Wage inequality, tasks and occupations

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Abstract

This paper assesses the relationship between occupation attributes and changes in wage inequality finding partial support for the computerization hypothesis. While wages associated with non-routine cognitive tasks have risen; current versions of the hypothesis cannot explain the pattern of within occupation wage changes, the differential impact of various types of non-routine cognitive tasks and the declining return to tasks that complement machines. Despite significant employment shifts, occupational composition alone matters little for changes in wage inequality. Changes in wage dispersion within occupations are quantitatively just as important as wage changes between occupations for explaining wage inequality between 1980 and 2000.

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1 Introduction

The distribution of wages in the United States widened considerably during the 1980s. During the 1990s the upper portion of the distribution continued to grow more unequal, while the lower portion of the male wage distribution compressed and the lower portion of the female wage distribution grew slightly more unequal. Recent research has focused on the changing demand for particular skills, tasks or ability attributes resulting from technological change, especially computerization, to explain the changing shape of the wage distribution. In particular, beginning with Autor, Levy, and Murname (2003), hereafter ALM, research has documented significant shifts in occupational and task composition. According to the computerization hypothesis, demand for some "routine" tasks that are easily replaced by computerization decreased while demand for other "non-routine" cognitive and manual tasks that are not as easily replicated by computerization rose. Since non-routine manual tasks tend to be associated with occupations in the lower portion of the wage distribution while non-routine cognitive tasks tend to be linked to occupations in the upper portion of the wage distribution, the computerization hypothesis can potentially account for the polarization of employment growth. [1] Despite the prominence of the computerization (or routinization) hypothesis, there is very little empirical research that statistically links changes in job task-content to changes in the wage structure.[2] (Firpo, Fortin and Lemieux (2011), hereafter FFL, is an exception and is discussed below.)

This paper takes a step toward filling that gap by constructing measures of occupational attributes that can be categorized in accordance with the computerization hypothesis and by assessing their relationship to wage structure changes between and within occupations and thus to overall wage inequality trends. The investigation

[1] Work documenting the polarization of employment growth includes Autor, Katz and Kearny (2006, 2008), Acemoglu and Autor (2011), Goos and Manning (2007) and Goos, Manning and Salomans (2009).

[2] Most evidence documents employment shifts linked to changing task demand, but does not directly link employment shifts to wage structure changes.

uses 1% IPUMS decennial census data from 1980, 1990 and 2000. A time-consistent census-based occupation classification is matched with O*NET occupation attributes to assemble a data-set with extensive occupational representation. The use of census data allows the occupation based analysis to be conducted at the three-digit level with at least 100 observations in 264 occupations in the male sample and in 183 occupations in the female sample giving sufficient observations to calculate within occupation wage dispersion statistics. Principal components analysis (PCA) is used to aggregate 184 relevant O*NET measures into 13 occupation attribute-bundles that are easily interpreted within existing task-based frameworks. Heuristically, one can think of the PCA analysis as grouping the universe of occupations (in this sample) into 13 types of occupations. Each occupation is then assigned a factor score based on the weights given to each attribute for that occupation-group and the importance of that attribute in that occupation. Thus, the PCA methodology allows the data to determine occupation types and results in a more disaggregated taxonomy than used in previous work. (FFL create five occupation categories and Acemoglu and Autor (2011), hereafter AA, create six categories.)

For example, the PCA separates the interpersonal skills into those where there is freedom in decision making and communication occurs mostly through email or telephone and those that deal directly with people or groups and have frequent decision-making but not the freedom of decision-making. The former is dominated by professional and sales occupations while the latter by health-care and education service occupations.[3] In another instance PCA separates fine motor skills (e.g. finger dexterity and wrist-finger speed) from general physical skills (strength, coordination, control, and balance). The former skills tend to be used in occupations where some hand-crafting tends to occur (laboratory technicians, precision instrument makers, tailors) while the latter is dominated by occupations that require driving or operating equipment). The statistical procedure also provides a comparison and robustness

[3]The first attribute-bundle is denoted as interpersonal professional and the latter as interpersonal service.

check for the more parsimonious and subjective specifications used in FFL.

The results are mostly consistent with the pattern of results presented in FFL. However, this paper's findings expand on FFL's results in two major ways: (1) the analysis in this paper is able to identify where in the occupation-specific wage distributions the attribute-bundles impinge on the wage structure (and this lends insight into the the factors affecting overall wage inequality particularly during the 1990s) and (2) the use of 13 occupation types refines the link between tasks and wage structure. As an example, this paper finds that a subset of non-routine cognitive attribute bundles is associated with wage increases throughout their occupation wage distributions during the 1980s, but during the 1990s, any remaining positive influence tends to fall on the workers in the upper portion of their occupation wage distribution. Moreover, the returns to two non-routine cognitive attributes (those associated with supervisory and lower level management occupations and interpersonal service occupations) fell during the 1990s. [4]

In other words, some non-routine cognitive attribute-bundles matter more than others for explaining changes in the wage structure. Specifically, attribute-bundles associated with communication and professional interpersonal skills (teachers, professional sales, doctors, lawyers, for example) are associated with the largest returns in median occupation wages during the 1980s. While a logical corollary of the computerization hypothesis would imply that tasks that are more complementary to computerization would experience larger wage gains, at present, the computerization hypothesis does differentiate between types of non-routine cognitive tasks. Is it the case that the tasks performed by teachers, professional sales-people, doctors and lawyers are more complementary to computers than others? Also, the results below will also show that, in accordance with the computerization hypothesis, returns to

[4]For females the positive association of the three non-routine cognitive bundles with wages throughout the wage distribution continues into the 1990s. The non-routine cognitive attribute-bundles associated with supervisory and lower level management occupations and personal service occupations are not statistically significantly associated with wages for the female sample during the 1990s.

general routine work declined during the 1980s; however, during the 1990s the returns stabilized for males and rose for females. Furthermore, the attribute-bundle associated with routine physical (psychomotor) work is not statistically significantly related to any wage structure change.[5]

Another novel result presented below documents that the contribution of within occupation wage changes are quantitatively equal to or larger than the contribution of between occupation wage changes for explaining overall wage inequality. Moreover, during the 1990s the task measures explain more of the within occupation dispersion (for males) than of changes in median wages between occupations. This occurs, in part, because (as stated above) some non-routine cognitive attribute-bundles are associated with rising wages in the upper portion of the occupation wage distribution while attribute-bundles that complement machines, manual non-routine attribute-bundles and the interpersonal service attribute-bundle are associated with declining wages in the upper portion of their occupation wage distribution. Finally, a set of estimates examines the association between employment reallocation between occupations and the attribute-bundles. The findings suggest that female re-allocation of labor across occupations has been more responsive to changes in task demand than has male re-allocation, but the re-allocation (or not, for males) contributes little to wage structure changes. Alterations in the composition of the workforce, including occupational composition, are relatively unimportant for explaining changes in wage dispersion holding constant wage structure changes.

In the remainder of the paper, section 2 relates the work in this paper to previous work, section 3 documents the relative importance of within and between occupa-

[5]Empirical studies have also found that deunionization helps to explain the changing pattern of the wage distribution. See, Card (1996, 2001), Freeman (1993), Dinardo, Fortin and Lemieux (1996) and FFL. Therefore, this study will also estimate the impact of occupational union coverage on the wage structure. The results are quite robust for the male sample: unionization is positively associated with wages at the $50^{\text{th}}$and 10^{th}wage percentiles. So deunionization would result in an increase occupation-specific wage dispersion in the upper portion of the distribution with both the coefficient size and magnitude of deunionization being largest in the 1990s. This is consistent with the findings in FFL. In the female sample the magnitude of the impact of de-unionization is smaller and only robustly statistically significant during the 1990s.

tion wage changes for overall wage inequality, section 4 describes the occupation attribute-bundles, section 5 relates occupation wage structure changes to the occupation attribute bundles and section 6 concludes.

