decomposing the closing of the gender wage gap into relative task and relative price changes, we find that relative task changes would have resulted in wage convergence that is as large as 85 percent of the one we actually observe. Interestingly, relative changes in analytical task inputs appear to be the largest single contributor to this development. The results also show, however, that relative prices did not stay constant and that their relative movement had a mitigating effect on the convergence of wages of men and women. Relative task and relative price changes together can explain more than 40 percent of the wage convergence between the genders.

We then turn to possible explanations for these task changes. Our analysis reveals that – consistent with the technological change hypothesis – task changes were most pronounced *within* industry/occupation cells. Only minor parts of the aggregate trends are attributable to women moving towards more skill intensive occupations or industries, a phenomenon that has attracted much attention in the literature.[2] 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

[2] See, for example, Katz and Murphy (1992).

job content has evolved differently for men and women along several dimensions.[3] While the relative changes in interactive task input and changes in relative prices for this task category play an important role in explaining part of the closing of the gender pay gap, the results suggest that the relative evolution of analytical and routine manual task inputs is also important.

A by-product of the task-based framework is that it has reinvigorated the discussion on the “polarization” of the labor market that began at the beginning of the 1990s.[4] In the task-based 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 expect the largest effect of workplace computerization on middle-educated workers who are most likely to be engaged in routine manual and routine cognitive skills. Given the distribution of tasks in 1979, we would also expect to find stronger polarization of employment among women relative to men. We do 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 in recent decades.

The paper unfolds as follows. Section 2 reviews the relevant literature, Section 3 presents the data set, and Section 4 presents the patterns of task changes between 1979 and 1999. Section 5 relates these changes to the closing of the gender wage gap. Section 6 examines possible explanations: in particular, changes in technology. Section 7 exam-

[3] See, for example, Borghans, ter Weel and Weinberg, 2006, and Weinberg, 2000.
[4] See, for example, Levy and Murnane, 1992, Goos and Manning, 2007, and Autor, Katz, Kearney, 2006.

ines the relationship between task changes and the polarization of the labor market. Section 8 then 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).[5] 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), who document the relationship between computer adoption and changing tasks at the aggregate level, within industry (ALM, using U.S. data) and within occupations (Spitz-Oener, using data for West Germany). As predicted, the evidence suggests that tasks have shifted from routine manual and routine cognitive tasks towards analytic and

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

interactive non-routine tasks at all levels of aggregation in recent decades. The framework thereby identifies the mechanism that underlies the relative increase in the demand for high-educated employees. However, there is little work using the task-based framework to analyze how the content of work has changed for women relative to men.

So far, most of the literature on the gender wage gap has focused on supply side explanations such as changing education and experience.[6] However, there are a number of studies that also looked at demand side factors, though with a conceptually different approach than the one we are using. Katz and Murphy (1992), for example, showed that there have been changes in product demand that are associated with shifts in employment towards sectors that are female intensive.[7] Unlike this earlier work, we are able to focus on *within-occupation* task changes for women relative to men while previous work mainly emphasized *between-occupation* (industry) employment shifts.

There are also 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 the role of changing task prices in explaining rising wage inequality and a declining gender wage

[6] Again, see work by Blau and Kahn (1997, 2003, 2004). Another study is O'Neill and Polachek (1993).
[7] Other studies are Black and Juhn (2000) and Goldin (2004). Welch (2000) attributes the closing of the gender wage gap to the expansion in the value of brains relative to brawn. In addition, recent work by Olivetti and Petrongolo (2006) introduces evidence of differential labor market participation as an explanation for across-country differences in the gender wage gap. Mulligan and Rubinstein (2005) also stress the importance of changes in the selection process over time into employment in explaining changes in the U.S. gender gap.

gap and conclude that price changes can explain a large fraction of the decline in the gender wage gap. 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.[8] 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.[9]

Finally, the paper most closely related 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.[10] However, they neither provide evidence on how interpersonal task inputs have evolved across genders, nor on how the evolution of interpersonal task inputs is related to the closing of the gender wage gap in recent decades. In addition, our evidence suggests 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. Thus, by focusing on a broader spectrum of tasks, including analytic, interpersonal, routine cognitive, routine manual, and non-routine manual, we provide a comprehensive analysis of how work has changed for women relative to men and how these changes are related to the closing of the gender wage gap.

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[8] 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.

[9] 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.

[10] For the analyses concerning West Germany, they use the same data as this study.

III. Data

We use two data sets for our analysis, the "Qualification and Career Survey" and the IAB employment sample. The main advantage of the "Qualification and Career Survey" is that it includes information on both the activities that employees perform at work as well as computer use. This data is then matched to the IAB employment sample, an administrative data set with the major advantage of providing precise information on wages. The matching is done at the occupation level as both data sets follow the same occupational classification.

The "Qualification and Career Survey" is 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.[11] For ease of exposition, we use the 1979 and 1999 waves for our analysis, including only those occupations with both men and women in both years.[12]

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 questions related to tasks — these data use a consistent set of occupational classifications; the constant occupational titles thus provide the reference point for the analysis.[13] Another

[11] For details on the data set see Spitz-Oener (2006).
[12] We lose approximately 10% of our sample by restricting the data in this way. However, results are insensitive to this restriction.
[13] Appendix Table 1 provides a list of the occupational classifications at the two digit level.

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, and 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.[14]

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.[15]

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

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

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

[14] 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.

[15] 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.[16]

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 use any of the following on the job: computers, terminals, and electronic data processing machines.

Employees are classified based on their vocational education:[17] (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.

