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.

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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 recent changes have been more favorable for women than for men. However, a substantial portion of the improvement in women's labor market opportunities 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 from 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

[1] See work by Blau and Kahn (1997, 2003, 2006).

and 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 applying a fixed-coefficient model to quantify how much of the closing of the gender wage gap is accounted for by differential task changes, we find that relative task changes could explain as much as 50 percent of the convergence we actually observe.

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, changes were predominantly within cohorts, suggesting that it is not changing selection into the workforce. Task changes occurred most rapidly in occupations in which computers have made major headway.

The paper unfolds as follows. Section 2 discusses the conceptual framework, Section 3 describes 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. Section 7 discusses implications of this work in terms of the polarization of the labor market, and Section 8 then concludes.

II. Conceptual Framework

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

In an effort to better understand the link between technology 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, 1992). 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 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

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

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.[4]

Because computers are substitutes for routine tasks, the task framework implies that demographic groups (in our case men and women) that differ initially in their routine task intensity will be affected differentially by workplace computerization:[5] First, groups with higher initial routine task intensities will experience faster rates of computer adoption. Second, they will experience larger relative shifts away from routine tasks towards non-routine tasks. Third, depending on the magnitude of the elasticity of substitution between routine tasks and computers, the demographic groups will experience differential changes in their wages. In the ALM-model, computer capital and labor are assumed to be perfect substitutes in carrying out routine tasks. As a consequence, the evolution of computer prices (which is the driving force in the model) determines the evolution of prices for routine tasks one-for-one. Technological advancements in computer production and the resulting declining price of computer capital thus lead to declining prices for routine

[4] So far, most of the literature on the gender wage gap has focused on supply side explanations such as changing education and experience (Again, see work by Blau and Kahn (1997, 2003, 2006)). 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, and Welch (2000) attributes the closing of the gender wage gap to the expansion in the value of brains relative to brawn. Unlike this earlier work, we are able to focus on within-occupation task changes for women relative to men. There are also a number of recent studies that examine the relationship between computer adoption and gender (see Weinberg, 2000, and Bacolod and Blum, 2006). 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. 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.

[5] Autor and Dorn (2007) apply the same reasoning with respect to commuting zones.

tasks. Hence, relative prices of non-routine tasks rise owing to the declining prices of routine tasks.[6]

While the model is general equilibrium in nature and refers to a single macro-economy, it can be applied to the question of how the skill content of work of different demographic groups is related to computerization if these demographic groups started with different initial conditions. As we will show later, women's routine task intensity in 1979 was much higher than men's routine task intensity; an observation that supports the notion that computerization will have a differential effect on men and women.

III. Data

We use two West German 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 wom-

[6] In the model, computers are also relative complements to non-routine cognitive tasks which additionally contributes to rising relative prices for non-routine cognitive tasks. We will not directly look at this channel here. See Spitz-Oener (2007) for a detailed analysis of this channel.

en.[7] 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.[8]

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.[9] 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.[10]

Occupational skill requirements are based on the activities that employees have to perform at the workplace. We pool these activities into five task categories, and each occupation has a value for each task category. The task categories 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.[11]

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

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[7] For details on the data set see Spitz-Oener (2006).

[8] We lose approximately 10% of our sample by restricting the data to those occupations that include both men and women. However, results are insensitive to this restriction.

[9] Appendix Table 1 lists the occupations considered.

[10] 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.

[11] 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.

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

where t=1979, 1986, 1992 and 1999; and k 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 performs two interactive tasks and the category includes four tasks in total, then her interactive task measure is 50.[12]

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:[13] (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 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.

Our wage data come from the Administrative Social Security Records, also known as the IAB employment sample, 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

[12] 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.
[13] 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.

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 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.[14]

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.[15] 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.[16]

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. 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

[14] This could introduce selection issues into our study. However, recent evidence suggests that the gender wage gap convergence has been the most pronounced for low and medium educated employees (Fitzenberger and Wunderlich, 2002). In addition, as we will show in Section IV, task changes have been more pronounced for low and medium educated employees than for high educated employees.
[15] Because of retirement incentives, employees over the age of 55 are a highly selected group; as a result, we focus only on prime age workers between the ages of 25 and 55. However, the patterns we observe in tasks over time are insensitive to the inclusion of older workers.
[16] Our results are robust to alternative weighting schemes.

inputs were more than twice as high as those for women, while women had higher routine cognitive and routine manual task inputs. 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.[17]

These patterns are very similar across education groups. Table 2 also 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.[18]

V. Role of Changing Tasks on the Gender Wage Gap

Given these patterns, we next examine how these changes in tasks relate to the change in the gender wage gap over this period. Between 1979 and 1999, the gender

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[17] 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.