2 Relation to previous research

The research relating occupational task content to wage inequality is relatively new.[6] AA show that in a typical wage regression the explanatory power of occupation task measures is as large as the explanatory power of occupation dummies (using 10 occupation groups) and the power has doubled over the last three decades. While most other research has related employment shifts to occupation attributes, FFL is the paper most closely related in objective to this paper: to statistically assess the importance of occupation attributes to wage structure.

Because the O*NET measures a large number of occupation attributes, using the data to parsimoniously quantify occupation characteristics can be cumbersome and/or subjective. Typically, a few attributes out of the several hundred available, are selected to measure a specific occupation characteristic. For example, FFL select five attributes to measure routine manual tasks. AA select three measures (2 are the same as FFL) and ALM and Autor and Dorn (2011), use one attribute. [7] In this paper, I use principal components analysis (PCA) separately on four pertinent subsets of the O*NET data: (1) "skill attributes" from the work requirements section of the O*NET data, (2) "ability attributes" from the abilities sub-section of the worker characteristics section, (3) "task attributes" from the general work activities sub-section of the occupational requirements section and (4) "work context

[6]There is an extensive literature that attempts to understand the increase in U.S. wage inequality in the last 30 years. The current emphasis on changing task demand arising from computerization and/or off-shoring has its origin in the skill-biased technological change hypothesis (see the surveys Acemoglu (2002), Hornstein, Krussel and Violante (2005) and Acemoglu and Autor (2011) and the references therein).

[7]ALM used data from the *Dictionary of Occupational Titles* (DOT). The Occupation Information Network (O*NET) is the more comprehensive successor to the DOT classification. AA construct measures from both DOT and O*NET data. FFL use O*NET data.

attributes" from the work context sub-section of the occupational requirements section. The four subsets contain 35, 52, 41 and 56 individual attributes, respectively, and PCA reduces the first 3 subsets to 3 factors and the last subset (work contexts) to 4 factors.[8] FFL pull elements only from the general work activities and work context subsets for their measures, while AA also include two elements from the ability attributes.[9] Inclusion of the ability attributes allows me to also characterize occupations by the types of cognitive and physical skills used on the job and the skill attributes subset divides occupations into those that use communication and technical skills.[10] These are distinctions that are pertinent to the computerization hypothesis.

FFL construct two variables from the O*NET data for 40 broad occupation groupings that measure the information content (reflecting non-routine cognitive attributes) and the automation/routinization of the occupation, respectively. Together these two variables are intended to capture the potential impact of computerization. FFL also construct three variables to measure the potential for off-shorability.[11] To assess statistically the importance of the task measures on wage structure, FFL implement a two-step procedure that first regresses the change in the wage on initial wage levels for each decile of wages in each of the 40 occupations: their wage profile equation.[12] The intercept and slope coefficients from the wage profile equation are then regressed on the task measures. The finding that the slope coefficient is pos-

[8]ALM (in one specification) and Crino (2010) also use principal components analysis to construct occupation measures from the DOT and O*NET, respectively. In both cases, principal components analysis was used to produce one measure from a few attributes that had been preselected to measure a particular taxonomy (e.g. routine manual work). That is, PCA was used to combine the preselected elements rather than simply summing the values of each individual element as in FFL and AA. In this paper, PCA is used as a data reduction tool to statistically assesses and quantify occupation types as a function of the occupation attributes. Additional details are given in Section 4 and in the Data Appendix.

[9]AA use the elements "manual dexterity" and "spatial orientation" from the ability attribute sub-section in their non-routine manual physical measure.

[10]As will be described below the PCA produces two types of physical skills from the ability elements and two types of technical skills from the skill elements.

[11]Also see, e.g. Blinder (2007), Grossman and Rossi-Hansberg (2008) and Crino (2010) for studies relating task measures to trade or off-shoring.

[12]They restrict the analysis to male workers.

itively related to the task measures indicates higher values of the task measure are correlated with larger changes in dispersion while a positive coefficient on the intercept indicates the task measure is positively correlated with wage changes. This procedure allows FFL to examine the impact of the task measures on both wage changes and wage dispersion changes at the occupation level. They use CPS data with initial and ending periods that pool three years of data in order to work with a sufficient number of observations in each occupation.[13] In addition, FFL also use a decomposition technique that combines kernel re-weighting (as in DiNardo, Fortin and Lemieux (1996)) and re-centered influence function regressions to create counterfactual decompositions that keep a subset of the covariates (e.g. the computerization measures) constant. The decomposition permits separate identification of composition and wage structure effects.

In this paper, I use the larger samples in the decennial census data to include 264 occupations (183 in the female sample). Each occupation is represented by at least 100 observations in each decennial survey. This allows me to estimate the impact of the occupation-attribute bundles on the change in the wage at individual percentiles of the wage distribution. So, unlike the analysis in FFL, I can identify where in the occupation-specific wage distributions the occupation-attribute bundles have affected the distribution.[14]

The PCA generates two attribute-bundles that are very similar to two measures constructed by FFL. The routine work attribute-bundle has heavy factor loadings on four of the five elements in FFL's automation/routinization measure.[15] The manual or technical attribute-bundle has heavy loadings on all of the attributes in

[13]Their "main period of analysis" includes pooled data from 1988-1990 as the initial point and from 2000-02 as the end point.

[14]And, as described in more detail below, I re-weight the data so that the impact of the occupation attribute bundles can be disentangled from composition effects. The next section of the paper will show that understanding within occupation wage dispersion is crucial for understanding the pattern of overall wage inequality.

[15]The four over-lapping attributes are "degree of automation", "importance of repeating same tasks," "pace determined by speed of equipment," and "spend time making repetitive motions." The measure in this paper also places heavy weight on the attributes "importance of being exact" and "time pressure"

FFL's on-site job measure (intended to capture the potential off-shorability of an occupation) while also weighting three other attributes heavily.[16] The implications for wage structure for these two occupation-attribute bundles are roughly similar to FFL's while also providing some additional insights. FFL find that their automation/routinization measure is negatively related to wages and to within occupation dispersion. I find that this negative relationship occurs during the 1980s and that routine work was associated with larger declines in wages at the 10$^{\text{th}}$ and the 90$^{\text{th}}$ percentiles relative to the 50$^{\text{th}}$ percentile. That is routine work was associated with increasing lower tail inequality and upper tail compression within occupations. In the 1990s, however, my results show a moderate increase in median wages for occupations with high measures of routine work. FFL's on-site job measure is associated with falling wages and within occupation compression. I find that in the 1980s the wage declines associated with my mechanical or technical attribute bundle occur in the middle and upper portions of the occupation wage distribution while during the 1990s wages declines occur only in the upper portion. That is compression occurs from the top of the occupation distributions.

Additionally, FFL find that information content is positively associated with both occupation mean wages and within occupation dispersion. The attribute-bundle most closely related to the FFL measure (gathering and processing information) is also associated with rising occupation wages and within occupation dispersion in this study. However, the results here point out that during the 1980s the within occupation dispersion arises from the median wage rising more than wages in the lower portion of the occupation distribution while during the 1990s within occupation dispersion is driven by an increase in upper-tail inequality. FFL's other two measures, "face-to-face" and "decision-making" are not easily comparable to any attribute bundle in this study.[17]

[16] Those three additional attributes are "monitor processes, materials, or surroundings," "performing general physical activities," and "drafting, laying out, and specifying technical devices, parts, and equipment."