The Administrative Social Security Records, also known as the IAB employment sample, is a two percent representative sample of administrative social security records in Germany covering 1975-2001. The sample, which includes more than 200,000 employment spells per year, provides precise information on daily wages for all individuals who contribute to the social security system; this represents about 80 percent of the German workforce (among the excluded groups are the self-employed and civil servants). The major shortcoming of the data is that it is right-censored at the contribution assessment ceiling for the pension insurance (a similar problem encountered by researchers using the Current Population Survey). The deficit mainly concerns employees with high levels of

[16] We tested the sensitivity of our results to our choice of task measure by also trying the share of total tasks an individual performs in each category. The results are robust to this choice.
[17] 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.

education, for which censoring affects more than 50 per cent of the wage observations. Because of this, we restrict the wage analysis to employees with low and medium levels of education only.[18]

Our wage sample consists of prime-age workers (aged 25-55) in West Germany who are working full-time (38+ hours per week), though they need not work all year round. Our wage measure is the daily wage, averaged over the number of days the worker worked in the respective year. In order to adjust for the differences in working days, we additionally weight the observations by the number of days worked per year in the analysis.[19] We present summary statistics of the wage sample in Appendix Table 3.

IV. Patterns of Task Changes

Figure 1 illustrates the evolution of task inputs of women relative to men between 1979 and 1999 by showing the proportional difference in task changes relative to 1979; that is, growth in female task inputs minus growth in male task inputs. Table 2 shows the absolute values of task categories for men and women in this period and demonstrates again how differently they have evolved.[20] 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

[18] The impact of this restriction is less severe than it might first appear. The reason is that relative changes in task inputs across the genders were most pronounced for low and medium educated employees; hence, they appear to be the most interesting groups to look at. In addition, the gender wage gap convergence has been the most pronounced for low and medium educated employees (Fitzenberger and Wunderlich, 2002).

[19] Our results are robust to alternative weighting schemes.

[20] Appendix Table 2 presents the summary statistics using an alternative measure of task inputs: the fraction of total tasks performed by an employee in each category. The conclusions are consistent across task measures. From now on we focus on the overall period, although Figures 1 and 2 suggest that there are differences across sub-periods that might be interesting to analyze in more detail. However, for the sake of exposition of this study, we leave this for future research. Results are presented for full-time workers only. Results for all worksers are similar.

cognitive and routine manual task inputs.[21] However, by 1999, women appear to be catching up to men in terms of analytic skills and, even more, in terms of interactive skills. For routine cognitive and routine manual skills, where women had dominated 20 years earlier, men have taken over; and 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.[22]

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 is small by 1999, while for high educated the difference is still notable in 1999. The difference in interactive task inputs between the genders is small for all education groups by 1999. 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.[23, 24]

V. Role of Changing Tasks on the Gender Wage Gap

[21] Results are presented for full-time workers only. We performed a similar breakdown for all workers for which the descriptive statistics turned out to be very similar.

[22] To get a sense of what types of occupations are most affected, sales representatives, bank and insurance clerks, and engineers experienced large declines in routine cognitive tasks, electricians, precision mechanics workers, assemblers, gardeners, librarians, and judicial officers all experienced large declines in routine manual tasks, and technical service workers, teachers, clergymen, and social workers experienced large increases in non-routine manual tasks.

[23] 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 4 and 5). 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.

[24] We restricted the analysis to those occupations that include both men and women, therefore segregated occupations are excluded from our analysis. We did analyze occupational segregation, however. The main finding is that – similar to the developments in the U.S. – occupational segregation has declined in West Germany in recent decades. Most importantly for our analysis is that the pattern of task changes in segregated occupations is very similar to those in non-segregated occupations.

Given these patterns, we next examine how these changes in tasks relate to the change in the gender wage gap over this period. Figure 2 shows the evolution of the gender wage gap for low and medium educated employees in West Germany. Between 1979 and 1999, the gender wage gap declined by 9.3 percentage points in West Germany. To investigate the role of task changes, we do a simple decomposition of the rate of wage convergence into its components, namely, relative task changes and relative price changes. The decomposition is as follows:

$$\underbrace{(\overline{W}_M - \overline{W}_F)_{99} - (\overline{W}_M - \overline{W}_F)_{79}}_{(1)} = \underbrace{\sum_j \overline{p}_M (\overline{Y}_{M99} - \overline{Y}_{M79})}_{(2)} - \underbrace{\sum_j \overline{p}_F (\overline{Y}_{F99} - \overline{Y}_{F79})}_{(3)}$$
$$+ \underbrace{\sum_j \overline{Y}_M (p_{M99} - p_{M79})}_{(4)} - \underbrace{\sum_j \overline{Y}_F (p_{F99} - p_{F79})}_{(5)}$$

where $\overline{W}_{gt}$ is the average log wage for gender g (M=men; F=female) at time t, $\overline{Y}_{gt}$ is the average value of the skill for gender g at time t, and p_{gt} is the price of the skill for gender g at time t. Terms (2) and (3) represent the changes in male (2) and female (2) wages that can be attributed to changes in the "quantity" of tasks – holding prices constant at the average level over the two time periods. The fourth and fifth terms represent the changes in male (4) and female (5) wages that can be attributed to changes in the gender-specific returns – holding gender-specific task inputs constant at the gender average level for the two periods.