[18] 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.

wage gap among low and medium educated workers declined by 9.3 percentage points in West Germany. Our simple thought experiment is, "how would the gender wage gap have evolved if prices and other characteristics had remained constant but tasks had changed?" That is, in the absence of any price changes, how much of the closing of the gender wage gap could we explain just by changing tasks?

To do this, we use a fixed-coefficients model where we calculate gender-specific task prices using data from 1979. Task prices are estimated from a log-wage equation with gender specific controls for age and education; the unit of observation is the gender-occupation cell. Using the coefficients on the individual tasks as our "prices", we then predict how the gender wage gap would have changed had only the task composition changed and everything else been held constant at the 1979 level. When we do this exercise, we can explain almost 50% of the change in the gender wage gap over this period.[19]

VI. Sources of Task Changes

What can explain the changes in tasks that we observe? There are a number of hypotheses, including changing selection of workers into the labor market, changing product market demand due, for example, to increased international trade, and technological change. We next evaluate the evidence on sources of task changes.

Changing Worker Selection

One hypothesis is that the patterns we observe are being driven by changing characteristics of working women (and men) over time.[20] 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 evo-

[19] Regressions available from the authors upon request.
[20] See recent work by Mulligan and Rubinstein (forthcoming).

lution of tasks within cohorts (see Appendix Table 2). 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.

Changing Employment Demand

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, representing a change in the production process. Changes across industries would be more consistent with changing product demand.

To distinguish these hypotheses, 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 and those that are due to differential changes in task inputs within cells.[21] We do the decomposition for occupation cells, industry cells, and industry*occupation cells. Overall, the decompositions suggest 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.

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

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

where $\overline{Y}_{gtj}$ is the average value of the tasks for gender g (M=men; F=female) at time t in cell 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, while 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.

Interestingly, for all task categories and all cells, within cell task changes have been larger for women than for men.[22]

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.

We next test the substitution and complementarity effects between computerization and task inputs predicted by the task framework. We collapsed the data set into occupation-gender-year cells for this purpose. Table 3 shows the results of the first-difference relationship between workplace computerization and workplace tasks. As before, we restrict the analysis to the overall period, 1979-1999, so the difference is between the 1979- and 1999-waves. The dependent variables are the changes in the respective task measures between 1979 and 1999. Each column represents a separate OLS regression.

The results show that occupations that saw greater increases in computerization witnessed larger increases in analytical and interactive task requirements combined with greater declines in routine manual and routine cognitive task requirements. We can use these results to quantify how much of the gender-specific task changes could be accounted for by computerization. The coefficients of the analytical task equation in column (1) indicate that about 72 (8) percent of the changes in analytical tasks of women

[22] The detailed results can be found in the NBER Working Paper version of this paper.

(men) were accounted for by computerization.[23] In the case of interactive tasks, the figures are 94 percent for men and 54 percent for women. Computerization more than fully accounts for the changes in routine cognitive tasks for both men and women, and for the routine manual task changes for men.

VII. Polarization

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.[24] 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. We, indeed, 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.[25]

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

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[23] The unconditional (weighted) means of the dependent variables are shown at the bottom of Table 3. The figures indicate an average increase in the analytical task measure for women of 9.52 percentage points. Using the coefficient of .124 (.011+.113) and the mean value of changes of computer utilization for women (55 percentage points), this implies that approximately 72% of changes in analytical tasks is accounted for by changes in computer use.

[24] See, for example, Acemoglu, 1999, Levy and Murnane, 1992, Goos and Manning, 2007, and Autor, Katz, and Kearney, 2006.

[25] Again, the detailed results can be found in the NBER Working Paper version of this paper.

demand side explanations have played only a minor role. In this study, we apply a task-based framework to examine the role of differential task changes on the closing of the gender wage gap. 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.

We find that changes in work content have been larger for women than for men along all dimensions we consider. In particular, 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.

In addition, we find that relative task changes are important in explaining the closing of the gender wage gap. Task 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.