[17] The "face-to-face" measure includes one attribute that is heavily weighted in my "interpersonal

3 Within and between occupation changes

The recent emphasis on changing task demand has led to increased awareness of skill and wage dispersion within occupations. [18] In FFL's occupation wage equation, each occupation uses all skills to varying degrees and each worker possesses some level of each skill. If the return to a particular skill rises (say the return to non-routine cognitive skills), then the variance of wages within an occupation will rise since each occupation contains workers with different levels of that skill. Reallocation of workers in response to those price changes may enhance the dispersion created by the price change.[19]

The analysis below examines to what extent changes in overall wage dispersion are created by wage changes within and between occupations. The results will show that (1) dispersion changes within occupations are quantitatively as important or more important than between occupation wage changes in explaining the changes in overall wage dispersion between 1980 and 2000 but (2) shifts in occupational composition (holding constant wage structure) are relatively unimportant for explaining overall wage inequality trends.

In the first calculation, the variance of the overall wage distribution is decomposed into the portion arising from changes to wage dispersion within occupations and the component arising from changes in mean wages between occupations. The following expression details the difference between the variance for the entire sample (σ^2) and

service" bundle and the remaining 4 elements are heavily weighted in my "coordinate, oversee, and advise" bundle. Each of those bundles also heavily weight other individual attributes. So, while FFL find that "face-to-face" is positively correlated with wage changes and within occupation dispersion during the 1990s, both the "interpersonal service" and "coordinate, oversee, advise" bundles are associated with decline wages in the upper portion of the occupation distribution and upper tail compression in the 1990s in my results. FFL's "decision-making" bundle contains three individual attributes that are heavily weighted in my "gathering and processing information" bundle and two individual attributes that are heavily weighted in my "interpersonal service" bundle.

[18] The literature on wage inequality has a long history in attempting to disentangle the relative importance of between and within group wage changes. See, e.g,, Juhn, Murphy and Pierce (1993), Lemieux (2006), Acemoglu, Autor and Kearney (2008).

[19] The task-based model in AA as well as the unbalanced productivity growth model in Autor and Dorn (2011) offer models of labor re-allocation across tasks. However, neither model lends itself to predictions about variance within occupations.

the sum of the variances by occupation weighted by occupation employment share $\left(\sum_{k=1}^{K} \theta_k \sigma_k^2\right)$

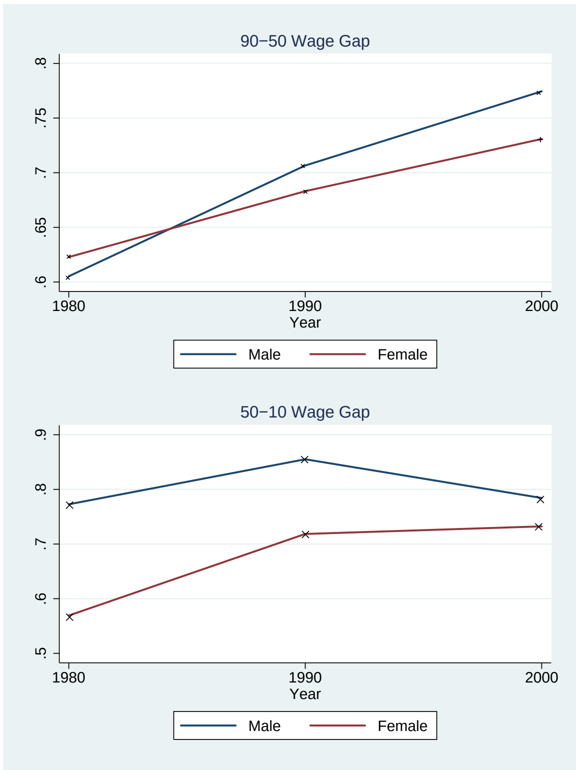
$$\sigma^2 - \sum_{k=1}^{K} \theta_k \sigma_k^2 = \bar{w}^2 - \sum_{k=1}^{K} \theta_k \bar{w}_k^2 - \frac{2}{N} \sum_{k=1}^{K} (\bar{w} - \bar{w}_k) \sum_{i=1}^{n_k} w_{ik} \tag{1}$$

where σ_k^2 is the variance in occupation k, θ_k is the employment share in occupation k, $\bar{w}$is the mean overall wage, $\bar{w_k}$ is the mean wage in occupation k, w_{ik} is the wage of individual i in occupation k, and n_k is the number of workers in occupation k. As equation (1) indicates, the weighted variance measure deviates from the overall variance because of differences in occupation mean wages from the overall mean wage. The portion of the overall variance not explained by changes to the weighted variance can be attributed to changes in the dispersion of mean wages across occupations. Changes in the weighted variance will be driven by within occupation variance changes and changes in the distribution of employment across occupations. To separate the contribution of occupational shifts from within occupation wage dispersion on overall wage dispersion, a counterfactual weighted variance is constructed for 1990 using 1980 employment shares and for 2000 using 1990 employment shares. The difference between the change in the actual and counterfactual weighted variance gives the portion of variance change due to within occupation wage dispersion.

Between 1980 and 1990, median male wages stayed approximately the same while the distance between the median wage and other wage percentiles grew. That is, inequality increased throughout the wage distribution. The female wage distribution exhibited similar patterns, but with an increase in the median wage. Between 1990 and 2000, again median male wages continued to stagnate while inequality in the lower portion of the male wage distribution decreased. In the female wage distribution, median wages increased modestly and inequality in the upper portion of the distribution slightly widened. Figure 1 displays these trends.[20]

[20]The data come from the 1% Integrated Public Use Micro-files of the decennial census data. The wage data in the decennial census refer to the previous year's wages; however, for convenience I will reference the data using the decennial year. The sample includes workers between the ages

Figure 1: Wage Gaps



Since the 1980s male wage distribution changes were nearly symmetric about the median, the variance change between 1980 and 1990 provides a reasonable characterization of the changes in the overall wage distribution. However, between 1990 and 2000 the opposing trends in the lower and upper portions of the male wage distribution yield an overall variance that is very small. Similarly, changes in the female wage distribution are asymmetric about the mean, particularly so during the 1990s.

Therefore, in addition to the variance decomposition, two additional counterfactual wage distributions are calculated. In one counterfactual exercise the within occupation wage distribution is held constant between periods but occupation median wages are permitted to change as observed in the data. The wage distribution statistics calculated from this counterfactual distribution simulate the impact of changes in median occupation wages on the overall wage distribution. In the other counterfactual construction median occupation wages are held constant between periods while the occupation wage distribution takes on its observed structure each period. The wage statistics calculated from this counterfactual distribution simulate the impact of within-occupation wage changes to the overall wage distribution. In both constructions, the entire distribution of wages is recreated and enables the examination of changes in different portions of the distribution. Rather than assume a particular distribution for wages within occupations, the distribution is approximating by measuring the distance between the median wage in occupation k time t (w_{kt}^{50}) and the wage at any percentile (w_{kt}^{p}) in the same occupation and time period as:

of 16 and 64 with wage and salary income who worked at least 40 weeks in previous and usually worked at least 35 hours per week in the previous year. Wages were converted to hourly rates by dividing annual wage and salary income by total hours worked. The latter is the product of the number of weeks worked that year and usual hours worked per week. Hourly wages were converted to real values using the PCE index and outliers were trimmed from the data. Top-coded values for annual income were multiplied by 1.45. The sample is weighted both by census sample weights and hours usually worked. Additional data details are provided in the Data Appendix.

$$d_{kt}(p) = w_{kt}^{p} - w_{kt}^{50} \tag{2}$$

So, the occupation-specific wage at a given wage percentile is:

$$w_{kt}^{p} = w_{kt}^{50} + d_{kt}(p) \tag{3}$$

The counterfactual distribution of wages that holds the within occupation distribution constant is constructed by calculating a counterfactual wage for each individual by applying the distance function, equation (2), from the previous period to the current period's median wage. So, the individual who is at the p^{th}percentile at time t in occupation k will have a counterfactual wage, $\hat{w}_{kt}^{p}$ given by:

$$\hat{w}_{kt}^{p} = w_{kt}^{50} + d_{k,t-1}(p) \tag{4}$$

The counterfactual distribution of wages that holds occupation median wages constant calculates a counterfactual wage for each individual by applying the current period distance function to the previous period's median wage. So, the individual who is at the p^{th}percentile at time t in occupation k will have a counterfactual wage, $\widetilde{w}_{kt}^{p}$ given by:

$$\tilde{w}_{kt}^{p} = w_{k,t-1}^{50} + d_{kt}(p) \tag{5}$$

The advantage of the above methodology is that it allows the construction of the entire wage distribution under the two counterfactual scenarios and allows one to consider the impact of occupational wage structure on different parts of the overall wage distribution. The major disadvantage of the methodology is that it is not a decomposition. That is, for any given distributional statistic, the sum of the contributions of the between and within occupation changes will not necessarily equal the total change.