Appendix Table 6 presents the results from the simple wage equation used to generate the price measures used in the decomposition.[25] The log(wage) equations include controls for education, age, education-gender interactions and age-gender interactions, as

[25] Standard errors were adjusted to allow for clustering at the occupation level.

well as industry dummies. From Appendix Table 6, Column (1), it is interesting to note that, on average, women's rewards for analytical task inputs were much larger than those for men. This is also the case for the interactive and routine cognitive task category, although the difference in the coefficients is much smaller than in the case of analytic tasks. Both genders, on average, turn out to be negatively rewarded for routine and non-routine manual task inputs, with the penalty being larger (smaller) for women than for men for routine manual tasks (non-routine manual tasks). Both genders have experienced a decline in the price for analytical task inputs and non-routine manual task inputs (column 2); the size of the effect being larger (smaller) for women than for men for the first (latter) task category. Average prices for interactive tasks have decreased for men but increased for women. Returns to routine cognitive task inputs have decreased for women but increased for men, whereas average prices for routine manual task inputs have not changed much for men or women.

Table 4 summarizes the contribution of task changes and price changes to the gender wage convergence. Of the .093 decline in the gender wage gap over this period, Column 1 minus Column 2 gives how much of the change in the gender wage gap can be explained by changes in quantities of these tasks performed, while Column 3 minus Column 4 gives the amount that can be explained by changes in the prices of these tasks. Column 5 is the total amount that can be explained by changes in both prices and quantities (Column 1-Column 2+Column 3-Column 4) and Column 6 gives the total percentage that can be explained (([Column 5]/.093)*100). Overall, the results suggest that relative task changes (holding prices fixed at average levels) could explain about 86 percent of wage convergence ((.08/.093)*100). However, this positive effect of relative task changes was offset by the changes in prices, which would have increased the gender wage gap by about 45 percent if quantities had been held constant ((-.042/.093)*100).

There are large differences across task categories in how changes in task inputs have contributed to the gender wage convergence; the relative change in the analytical task inputs is the largest single contributor to wage convergence (96 percent), followed by the routine manual task category (66 percent) and the interactive task category (56 percent). The relative changes in the routine cognitive task inputs, by contrast, would have resulted in a large increase in the gender wage gap (124 percent; that is more than we actually observed). For this task category, relative price changes add to this pattern, as they also work in the direction of increasing the gender wage gap (159 percent). For the interactive task category, in contrast, relative price changes also contributed to the closing of the gender wage gap (80 percent), so – taking task and price changes together – this task category was the largest single contributor to wage convergence (135 percent). However, by solely focusing on this category, one would largely overestimate the gender wage convergence. The results suggest that in order to being able to identify the factors contributing to wage convergence, it is important to consider a broader spectrum of tasks.

VI. Sources of Task Changes: Technological Change

Decomposition

What can explain the changes in tasks that we observe? The gender-specific changes in tasks over time can be broken into two components: (1), changes in the distribution of men and women across occupations and/or industries and, (2), changes in the task composition within occupations and/or industries. The technological change hypothesis predicts that changes in tasks should be observed within industry/occupation to representing a change in the production process. Changes across industries would be more consistent with changing product demand, perhaps through increased globalization.

In a first effort to understand the causes of the patterns we observe, we apply a decomposition similar to that which we did for the change in the gender wage gap. 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 cells (how much of the difference can be explained by differential shifts in employment across occupation and/or industry cells) and those that are due to differential changes in task inputs within cells (how much of the difference can be explained by the fact that woman and men experience different task changes within occupations and/or industry cells).

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

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

where $\bar{Y}_{gtj}$ is the average value of the skills for gender g (M=men; F=female) at time t in occupation j and α_{gtj} is the proportion of gender g employed in cell 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 cells, with the first and second terms representing within cell task changes for men and women respectively – holding gender-specific employment shares constant at the average level. 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 cells – holding gender-specific task inputs constant at the average level. The fourth term captures the portion that can be attributed to the changing employment share of men and the final term refers to the portion that can be attributed to the changing employment share of women.

Table 5 presents the results of this decomposition. The first panel presents results when we look at occupation cells (and decompose changes in the gender gap in tasks to within occupation changes and across-occupation changes). The second panel present results when we look at industry cells, and the final panel presents results when we decompose industry*occupation cells.

Column 1 shows the total change in the difference in task inputs of men and women. Columns (2) and (3) show the within cell 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 distribution of employment across cells.

From looking down the columns, it is clear that the largest portions of the changes are coming from within cell task changes, which is consistent with the idea of technological change altering the task composition of jobs. Interestingly, for all task categories and all cells, within cell 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 changes across cells. The small decline in the gender gap in analytical tasks is due to the fact that within cell changes in analytical tasks have been larger for women than for men. 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 cells for both men and 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 (only exception: routine cognitive task category within industries). Similar to the non-routine cognitive task categories, the changes have been most pronounced within cells 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 gender gap in the non-routine manual task category experienced the largest decline between 1979 and 1999. Again, task changes within cells account for the largest part of the change. The decline in the gap is a result of a considerable relative increase in non-routine manual activities within cells for women.

Overall, this decomposition suggests that task changes have occurred primarily within occupations and industries, which is consistent with the idea that technological developments are a major cause for the changing skill patterns we observe.

Computer Adoption

In this paper, we focus on workplace computerization as our measure of technological change. The last column in Table 2 shows that not only the evolution of tasks has been different between the genders; the proliferation of computers has also evolved differently. In 1979, men were about 20 percent more likely to use computers than women, while the difference in computer use had declined to 6 percent by 1999.

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, and (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. We test them by fitting the following model:

$$\Delta C_{j,1979-1999} = \alpha + \beta T_{j,1979} + \varepsilon_j ,$$

where $\Delta C_{j,1979-1999}$ is the percentage point change in the share of employees using a computer in occupation j between 1979 and 1999, $T_{j,1979}$ is the measure of task intensity in occupation j in 1979 and ε_j is an error term.

Table 6 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 1999. 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 content 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.

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:

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

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 gender-specific-education and occupation controls. 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). As the specification includes occupation dummies, we test the relationship between changes in computer use and changes in task inputs within occupations.