Finally, this 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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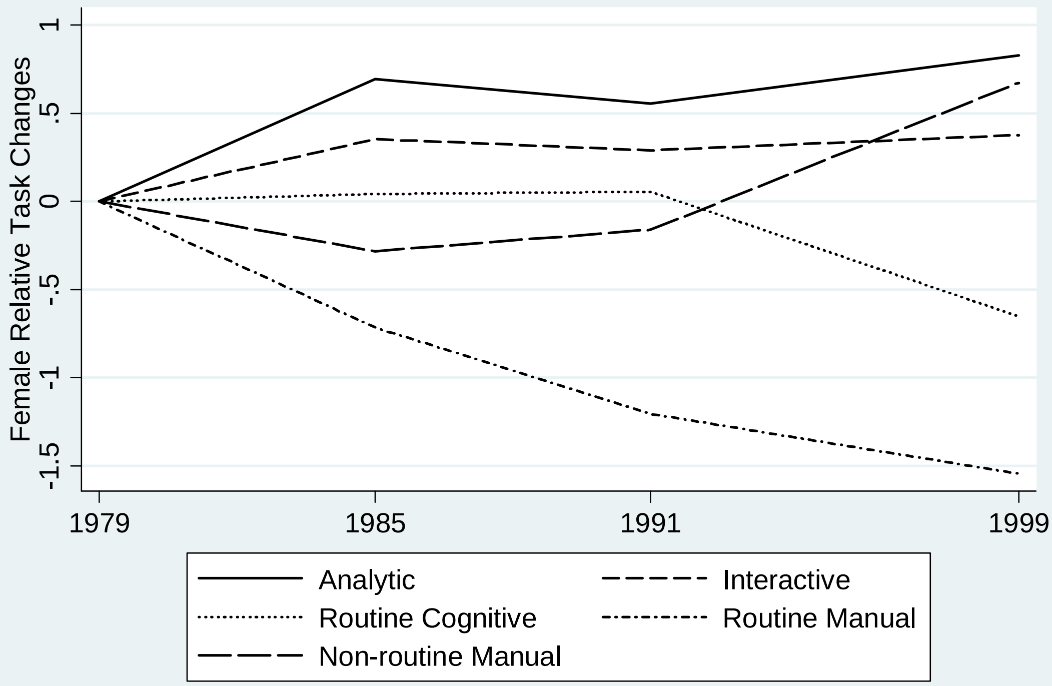

Note: Female relative task changes are defined as growth in female task inputs minus growth in male task inputs (both relative to 1979). Data source: BIBB-IAB

Figure 1: Female Relative Task Changes.

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
(Standard Deviations in Parentheses)

	Analytic	Interactive	Routine Cognitive	Routine Manual	Non-Routine Manual	PC Use
			All Workers			
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)
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)
			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 3
Skills and Computerization

Dependent Variable:	**Δ Nonroutine Analytic**	**Δ Nonroutine Interactive**	**Δ Routine Cognitive**	**Δ Routine Manual**	**Δ Non-Routine Manual**
ΔPercentage Using a PC	.011 (.030)	.353 (.037)	-.490 (.186)	-.284 (.150)	.508 (.139)
ΔPercentage Using a PC*Female	.113 (.047)	-.117 (.058)	-.418 (.285)	-.369 (.230)	-.282 (.214)
Female	-2.34 (2.99)	10.40 (3.65)	-11.65 (17.97)	-32.94 (14.50)	35.46 (13.47)
ΔPercentage with Medium Level of Education	.041 (.091)	-.218 (.112)	-.981 (.550)	-.557 (.444)	.318 (.412)
ΔPercentage with High Level of Education	.401 (.084)	.005 (.103)	-1.75 (.510)	-.818 (.411)	.110 (.382)
ΔPercentage with Medium Level of Education*Female	-.054 (.117)	.190 (.143)	1.05 (.70)	.991 (.570)	-.053 (.530)
ΔPercentage with High Level of Education*Female	-.240 (.140)	-.008 (.171)	1.63 (.841)	1.55 (.679)	-.764 (.631)
R^2	.411	.636	.369	.440	.215
Weighted mean dependent variable:					
Men	8.22	21.25	-8.79	-8.28	26.27
Women	9.52	24.04	-29.27	-46.64	44.58

Note: Unit of observation is the occupation cell. The number of observations in each regression is 92. Robust standard errors are in parenthesis; regressions are weighted by the number of observations within occupation groups. Data: Qualification and Career Survey.

Appendix Table 1
List of Occupations

Potter, Ceramist, and Gaffer	Technical service worker
Chemistry worker	Sales person
Paper and Pulp processing	Bank and insurance clerk
Printing and related trades worker	Other (unspecified) sales person
Metal construction worker	Land traffic operator
Sheet metal and construction worker	Communication worker
Vehicle/aircraft construction/maintenance worker	Management Consultant
Precision mechanics worker	Computer scientist/accountant
Electrician	Office clerk
Assembler	Entrepreneurs
Weaver, spinner	Guard/watchmen
Textile producer	Security personnel
Leather and fur processing worker	Judicial officer
Baker	Librarian/translator/publicist
Butcher	Artist/performer
Cooks	Physician/pharmacist
Interior decorator	Medical service worker
Painter/varnisher	Social worker
Product tester	Teachers, Scientist, Clergyman
Unskilled worker	Hairdresser/cosmetician/personal hygiene worker
Machine operator	Hotel and guesthouse worker
Engineer	Housekeeper/dietician
Chemist, Physicist, Mathematician	Cleaning and waste disposal worker

Appendix Table 2
Cohort Analysis

Year of Birth:	Analytic		Interactive		Routine Cognitive		Routine Ma-nual		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.