3.1 Results

Table 1 shows the calculated contribution of between and within occupation wage changes to the change in the variance of male and female wages during the 1980s and the 1990s.[21] During the 1980s changes to within occupation variance account for 54% of the total change in the male variance and 78% of the total change in female variance.[22]

Table 2 presents changes to the 90-50 and 50-10 wage gaps that would have occurred under the two counterfactual wage scenarios. For example, the second row of column 1 of Table 2 shows that the 90-50 male wage gap increased by .0778 when comparing the actual 1980 values to the 1990 values from the counterfactual wage distribution that keeps occupation median wages fixed. Similarly, the 2nd row of the third column shows that the 90-50 male wage gap increased by .0342 when comparing values from the actual 1990 distribution to the counterfactual 2000 distribution that keeps the occupation median wage fixed. In nearly all instances, changes to within occupation wage dispersion have a larger contribution to the total change than between occupation wage changes. The only instance where between occupation wage changes dominate is in the upper portion of the female wage distribution during the 1980s. However it is shown below that once composition effects are accounted for, the importance of between occupation wage changes is diminished.

Table 3 recalculates the counterfactual wage distributions as in Table 2, but re-weights the counterfactual wages to replicate the composition of the sample in the previous period. The re-weighting uses the methodology in DiNardo, Fortin and Lemieux (1996) where a logistic regression estimates the probability of an observation

[21] The distance between percentiles is calculated for each unit wage percentile (1-99). Wages falling within those units are assigned a linearly interpolated distance between the two unit percentiles containing that wage observation.

[22] While all of the top-coded wage values are above the 90^{th}percentile of the overall wage distribution, there are a few occupations where the extent of top-coding may bias mean and variance estimates. All of the results that rely on occupation means or variances, are calculated from means and variances that are adjusted to account for truncation of the distribution. (See the Data Appendix for details.)

Table 1: Variance Decomposition

	Male		Female	
	1980-90	***1990-2000***	***1980-90***	***1990-2000***
Total change in variance	.0716	-.00088	.0741	.0257
Due to within occupation	.0390	-.00194	.0578	-.0117
Due to between occupation	.0272	.00094	.0151	.0367
Due to occupation shifts	.0054	-.00834	.0012	.0007

Table 2: Changes in the 90-50 and 50-10 Wage Gaps

	Male			
	1980-90		1990-2000	
	90-50	***50-10***	***90-50***	***50-10***
Total change	.1035	.0886	.0660	-.0774
Due to wage dispersion within occupations	.0778	.0507	.0342	-.0537
Due to wage changes between occupations	.0588	.0257	.0184	-.0154
	Female			
	1980-90		1990-2000	
	90-50	***50-10***	***90-50***	***50-10***
Total change	.0592	.1526	.0368	.0153
Due to wage dispersion within occupations	.0292	.1074	.0343	.0044
Due to wage changes between occupations	.0417	.0660	.0103	-.0045

belonging to one of two time periods (e.g., 1990 versus 1980) as a function education, experience and occupation. [23] The second row of Table 3 shows the change in the wage gaps calculated from the re-weighted distributions that keep constant the education, age and occupational composition of the workforce. Comparing actual total changes to composition adjusted total changes for the male distribution indicates that composition played a minor role in changing the wage structure. The largest impact of composition occurs in the lower portion of the distribution during the 1980s where composition changes account for about 20% of the increase in the 50-10 gap. Female distributions tend to have been more influenced by composition changes. Adjusting for composition changes diminishes the importance of between occupation wage changes in the upper portion of the female distribution during the 1980s and is responsible for all of the relatively small increase in inequality in the lower portion of the female distribution during the 1990s. Without the change in composition, female lower tail inequality would have decreased during the 1990s as did its male counterpart. Composition changes also diminished the increase in upper tail inequality during the 1990s. Without composition changes the 90-50 wage gap would have increased 30% more than the observed change. This time period saw a large increase in educational attainment, particular at the collegiate level, as well as shifts of female employment into traditionally non-female jobs. Therefore, it seems reasonable that composition changes might play a larger role in the female wage structure.

So, the results from the variance decomposition and the counterfactual distributions both indicate that changing occupational structure contributes little to the overall male wage inequality patterns between 1980 and 2000 and modestly to some

[23] More specifically, the regression includes dummy variables for eight education categories and ten age categories, each education dummy is interacted with a quartic in age, and a full set of occupation dummies. Therefore, the re-weighted 1990 wage distribution mimics the composition of the 1980 sample in terms of age, education and occupational affiliation. The 2000 wage distribution is re-weighted to mimic the composition of the 1990 sample. The analysis is then conducted looking at changes, so the the change in distributional statistic between 1990 and 2000 compares the actual 1990 values to the 2000 counterfactual values.

Table 3: Changes in the 90-50 and 50-10 Wage Gaps

	Male			
	1980-90		1990-2000	
	90-50	***50-10***	***90-50***	***50-10***
Total change	.1035	.0886	.0660	-.0774
Total: composition constant	.0908	.0700	.0605	-0.0802
Due to wage dispersion within occupation	.0588	.0427	.0368	-.0778
Due to wage changes between occupations	.0369	.0186	.0361	-.0337
	Female			
	1980-90		1990-2000	
	90-50	***50-10***	***90-50***	***50-10***
Total change	.0592	.1526	.0368	.0153
Total: composition constant	.0554	.1287	.0476	-.0208
Due to wage dispersion within occupation	.0237	.0775	.0225	-.0211
Due to wage changes between occupations	.0283	.0301	.0059	-.0295

portions of the change in the female wage distribution. While certainly there have been significant changes in occupational composition, it is shifting wage structure, not shifting employment, that explains the vast majority of wage dispersion. Moreover, within occupation wage dispersion changes are at least as important as between occupation wage changes for understanding the determinants of overall wage inequality.

4 Occupation attribute bundles

To implement the PCA, I match each of the consistent 1990 census occupation codes to their matching occupation(s) in the O*NET data (the latter used the 2000 SOC occupational classification) using the crosswalk between 2000 census and 2000 SOC codes and the crosswalk between 1990 and 2000 occupation codes. Factors for each of the four subsets are estimated separately, resulting in the estimation of 13 occupation types (factors). The PCA analysis produces three factors each for the skill, ability and task attributes and 4 factors for the work context attributes. Table 4 summarizes the major attributes and the occupations with high scores for each of the attribute-bundles. [24]

Each of the factors (occupation types) are fairly easily interpretable in terms of their bundle of attributes. The first skill attribute-bundle has heavy factor loadings on all of the basic skill, cross-functional management resource attributes as well as the complex problem solving attributes.[25] These are occupations that require communication, problem solving and complex interpersonal skills. For brevity, denote this attribute bundle as "communication skills." Occupations that rank high in the communication skills attribute bundle tend to be teachers, lawyers, judges and medical professionals. These are occupations that require both higher level cognitive skills and the ability to communicate ideas to others. The second skill attribute bundle has heavy factor loadings on all of the cross-functional: technical attributes. These encompass skills related to selecting, installing, monitoring or repairing equipment so denote this attribute bundle as "machine skills." The third attribute bundle loads heavily on attributes that O*NET describes as "capacities used to understand, monitor, and improve socio-technical systems." Denote this attribute bundle as "socio-technical skills" and note that professional technical, engineering and some management occupations rank high in socio-technical skill.