Table 7 shows 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.[26]

We first look at analytic skills (Column 1). We can see from the interaction of PC and 1999 that increasing computer use is associated with an increase in analytical tasks. 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). Given that women started out with lower levels of ana-

[26] Results are robust to the exclusion of some/all of the controls.

lytical task inputs, this catching up effect for female computer users is not very surprising.

The results for the interactive task category are shown in Column 2. As with the analytical task category, computer adoption is associated with an increase in interactive skills. The effect is much stronger for men relative to women. 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. Column 3 shows the results for the routine cognitive task category. Female computer users and male computer users have experienced declines in routine cognitive task inputs, though the effect is larger for women. Column 4 then shows that the results are similar for the routine manual task category. Again, 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.[27] However, for these two task categories, it is actually also interesting to note that the coefficient for the interaction term "Female*1999" is significantly negative and large in size (much larger than the time effects for men; Year_1999); so the results suggest that part of the larger declines in routine tasks inputs for women is not explained by computerization.

Based on the task framework, we do not have testable hypotheses about the relationship between computers and non-routine manual activities. However, as the relation-

[27] In order to examine this further, for each task category we break our occupations into 10 deciles based on the 1979 distribution of individual tasks. We then allow the effects to vary by decile of this distribution and 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.

ship might still be interesting, Column 5 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. In addition, for men and (even more so for) women, changes in non-routine tasks not explained by workplace computerization is large.[28]

VII. Polarization

There is one dimension along 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 Autor, Katz and Kearney, 2006, Goos and Manning, 2007, 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 bookkeepers 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 or 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.

[28] We also analyzed the relationship between task changes and workplace computerization for each education group separately. Our overall conclusions also hold within education groups.

Given the initial distribution of tasks in 1979, we suspect that the polarization pressure in the labor market was larger for women than for men in the last three decades. The question of polarization concerns the evolution of employment across occupations based on their levels of skills. As a proxy for skills, we divide occupations into 10 deciles based on their median wages in 1979 (separately by gender), so that the occupations in the first group have the lowest median wages in 1979 and the occupations in the 10th group have the largest median wages in 1979. Figure 3 shows the proportion change in (full-time) employment shares between 1979 and 1999 for the ten groups 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 the employment share for men has grown by about 37 percent and that of women by more then 100 percent in the tenth group between 1979 and 1999, the decline in the employment share in the first group was smaller for women (about 10 percent) than for men (close to 20 percent). In contrast, the decline in employment shares in the "middle" occupations has been more pronounced for women, with the largest difference being in the second group in which the employment share has shrunk by 52 percent for women and by 23 percent for men.

VIII. Conclusion

Since the 1970s, women have experienced great improvements in terms of labor market success. Most research has attributed this success story to supply factors, whereas demand side explanations played only a minor role. In this study, we investigate the closing of the gender wage gap using direct measures of job tasks. The advantage of this task-based approach is that we are able to directly compare the content of women's work to that of men. In addition, we are also able to relate the changes to technological developments, a major argument for demand side changes in the labor market.

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 analyzed a number of specifications that 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.[29] In addition, 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.

We find that changes in work content have been larger for women than for men along all dimensions we consider, a result that is 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 striking difference between the genders is the marked decline in routine tasks experienced by women and almost not at all by men.

[29] The results in ALM (2003) and Spitz-Oener (2006) show that aggregate task changes have followed the same pattern in both 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.

In addition, we find that relative task changes are important in explaining the closing of the gender wage gap. Task changes and price changes are able to account for a substantial fraction of the closing of the gender wage gap in recent decades.

When investigating the potential sources of task changes, we find that technological change might be important in explaining the phenomena, as 1) task changes were most pronounced *within* industries and occupations, and 2) task changes occurred most rapidly in occupations in which computers have made major headway.

The paper also contributes to the discussion on polarization that has experienced revitalization owing to the task-based approach. We find evidence of polarization in employment 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 in recent decades.