The ability attribute-bundles separate occupations using cognitive abilities from two types of occupations that use psychomotor abilities. The "cognitive ability" attribute-bundle has high factor loadings on most of the expression, comprehension, and reasoning abilities. The occupations that rank high in this bundle include professional occupations that require a high degree of reasoning or mental flexibility such as physicists, engineers, physicians, dentists, veterinarians, lawyers, actors and di-

[24] Most attributes clearly load most heavily on one factor; however, 14 attributes (out of 184) have factor loadings that are approximately equal across two factors. The Data Appendix presents the values of the factor loadings for each subset of attributes and some additional details. The factor loadings are the values obtained using the orthogonal varimax rotation. Quartimax rotation produced very similar results.

[25] These are sub-groups of attributes as described by O*NET. For a detailed description of the sub-groups of attributes in each subset of the O*NET content model, see http://www.onetcenter.org/dl_files/ContentModel_DetailedDesc.pdf. See the Data Appendix for a list of occupations that score high in each of the 13 estimated occupation types.

Table 4: Attribute Bundles and Related Occupations

Skill bundles

Communication skills: Communication, complex interpersonal skills, problem solving.
Teachers, lawyers, judges, medical professions

Machine skills: equipment selection installation, reparation, monitoring skills.
Machine repairers, installers and maintenance workers.

Socio-technical skills: "understand, monitor, and improve socio-technical systems"
Engineers, scientists, accountants, some managers.

Ability bundles

Non-routine psycho-motor abilities: general movement and strength attributes
Firefighters, drivers, miners and construction workers

Routine psycho-motor abilities: fine motor skills, visual skills and quick perception
Precision instrument makers, textile workers, tailors, upholsterers, medical technicians

Cognitive abilities: comprehension, expression, and reasoning abilities
Physicists, engineers, medical professionals, lawyers, actors, directors, air-traffic controllers

Task bundles

Gathering and processing information tasks: getting, analyzing, evaluating information.
Scientists, engineers, clinical and biological technicians

Manual or technical tasks: handles objects, operates, controls or repairs equipment
Miners, machinery repair and maintenance occupations, boilermakers and millwrights

Coordinate, oversee, advise tasks: scheduling, coordinates work, assists, trains, advises others
Managers and supervisors

Work-context bundles

Manual or hazardous work: works in unpleasant or hazardous conditions or body positions
Works with heavy machinery or equipment, fire fighters and roofers

Professional interpersonal work: sedentary work conditions, makes decisions, unstructured work
Professional sales, lawyers, judges, some managers, actors, directors, musicians.

Service interpersonal work: face-to-face, works with others, conflictual situations
Medical workers and supervisors of guards, personal service and cleaning jobs.

General routine work: repetitive motions or tasks, automatized, pace determined by equipment.
Telephone operators, dentists & dental workers, air traffic controllers, some machine operators, legal assistants, typesetters, data entry, dispatchers, postal workers, miners.

rectors and air-traffic controllers. The two psychomotor attribute-bundles divide occupations by the type of physical activity required on the job. The attribute-bundle denoted "non-routine psychomotor" favors balance, coordination and strength attributes and the occupations ranked high in this category include firefighters, drivers, miners and construction workers. The "routine psychomotor" attribute bundle favors fine motor skills and attributes related to visual skills and quick perception. Occupations with high values for the routine psychomotor attribute-bundle include makers of precision instruments, sewing machine operations, tailors, upholsterers, some dental and clinical technicians and art-makers.

Of the three task attribute-bundles, the bundle denoted "manual or technical tasks" separates out occupations utilizing physical or technical tasks from the other two task attribute-bundles that favor professional tasks. Occupations with high values in the manual or technical tasks attribute-bundle include miners, machinery repair and maintenance occupations, boilermakers and millwrights. The other two task attribute-bundles separate occupations into those that focus on gathering and processing information and those that focus on coordinating, overseeing or advising other. The "gathering and processing information" attribute-bundle give scientists and engineers high factor scores. The "coordinate, oversee and advise others" attribute-bundle gives administrators and supervisors high factor scores.

Finally, the work context attribute-bundles divide work context into four categories. The first, denoted "manual or hazardous work" gives large factor loadings on attributes associated with physically difficult or unpleasant work conditions. Occupations that involve working with heavy machinery or other equipment, fire fighters and roofers have high factors scores for this attribute bundle. Two attribute-bundles emphasize an interpersonal work environment. The attribute bundle denoted "professional interpersonal" has large factor loadings on occupations that use email, memos and letters to communicate, that do not involve much physical activity, have a less-structured work environment and involve decision-making. The attribute-bundle denoted "service interpersonal" has large factor loadings on communication environments that involve face-to-face contact, group interactions or working with the public. These occupations also tend to have environments where there is a high level of conflict and contact with unpleasant or angry people. Lawyers, judges, salespersons and some managers receive top factor scores in the professional interpersonal attribute-bundle, while health-care workers and supervisors of guards, personal service and cleaning jobs receive high factor scores in the service interpersonal attribute bundle. The fourth bundle in this category heavily weights attributes associated with repetitive tasks where speed is important and is denoted "routine work." Occupations that rank high in the routine attribute-bundle include some occupations that are more easily automated (e.g. telephone operators, legal assistants, some machine operators) but also includes dentists and air traffic controllers since these are occupations where the physical actions may be repetitive.

In summary, PCA has been used to characterize occupations into bundles of attributes, reducing 184 occupation attributes to 13 bundles that group occupations by their task content. FFL, AA and ALM hand-picked occupation attributes that appeared consistent with the skills or tasks associated with key model-based concepts. While this may appear to generate a clean match between concept and empirical implementation, the resulting empirical results may actually link to the model imprecisely since any one attribute or small set of attributes are also correlated with other attributes that may not link precisely with the model. Nonetheless, two of the resulting bundles, "routine work" and "manual and technical tasks" are very similar to the "automation/routine" and "on-site job" measures, respectively, used by FFL.

5 Occupation attributes and wages

5.1 Regression results

Seven of the attribute-bundles (communication skills, socio-technical skills, cognitive ability, coordination, overseeing and advising tasks, gathering and processing information tasks, professional interpersonal context and service interpersonal context) measure differentiated bundles of non-routine cognitive attributes. One attribute-bundle (non-routine psychomotor) measures non-routine physical tasks, two attribute-bundles (manual or technical and machine skills) measure tasks involving repairing, operating, or installing machines and could also be categorized as non-routine manual. These bundles also capture a measure of complementarity with machine production. Two attribute bundles measure routine tasks: the routine psychomotor bundles captures mostly manual tasks while the routine work bundle measures the degree to which an occupation necessitates repetitive tasks in general. Finally, the manual or hazard attribute bundle describes physically difficult or hazardous working conditions and fits less directly into the task taxonomy but is generally characterized by occupations that are physically demanding and would be difficult to automate.

The construction of the factor scores ensures that each attribute-bundle is orthogonal to the others within its O*NET subset.[26] However, between O*NET subsets, the attribute-bundles can be correlated. In fact, there are two groups of three attribute bundles that are highly correlated: (1) the manual or technical bundle from the tasks subset, the manual or hazard bundle from the work context subset and the non-routine psychomotor bundle from the ability subset are highly correlated (correlation coefficients between .71 an .78) and (2) the cognitive ability bundle is highly correlated with both the gathering and processing tasks bundle and the

[26]Since the PCA was conducted separately for each O*NET subset. Also note that each attribute bundle, by construction of the factor scores, has a mean of zero and a standard deviation equal to one.

communication skills bundle.[27]

To examine the relationship between the attribute-bundles and wage structure, I conduct OLS regressions of the change in occupation wages at the 90^{th}, 50^{th}, 10^{th} percentiles of the occupation-specific wage distributions on each subset of occupation attribute-bundles and on the change in union coverage. [28] I estimate the following regression equation for each subset of occupation-bundles, for each gender and for two time periods: 1980-1990 and 1990-2000.

$$\Delta w_{kt}^{p} = \beta_{0t}^{S} + \sum_{i=1}^{N^S} \beta_{it}^{S} A_{ik}^{S} + \gamma_t \Delta U_{tk} + \varepsilon_t \tag{6}$$

where S denotes the O*NET sub-sets (skills, abilities, tasks and work contexts), A_i^S denotes the i^{th}attribute bundle in subset S, Δw_{kt}^{p} denotes the change in the wage at the p^{th} percentile in occupation k at between time t and the previous decennial census and ΔU_{tk} denotes the change in union coverage for occupation k at time t. The estimated coefficients on the occupation attribute-bundles are influenced by three major determinants: the change in the market return to that attribute-bundle, the change in the skill set of the workers who flow into the occupation and the relative labor supply into the occupation. It is likely that occupations with increasing returns will also experience an inflow of workers and employers will likely select the most highly qualified of those workers. The additional inflow of workers will dampen the wage increase while the selection of higher quality workers will enhance the wage increase. To partially parse out those effects, I also estimate equation (6) using a counterfactual wage that has been adjusted for the education, age and occupational composition of the workforce. That is, using the DiNardo, Fortin and Lemieux (1996) method, the actual 1990 and 2000 wage distributions are re-weighted to reflect the composition in 1980 and 1990, respectively and the occupation specific

[27]The Data Appendix presents the full set of correlation coefficients between bundles.

[28]The union data are described in Hirsch and MacPherson (2003) and are located at www.unionstats.com. The variable used is the percentage of employees in the occupation covered by a collective bargaining agreement.

wage percentiles are calculated from the counterfactual distributions. The estimates from the counterfactual wage regressions should produce less biased estimates of the impact on wages arising from the change in the returns to the attribute-bundles.

Tables 5-8 present the regression results. In general, returns to non-routine cognitive attributes rise during the 1980s. During the 1990s the returns either stagnate or occur only for higher wage earners (within the occupation) for males. The stagnation occurs in occupation types that are less professional and more supervisory. Female professional occupation types continue to experience positive wage increases throughout the occupation wage distribution in the 1990s. More specifically, three attribute-bundles (communication skills, gathering and processing information tasks and professional interpersonal contexts) are all consistently related to wage increases in both the 1980s and the 1990s for both males and females. In the 1980s, these bundles are related to increasing wages at the 10^{th}, 50^{th} and 90^{th} percentiles with larger wage increase occurring at the 50^{th} and 90^{th} percentiles relative to the 10^{th} percentile. Therefore, these attribute-bundles are associated with rising within occupation wage dispersion in the lower portion of the occupation wage distribution. In the 1990s the wage increases associated with these attribute-bundles occur only at the 90^{th} percentile for males and most strongly at the 90^{th} percentile for females, resulting in increasing wage dispersion in the upper portion of the occupation wage distribution. The returns to cognitive abilities also increased throughout the occupation wage distribution during the 1980s for both males and females while during the 1990s, wage growth was stagnant in the male sample for those attributes. In the female sample during the 1990s wage growth associated with cognitive abilities was concentrated in the upper portion of the occupation wage distribution. The coordinating, overseeing and advising bundle (supervisory and some management occupations) was associated with wage increases throughout the occupation distribution in the 1980s for both males and females. However, during the 1990s this bundle is associated with wage declines in the upper and middle portion of the male occupation wage distribution and no wage changes in the female occupation distributions. Finally, returns to the interpersonal service bundle increased in the middle and upper portions of the female occupation wage distribution during the 1980s but stagnated in the 1990s. Males returns to the service interpersonal bundle stagnate in the 1980s and decline in the upper portion of the occupation wage distribution during the 1990s, creating upper tail compression in the occupation wage distributions.

Occupation attribute-bundles other than non-routine cognitive bundles are associated with a much different pattern of wage changes. The occupation types that are complementary to machines and/or require physical tasks not easily replaced by automation (manual or technical tasks, manual or hazardous contexts and non-routine psychomotor ability) were associated with wage declines in the 90^{th}percentile of the male occupation wage distribution and upper tail compression of the occupation wage distribution during both the 1980s and the 1990s.[29] Occupations associated with routine work attributes experienced wage declines in the male sample throughout the occupation wage distributions in the 1980s with the declines most pronounced in the middle and the bottom of the occupation wage distribution. However, during the 1990s wages associated with routine work increased for both males (at the 50^{th} percentile) and females (at the 50^{th} and 90^{th} percentiles). Also note that the routine psychomotor bundle is never statistically significantly related to wage changes in any part of the occupation distribution. Finally, a change in union coverage is positively related to median and 10^{th} percentile wages but never to 90^{th} percentile wage changes.

From the above specifics, several notable generalities arise. First, during the 1980s a set of non-routine cognitive attributes raised wages throughout the occupation wage distribution while those attribute-bundles that continue to exert a positive influence on wages during the 1990s did so only in the upper portion of the occupa-

[29]Most of these occupations are typically male dominated. During the 1980s female wages show little statistical significance with respect to these attribute-bundles. Although, during the 1990s female wages associated with the manual or technical and non-routine psychomotor ability bundles decline at the 50^{th} and 90^{th} percentiles.

Table 5: Impact of Attribute Bundles on Change in Wage. Males 1980-1990

	50^{th}percentile		90^{th}percentile		10^{th}percentile	
	Actual	cf	Actual	cf	Actual	cf
Skill bundles						
Communication	.036***	.033***	.034***	.036***	.023***	.018**
	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
Machine	-.003	0.005	-.011*	-.007	.005	.006
	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)
Socio-technical	.007	.007	.006	.006	.006	.007
	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)
Ability bundles						
Non-routine psychomotor	-.013*	-.006	-.020***	-.018***	.004	.011
	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)
Cognitive	.030***	.026***	0.025***	0.028***	.026***	.022***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)
Routine psychomotor	-.009	-.009	-.006	-.005	-.005	-.005
	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)	(0.007)
Task bundles						
Gathering & processing	0.026***	0.023***	.023***	.024***	.017**	.012*
	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)
Coordinate, oversee, advise	0.018***	0.018***	.014***	.013***	.017***	.016**
	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)
Manual or technical	-0.008	0.003	-.019***	-.016**	.004	.010
	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)	(0.007)
Work context bundles						
Manual or hazardous	-.016**	-.008	-.022***	-.020***	-.005	.001
	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)	(0.007)
Professional interpersonal	.031***	0.031***	.026***	.028***	.021***	.020***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Service interpersonal	0.011	0.003	.012**	.011	.007	.002
	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)
Routine	-.022***	-.029***	-.011*	-.014*	-.019**	-.024***
	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)
Change in union coverage						
Skill attributes equation	.003**	.003*	.002	.001	.003**	.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ability attributes equation	.003**	.003*	.002	.001	.003**	.004**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Task attributes equation	.003**	.003**	.001	.001	.003**	.004**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Work context equation	.002*	.002	.001	.000	.002*	.003*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Adjusted R-squared						
Skill attributes equation	.302	.214	.281	.254	.157.	.110
Ability attributes equation	.308	.201	.283	.254	.192	0.139
Task attributes equation	.304	.211	.279	.235	.176	0.127
Work context equation	.308	.240	.272	.237	.169	0.148

Notes: A separate equation is estimated for each attribute bundle. *** denotes significance at the .1% level or better, ** at the 1% level, and * at the 5% level. cf - counterfactual.