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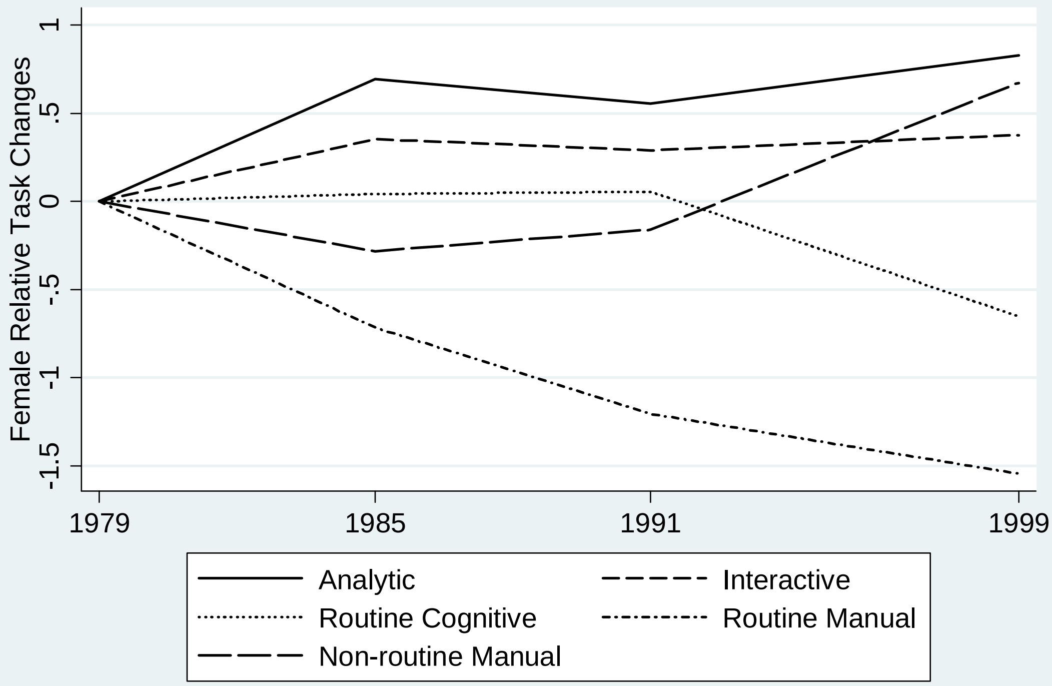
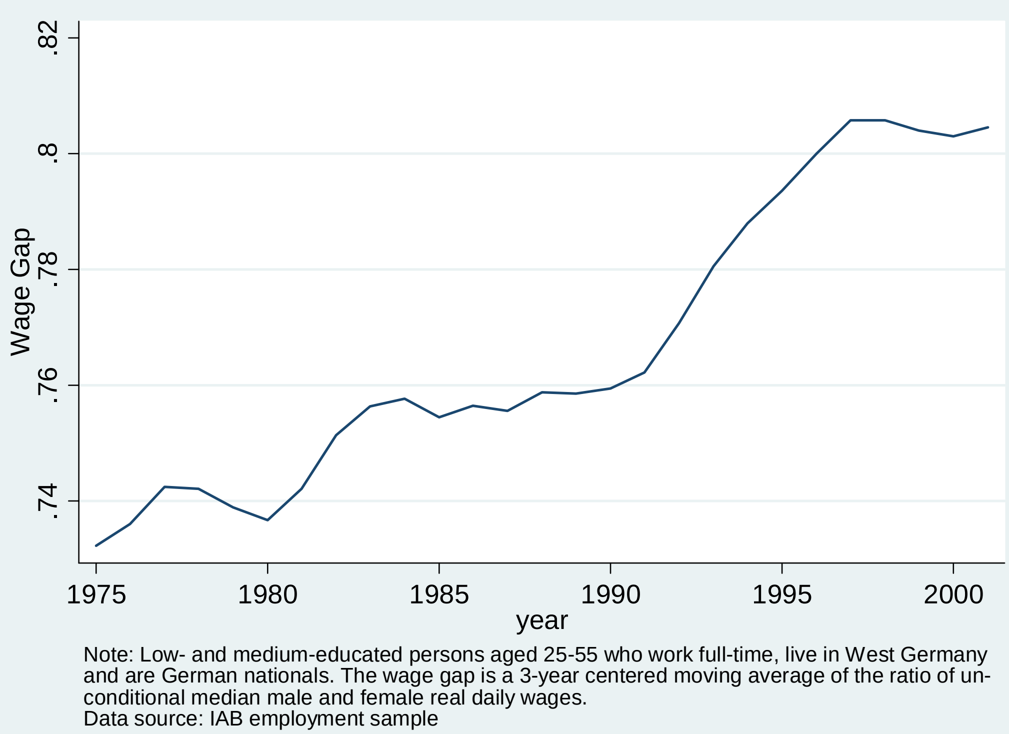


Note: Female relative task changes are defined as growth in female task inputs minus growth in male task inputs (both relative to 1979). Data source: BIBB-IAB

Figure 1: Female Relative Task Changes.



Note: Low- and medium-educated persons aged 25-55 who work full-time, live in West Germany and are German nationals. The wage gap is a 3-year centered moving average of the ratio of un-conditional median male and female real daily wages.
Data source: IAB employment sample

Figure 2: Evolution of the Gender Wage Gap—West Germany, 1975-2001.

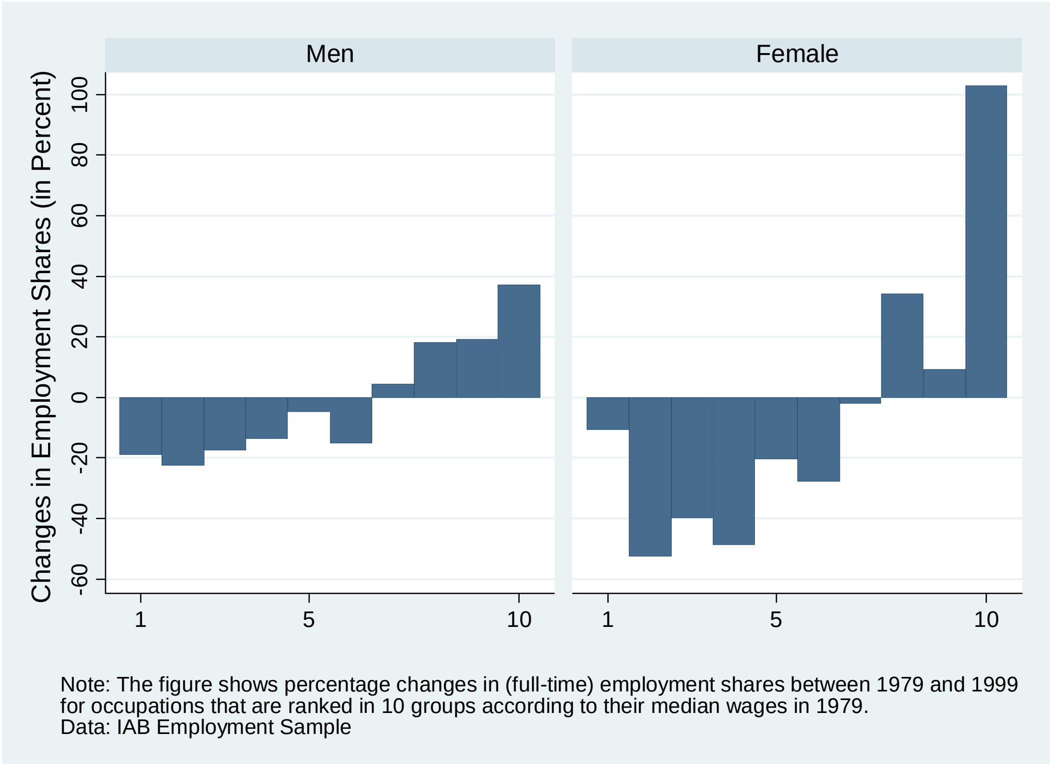


Figure 3: Changes in Employment Shares by 1979 Median Wages

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

Note: Overview of how activities asked for in the Qualification and Career Survey (column 2) are grouped into the task categories.