Table 6: Impact of Attribute Bundles on Change in Wage. Males 1990-2000

	50th percentile		90th percentile		10th percentile	
	Actual	cf	Actual	cf	Actual	cf
Skill bundles						
Communication	.012*	.004	.024***	.021***	.006	-.003
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Machine	-.001	.002	-.007	-.001	-.012*	-.013*
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Socio-technical	-.001	-.001	.008	.006	-.010	-.013*
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Ability bundles						
Non-routine psychomotor	-.009	-.003	-.030***	-.023***	-.006	-.000
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Cognitive	.002	-.004	.005	.004	-.002	-.008
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)
Routine psychomotor	.002	.003	.008	.011	-.004	-.006
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
Task bundles						
Gathering & processing	.017***	.012*	.031***	.030***	.005	-.004
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Coordinate, oversee, advise	-.011*	-.014**	-.015***	-.018***	-.009	-.007
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)
Manual or technical	-.009	-.004	-.019***	-.013*	-.017*	-.014*
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Work context bundles						
Manual or hazardous	-.006	-.002	-.020***	-.013*	-.005	-.001
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Professional interpersonal	.002	-.005	.019***	.017***	-.003	-.009
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)
Service interpersonal	-.001	-.004	-.017**	-.020**	.005	.005
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
Routine	.012*	.012*	.006	.007	.014*	.012
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
Change in union coverage						
Skill attributes equation	.005***	.006***	.002	.001	.004***	.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ability attributes equation	.006***	.006***	.002	.002	.005***	.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Task attributes equation	.005***	.006***	.001	.001	.004***	.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Work context equation	.006***	.006***	.002	.002	.005***	.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Adjusted R-squared						
Skill attributes equation	.173	.139	.136	.083	.109	.101
Ability attributes equation	.166	.140	.182	.111	.082	.076
Task attributes equation	.215	.181	.240	.188	.113	.091
Work context equation	.175	.152	.172	.119	.097	.083

Notes: A separate equation is estimated for each attribute bundle. *** denotes significance at the .1% level or better, ** at the 1% level, and * at the 5% level. cf - counterfactual.

Table 7: Impact of Attribute Bundles on Change in Wage. Females 1980-1990

	50^{th}percentile		90^{th}percentile		10^{th}percentile	
	Actual	cf	Actual	cf	Actual	cf
Skill bundles						
Communication	.047***	.032***	.053***	.045***	.030***	.014*
	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)
Machine	-.023**	-.022**	-.037***	-.032***	-.003	0.000
	(0.008)	(0.008)	(0.009)	(0.009)	(0.008)	(0.008)
Socio-technical	.024***	.025***	.024**	.023**	.021**	.015*
	(0.006)	(0.007)	(0.008)	(0.007)	(0.006)	(0.006)
Ability bundles						
Non-routine psychomotor	-.025**	-.020*	-.017	-.015	-.013	-0.13
	(0.008)	(0.008)	(0.010)	(0.010)	(0.008)	(0.008)
Cognitive	.051***	.038***	.046***	.038***	.037***	.020***
	(0.005)	(0.006)	(0.007)	(0.007)	(0.005)	(0.005)
Routine psychomotor	-.004	-.001	-.008	-.009	.010	-.005
	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)
Task bundles						
Gathering & processing	.047***	.039***	.045***	.042***	.033***	.025**
	(0.005)	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)
Coordinate, oversee, advise	.023***	.013*	.032***	.025***	.016**	.003
	(0.005)	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)
Manual or technical	-.014	-.006	-.012	-.004	-.004	-.000
	(0.007)	(0.008)	(0.009)	(0.009)	(0.007)	(0.008)
Work context bundles						
Manual or hazardous	.011	.003	.035*	.021	.017	.010
	(0.011)	(0.012)	(0.015)	(0.015)	(0.012)	(0.013)
Professional interpersonal	.049***	.036***	.051***	.042***	.036***	.022***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)
Service interpersonal	.036***	.030***	.039***	.038***	.019***	.007
	(.005)	(.006)	(0.007)	(0.007)	(0.005)	(0.006)
Routine	.009	.011	.009	.006	-.006	.000
	(.006)	(.006)	(0.007)	(0.007)	(0.006)	(0.006)
Change in union coverage						
Skill attributes equation	.002	.002*	.003*	.003*	.002*	.003*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ability attributes equation	.001	.001	.002	.002	.001	.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Task attributes equation	.001	.001	.002	.002*	.001	.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Work context equation	.001	.001	.002	.002	.001	.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Adjusted R-squared						
Skill attributes equation	.373	.255	.381	.323	.201	.085
Ability attributes equation	.399	.258	.244	.200	.263	.119
Task attributes equation	.427	.279	.359	.308	.265	.139
Work context equation	.499	.337	.423	.352	.287	.136

Notes: A separate equation is estimated for each attribute bundle. *** denotes significance at the .1% level or better, ** at the 1% level, and * at the 5% level. cf - counterfactual.

Table 8: Impact of Attribute Bundles on Change in Wage. Females 1990-2000

	50th percentile		90th percentile		10th percentile	
	Actual	cf	Actual	cf	Actual	cf
Skill bundles						
Communication	.036***	.018*	.044***	.030***	.032***	.020***
	(0.008)	(0.007)	(0.008)	(0.008)	(0.005)	(0.005)
Machine	-.019	-.017	-.010	-.008	-.009	-.008
	(0.011)	(0.010)	(0.011)	(0.011)	(0.007)	(0.007)
Socio-technical	-.005	-.008	.004	.005	.003	.001
	(0.009)	(0.008)	(0.009)	(0.009)	(0.006)	(0.006)
Ability bundles						
Non-routine psychomotor	-.041***	-.035***	-.054***	-.048***	-.013	-.003
	(0.010)	(0.010)	(0.010)	(0.010)	(0.007)	(0.007)
Cognitive	.023**	.007	.038***	.025***	.020***	.008
	(0.008)	(0.007)	(0.008)	(0.007)	(0.006)	(0.006)
Routine psychomotor	.001	.006	-.004	.000	-.009	-.005
	(0.008)	(0.007)	(0.008)	(0.008)	(0.006)	(0.006)
Task bundles						
Gathering & processing	.031***	.021**	.049***	.041***	.018**	.007
	(0.008)	(0.008)	(0.008)	(0.008)	(0.006)	(0.006)
Coordinate, oversee, advise	.009	-.003	.014	.005	.019***	.014*
	(0.008)	(0.007)	(0.007)	(0.007)	(0.005)	(0.005)
Manual or technical	-.038***	-.029**	-.038***	-.030**	-.015*	-.008
	(0.010)	(0.010)	(0.010)	(0.010)	(0.007)	(0.007)
Work context bundles						
Manual or hazardous	.016	.014	.016	.011	.004	.010
	(.017)	(0.016)	(0.016)	(0.016)	(0.012)	(0.012)
Professional interpersonal	.035***	.019**	.049***	.036***	.025***	.013**
	(0.007)	(0.006)	(0.007)	(0.007)	(0.005)	(0.005)
Service interpersonal	.002	-.007	.005	-.002	.009	.002
	(0.008)	(0.008)	(0.008)	(0.008)	(0.006)	(0.006)
Routine	.017	.022**	.017*	.019*	-.011	-.009
	(0.009)	(0.008)	(0.008)	(0.008)	(0.006)	(0.006)
Change in union coverage						
Skill attributes equation	.003*	.003*	.002	.002	.002*	.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ability attributes equation	.004*	.004*	.002	.002	.002*	.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Task attributes equation	.003*	.003*	.002	.002	.002*	.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Work context equation	.004*	.004*	.002	.002*	.002*	.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Adjusted R-squared						
Skill attributes equation	.165	.099	.166	.093	.229	.105
Ability attributes equation	.175	.133	.265	.195	.144	.045
Task attributes equation	.219	.154	.310	.226	.210	.089
Work context equation	.236	.188	.327	.248	.174	.068

Notes: A separate equation is estimated for each attribute bundle. *** denotes significance at the .1% level or better, ** at the 1% level, and * at the 5% level. cf - counterfactual.

tion wage distribution.[30] Second, in the 1980s for those attribute-bundles that were associated with wage increases, the net impact of attributes on within occupation wage dispersion was to widen inequality at the bottom of the occupation wage distribution. That is, even though wages increased throughout the distribution, they did so more in the middle and top of the distribution than at the bottom. Third, attributes that tended to decrease wages tended to so from top of the occupation wage distribution.[31] Finally, for occupation attributes that have a positive relationship with wages, the estimates using the counterfactual composition adjusted wages are similar to the estimates using the actual wage for males. However, in the female sample the estimates in the counterfactual wage regressions tend to be smaller than the estimates from the actual wage regressions indicating a more influential composition effect on female wages.