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

	Analytic	Interactive	Routine Cognitive	Routine Manual	Non-Routine Manual	PC Use
Male						
1979	8.3	13.3	48.8	31.0	23.4	7.8
(N=12,361)	(16.2)	(16.1)	(44.8)	(41.1)	(37.4)	(26.9)
1999	17.3	35.4	40.9	21.9	48.6	65.5
(N=9,986)	(24.2)	(29.1)	(48.5)	(32.7)	(49.1)	(47.5)
Change 1979-1999	9.0	22.1	-7.9	-9.1	15.2	57.7
Female						
1979	2.8	8.6	52.2	59.6	12.5	6.2
(N=6,389)	(9.6)	(11.4)	(46.9)	(44.5)	(28.8)	(24.0)
1999	12.9	34.2	24.0	9.9	56.1	61.6
(N=5,989)	(20.8)	(25.7)	(41.8)	(23.4)	(48.0)	(48.6)
Change 1979-1999	10.1	25.6	-28.2	-49.7	43.6	55.4
Difference (Male-Female)						
1979	5.5	4.7	-3.4	-28.6	10.9	1.6
	(.2)	(.2)	(.7)	(.6)	(.5)	(.4)
1999	4.4	1.2	16.8	11.9	-7.5	3.9
	(.4)	(.5)	(.8)	(.5)	(.8)	(.8)

Note: Sample includes persons aged 25-55 who work full-time, live in West Germany and are German nationals. Data: Qualification and Career Survey.

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	6.4	8.0	45.1	38.5	20.8	4.7
(N=2,094)	(14.2)	(12.5)	(42.3)	(40.1)	(31.7)	(21.2)
1999	8.8	16.4	30.8	27.2	36.3	31.3
(N=910)	(16.4)	(23.2)	(44.9)	(34.7)	(46.1)	(46.4)
Female						
1979	2.5	6.7	40.8	50.5	20.7	3.4
(N=1,909)	(8.6)	(9.7)	(44.6)	(42.2)	(33.7)	(18.1)
1999	7.2	18.8	21.4	17.5	42.5	30.5
(N=727)	(14.5)	(23.1)	(39.9)	(30.6)	(47.6)	(46.1)
			Middle Education			
Male						
1979	6.9	13.1	49.4	31.7	26.8	7.4
(N=8,910)	(14.3)	(16.1)	(44.7)	(41.6)	(39.4)	(26.2)
1999	14.5	32.7	43.6	24.9	52.8	62.2
(N=6,844)	(22.3)	(28.8)	(48.9)	(34.2)	(49.0)	(48.5)
Female						
1979	2.2	8.4	59.0	67.9	9.6	7.6
(N=4,061)	(8.3)	(11.5)	(46.4)	(43.1)	(26.4)	(26.5)
1999	12.5	33.7	23.7	9.9	58.8	63.5
(N=4,400)	(20.1)	(24.9)	(41.6)	(23.3)	(47.3)	(48.1)
			High Education			
Male						
1979	20.1	22.4	50.2	14.7	4.6	15.5
(N=1,357)	(23.9)	(17.5)	(48.8)	(34.5)	(20.4)	(36.3)
1999	29.5	51.3	37.0	10.5	40.6	89.6
(N=2,232)	(28.2)	(24.7)	(48.0)	(23.4)	(48.8)	(30.5)
Female						
1979	9.6	19.1	38.7	21.3	3.4	4.5
(N=419)	(19.1)	(12.2)	(48.1)	(40.2)	(17.7)	(20.8)
1999	19.7	49.1	27.2	4.2	53.2	77.1
(N=878)	(26.0)	(23.7)	(44.2)	(13.9)	(49.4)	(42.0)

Note: Sample includes persons aged 25-55 who work full-time, live in West Germany and are German nationals. Data: Qualification and Career Survey.

Table 4: Decomposition of the Wage Convergence: 1979-1999

Rate of Wage Convergence: .093	Changes in Quantities: Female (1)	Changes in Quantities: Male (2)	Changes in Prices: Female (3)	Changes in Prices Male (4)	Predicted Change in Gender Wage Gap (5)	Percentage of Change in Wage Gap Explained (6)
Analytic	.116	.027	-.016	-.011	.084	90.3
Interactive	.153	.100	.042	-.032	.126	135.5
Routine Cognitive	-.119	-.003	-.117	.031	-.263	-282.8
Routine Manual	.064	.002	.015	.003	.074	79.6
Non-Routine Manual	-.025	-.017	-.056	-.081	.018	19.4
Total:	.189	.109	-.132	-.090	.039	41.9
Predicted Change in Gender Wage Gap:	.08		-.042			41.9

Note: Task prices and changes in task prices are estimated using wage regressions; the detailed results of these wage regressions can be found in Table 6 in the appendix. Data: Qualification and Career Survey and IAB employment sample.

Table 5
Decomposition of the Change in the Task Difference: 1979-1999

	Total Change in Difference (1)	Within Male (2)	Within Female (3)	Between Male (4)	Between Female (5)
Occupation (N=46)					
Analytic	-1.1	8.1	9.4	1.0	.7
Interactive	-3.4	20.6	23.2	1.5	2.3
Routine Cognitive	20.5	-8.2	-29.0	.4	.7
Routine Manual	40.6	-7.8	-47.1	-1.3	-2.6
Non-Routine Manual	-18.3	25.2	41.5	.01	2.1
Industry (N=38)					
Analytic	-1.8	8.0	9.6	.6	.8
Interactive	-5.6	18.6	24.2	1.0	1.0
Routine Cognitive	28.6	1.5	-29.4	-.3	2.0
Routine Manual	44.6	-3.1	-47.8	-1.4	-1.4
Non-Routine Manual	-24.0	19.2	43.1	.4	.5
Industry x Occupation (N=288)					
Analytic	-.9	8.9	10.1	.9	.6
Interactive	-2.4	22.7	24.0	.5	1.6
Routine Cognitive	15.5	-14.6	-32.8	-.1	2.5
Routine Manual	37.1	-14.5	-47.8	-.6	-4.3
Non-Routine Manual	-15.4	28.9	43.7	1.9	2.4

Note: Sample includes persons aged 25-55 who work full-time, live in West Germany and are German nationals. Each panel represents decompositions at different levels, first within/across occupation, then within/across industry, and finally within/across industry*occupation cells. Means across panels are different because of slightly different samples; however, results are entirely consistent when calculated using a constant sample. Each row represents a separate component of the decomposition, where the columns are numbered as follows:

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

Data: Qualification and Career Survey.

Table 6: Predicting Occupational Computer Adoption
Dependent Variable: Change in PC Use (1979-1999)

1979 Value:	
Analytic	1.76 (.50)
Interactive	1.36 (.53)
Routine Cognitive	.81 (.10)
Routine Manual	.26 (.18)
Non-Routine Manual	-.68 (.13)
N=46	

Each cell represents the coefficient from a separate regression estimating the relationship between the 1979 mean occupational level of the specified task and the change in occupational PC use between 1979 and 1999. Regressions are weighted by the number of employees in occupations in 1979. Data: Qualification and Career Survey.

Table 7
Skills and Computerization

Dependent Variable:	**Analytic**	**Interpersonal**	**Routine Cognitive**	**Routine Manual**	**Non-Routine Manual**
PC	3.83	.54	13.55	2.11	-4.19
	(.71)	(.63)	(1.51)	(1.41)	(.89)
Year_1999	4.03	8.95	-1.82	-3.59	19.51
	(.31)	(.38)	(.91)	(.64)	(.87)
PC*Female	-3.75	-.89	-2.10	-2.46	3.79
	(.95)	(.87)	(2.67)	(2.66)	(1.30)
PC*1999	1.68	16.83	-20.76	-6.92	12.78
	(.81)	(.77)	(1.79)	(1.52)	(1.31)
PC*Female*1999	5.23	-4.70	-10.12	-7.08	-13.65
	(1.12)	(1.14)	(3.03)	(2.79)	(2.02)
Female	-5.83	-7.70	23.39	19.88	-13.81
	(1.68)	(2.83)	(14.35)	(11.08)	(10.85)
Female*1999	.92	7.02	-16.88	-37.32	24.21
	(.46)	(.63)	(1.45)	(1.06)	(1.40)

Regressions also include dummies for education and occupation, and the interactions of these variables with the dummy variable for females. Robust standard errors are in parentheses. The number of observations in each regression is 34,725. Data: Qualification and Career Survey.

Appendix Table 1
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		

Appendix Table 2
Summary Statistics: Full-Time Workers Only
Alternative Measure of Tasks
(Standard Deviations in Parentheses)

	Analytic	Interactive	Routine Cognitive	Routine Manual	Non-Routine Manual	PC Use
Male						
1979	10.0	31.1	24.8	16.6	17.5	7.9
(N=12,361)	(21.7)	(32.7)	(28.2)	(25.8)	(30.1)	(26.9)
1999	9.4	47.2	12.2	14.9	16.3	65.5
(N=10,012)	(15.7)	(31.1)	(15.9)	(22.7)	(20.1)	(47.5)
Change 1979-1999	-.6	16.1	-12.6	-1.7	-1.2	57.6
Female						
1979	3.8	25.3	27.8	33.1	10.0	6.2
(N=6,389)	(14.4)	(32.8)	(28.7)	(28.8)	(24.2)	(24.0)
1999	8.5	55.3	7.8	7.6	20.9	61.6
(N=6,007)	(16.4)	(29.6)	(14.3)	(18.5)	(22.8)	(48.6)
Change 1979-1999	4.7	30.0	-20.0	-25.5	10.9	55.4
Difference (Male-Female)						
1979	6.2	5.8	-3.0	-16.5	7.5	1.7
1999	0.9	-8.1	4.4	7.3	-4.6	3.9

Note: The task measure is the share of total tasks performed by an individual in each category. Data: Qualification and Career Survey.

Appendix Table 3
Summary Statistics: Wage Sample
Full-Time Workers Only

	N	Mean	Std. Dev.	Minimum	Maximum
All					
Age	334,359	38.73	8.57	25	55
Real Daily Wage (in €)	334,359	77.77	28.24	2.02	143.07
Fraction of Woman	334,359	40.76	49.14	0	100
Low Educated					
Age	51,182	41.18	8.54	25	55
Real Daily Wage (in €)	51,182	63.79	23.30	2.02	143.07
Fraction of Woman	51,182	51.21	49.98	0	100
Medium Educated					
Age	283,177	38.29	8.50	25	55
Real Daily Wage (in €)	283,177	80.30	28.32	2.02	143.07
Fraction of Woman	283,177	38.88	48.74	0	100

Note: Persons aged 25-55 who work full-time, live in West Germany and are German nationals. Data: IAB employment sample; Years 1979 and 1999.

Appendix Table 4
Cohort Analysis

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		11.9		26.8		40.8		24.0		56.1
1950-1969	7.0	17.9	10.7	36.0	46.6	42.1	35.8	22.7	28.4	48.0
1930-1949	9.0	19.2	14.4	39.1	49.3	37.9	28.6	18.4	22.3	45.4
Before 1930	7.7		13.2		50.0		31.4		19.8	
Average Change:										
Within Cohort	10.5		25.0		-7.9		-11.6		21.4	
Within Age	8.4		21.2		-8.3		-10.2		26.3	
Females										
After 1970		11.0		31.2		22.7		9.9		62.0
1950-1969	3.1	13.7	8.9	35.2	58.1	25.0	65.3	10.2	9.1	54.6
1930-1949	2.7	13.2	8.7	35.2	48.4	22.6	56.8	9.3	14.0	52.1
Before 1930	1.7		7.4		42.9		48.3		20.0	
Average Change:										
Within Cohort	10.5		26.4		-29.5		-51.3		41.8	
Within Age	10.1		25.6		-26.4		-47.0		41.8	

Note: Each cell represents the average value of the task measure for a particular cohort in a particular year. Data: Qualification and Career Survey.

Appendix Table 5
Cohort Analysis
By Education Group

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		9.9		15.1		31.4		25.7		43.6
1950-1969	8.2	8.6	6.8	16.4	46.6	31.6	45.4	28.5	16.3	35.6
1930-1949	6.0	8.1	8.3	17.6	43.2	27.8	35.9	25.1	22.5	31.2
Before 1930	5.3		8.4		47.5		37.3		21.7	
Females										
After 1970		6.9		18.8		18.6		14.5		58.0
1950-1969	3.8	6.9	8.2	19.2	51.1	23.1	54.5	18.9	14.1	39.5
1930-1949	2.1	8.1	6.1	18.1	37.1	20.3	51.2	17.2	22.6	33.7
Before 1930	1.2		5.5		32.5		43.1		26.8	
Middle Education										
Males										
After 1970		10.3		27.3		43.1		25.1		59.6
1950-1969	5.5	15.1	10.8	33.1	46.3	44.6	35.3	25.6	32.9	52.5
1930-1949	7.6	16.2	14.1	35.7	50.4	41.1	29.7	22.6	25.5	48.5
Before 1930	6.8		13.4		51.0		32.1		21.7	
Females										
After 1970		10.7		31.7		23.3		9.7		63.5
1950-1969	2.4	13.3	8.3	34.4	61.6	24.8	71.9	10.3	7.9	57.6
1930-1949	2.1	13.2	8.6	34.7	56.0	21.0	64.9	8.7	10.6	54.9
Before 1930	1.7		8.2		55.3		56.7		15.3	
High Education										
Males										
After 1970		27.9		37.5		34.1		13.1		44.1
1950-1969	19.4	29.5	18.4	51.6	49.9	38.8	21.1	12.2	7.9	39.4
1930-1949	20.5	29.7	23.5	53.7	50.8	33.4	13.6	6.2	4.4	42.5
Before 1930	19.1		22.5		48.4		12.2		2.2	
Females										
After 1970		19.8		44.0		22.1		5.3		51.0
1950-1969	9.8	20.0	18.4	48.6	40.0	27.0	22.2	4.0	5.0	52.2
1930-1949	10.4	18.3	20.0	54.1	39.6	31.2	20.1	4.1	2.9	58.2
Before 1930	5.4		17.7		30.3		23.5		0.0	

Note: Each cell represents the average value of the task measure for a particular cohort in a particular year.
Data: Qualification and Career Survey.

Appendix Table 6: Task Prices
Dependent Variable: Log Real Daily Wages

Analytic	.383 (.012)	.430 (.017)
Interactive	.593 (.006)	.810 (.013)
Routine Cognitive	.130 (.002)	.126 (.007)
Routine Manual	-.047 (.004)	-.064 (.007)
Non-routine Manual	-.086 (.003)	.007 (.007)
Analytic*woman	.838 (.029)	.893 (.053)
Interactive*woman	.085 (.016)	-.323 (.042)
Routine Cognitive*woman	.264 (.007)	.371 (.011)
Routine Manual*woman	-.080 (.009)	.028 (.013)
Non-routine Manual*woman	.016 (.006)	.061 (.016)
Analytic*d_99		-.112 (.025)
Interactive*d_99		-.154 (.016)
Routine Cognitive*d_99		.070 (.009)
Routine Manual*d_99		.010 (.010)
Non-routine Manual*d_99		-.214 (.010)
Analytic*woman*d_99		-.113 (.067)
Interactive*woman*d_99		.374 (.051)
Routine Cognitive*woman*d_99		-.392 (.017)
Routine Manual*woman*d_99		.034 (.023)
Non-routine Manual*woman*d_99		.059 (.020)
Woman	-.211 (.009)	-.285 (.016)
d_99	.010 (.002)	.073 (.009)
Woman*d_99		.116 (.017)
$R^{\wedge 2}$	.355	.359
N	334,359	

Note: The regressions are based on the IAB employment sample with task measures from the Qualification and Career Survey merged to the data on the occupational level. The regressions include controls for education, age (linearly), education-gender interactions and age-gender interactions, as well as industry dummies. Only employees with low and medium level of education are considered. Regressions are weighted by the number of days worked per year. Robust standard errors are in parentheses.