The increase in overall male wage inequality was in part a consequence of the decline in wages in the upper portions of the occupation wage distributions for occupations with attributes that require non-routine manual tasks or whose attributes complement machines coupled with an increase in wages in the upper portions of the occupation wage distributions for occupations with high scores in a few non-routine cognitive attributes. Moreover, this trend is more pronounced in the 1990s relative to the 1980s. The results also suggest that deunionization played a role in increasing inequality particularly during the 1990s. In the male sample, the magnitude of a change in unionization on median occupation wages is twice as large in the 1990s relative to the 1980s. The point estimates imply that one standard deviation decline in union coverage during the 1990s (-5.5) results in a .033 decline in the log of median occupation wages, while during the 1980s the impact of a one standard deviation decline in union coverage (-5.0) results in a .015 decline in median occupation wages. Interestingly in the male sample, only the gathering and processing information bun-

[30] Although in the female distribution some attribute bundles continued to increase wages at the bottom of the occupation wage distribution.

[31] With the exception of the machine skill and socio-technical skill bundles that are associated with wage declines only at the bottom of the distribution in the male sample during the 1990s.

dle is associated with larger increase in the 90^{th} wage percentile in the 1990s relative to the 1980s. Finally, note that the occupation attribute-bundles (along with union coverage) explain much less of the variation in wage changes during the 1990s relative to the 1980s.

5.2 Assessing the implications

5.2.1 Composition

Significant shifts in occupational employment shares and in the educational and age profile of the workforce occurred during the 1980s and 1990s. For example, AA show that the share of production workers and machine operators fell nearly 8% and the share of professional, managerial and technical occupations increased by approximately an equal amount. (See AA, Figure 13a.) However, the results in this analysis do not support the hypothesis that occupational shifts alone present a significant influence on the change in the dispersion of wages. That is, holding constant occupational wage structure (mean or median occupations wages and the within occupation dispersion of wages) the impact of changing occupational composition is minimal.[32] Table 1 shows that the contribution of occupational shifts to variance changes during the 1980s (when changes in the wage distribution were more symmetrical and variance changes give a decent representation of changes in the dispersion) is quite small: approximately 7.5% for males and 1.6% for females. Furthermore, occupation, education and age composition together account for only a modest portion of changes in the upper and lower portions of the male wage distribution: 12.5% and 8.33% of the 90-50 wage gap and 21% and 3.5% of the 50-10 wage gap in the 1980s and 1990s, respectively. (See Table 3.) These estimated composition effects appear reasonable since educational attainment increased most

[32]AD show that there was differential occupational displacement across metropolitan areas that depended on the metropolitan area's initial endowment of machine-replaceable jobs. However, they indicate the impact on wage distributions by comparing the actual and counterfactual smoothed regression estimates which do not enable an analysis of statistical significance.

sharply in the 1980s and increased throughout the male wage distribution, therefore, one might suspect that the proportional impact on the lower portion of the wage distribution during the 1980s should be larger than during the 1990s.[33]

Moreover, as shown in Table 9, OLS regressions of the change in employment shares on the occupation attribute-bundles and the change in union coverage for the male sample echo those results. Occupation re-allocation is not statistically significantly related to the occupation's task content and the explanatory power of the attribute bundles is extremely small for the male sample.[34] During the 1990s the regression using the work context occupation attribute-bundles has an adjusted r-squared of not quite 8%, the regression using the task occupation attribute-bundles has an adjusted r-squared of 3.7%, while the others are below 1%. The only statistically significant relationships between male employment share changes and occupation attributes occur in the 1990s for routine work (negatively) and professional interpersonal work and gather and processing information (positively). The timing suggests that there may be a significant delay in labor re-allocation arising from the imperfect substitutability of human capital investment.

Decomposition analysis for the female sample indicated that compositional changes were more influential on the wage structure, particularly in the lower portion of wage

[33]FFL show a larger impact for composition in the male distribution. However, they find that factors other than unionization move counterfactual inequality in the opposite direction as actual inequality during the 1990s and that unionization is the factor largely responsible for the composition effect. As in this paper, FFL estimate that the impact of education and age (experience) on observed inequality changes during the 1990s is modest. Also note that the occupational distribution is held constant in the counterfactual distributions in this paper but not in FFL. (Disaggregated results for the 1980s are not reported by FFL.)

[34]A separate regression is run for each sub-set of attribute-bundles. The regressions are weighted by the number of observations in each occupation and employment shares are multiplied by 100. Finally, occupation classification that are qualified as nec (not elsewhere counted) are not included since it may be possible that changes in employment share are influenced by shifts in what is counted as nec. This applies to both the male and female regressions. Therefore, there are 248 occupational classifications in the male sample and 148 in the female sample. Note that the estimates for union coverage are not included in the table for sake of space. The coefficient on union coverage was statistically insignificant with the exception of the ability attribute subset equation for males in the 1980s. That coefficient was statistically significant and positive. Without the union coverage variable, the adjusted r-squares are lower and the only change in statistical significance of the coefficients is that the estimate on routine work in the 1980s becomes significant at the 95% confidence level.

distribution. The regression analysis indicates that the explanatory power of the attribute-bundles ranges from about 13% to 24%, significantly higher than the male counterparts. In the 1980s the manual or technical, manual or hazardous and non-routine psychomotor ability attribute-bundles are positively related to change in employment shares. (The positive re-allocation into non-routine psychomotor attributes continues through the 1990s.) This could reflect a re-allocation of female employment away from traditionally "female work" into traditionally "male work." [35] In both the 1980s and 1990s, the attribute-bundles communication skills, socio-technical skills, coordinating-overseeing-advising tasks, and service interpersonal work are all positively related to employment share changes, while the cognitive attribute-bundle is positively related to employment share changes only in the 1990s. Finally, as in the male sample, routine work is negatively related to employment share changes, but in the female sample the re-allocation begins in the 1980s.

What drives the difference in labor re-allocation between genders? One possibility is that the timing of shifting task demand coincided roughly with increased female participation in the work-force and the beginning of the dissolution of standard gender roles. This may have allowed females to acquire the skills relevant for the changing market place more rapidly than their male counterparts.[36] If one allows that female labor embodies a differentiated set of skills relative to male labor, then two additional possibilities arise.[37] First, the increased supply of female labor endogenously created an increase in jobs complementary to female characteristics. Second, that the change in task demand was, by nature of the changing marketplace, more complementary to female characteristics. [38] Obviously, these are

[35]Secretaries, typists, bookkeepers, general office clerks and correspondence and order clerks all rank near the bottom in one or more of those attribute bundles and are also among the group of occupations with the largest employment share declines.

[36]Black and Spitz-Oener (2010) found that in West Germany non-routine analytical and interactive (interpersonal) tasks female task input increased relative to males between 1979 and 1999. Moreover, most of the change occurred within occupations. Also, Bacolod and Blum (2010) found increased use of cognitive tasks for females between 1968 and 1990.

[37]Alternatively, females may select into a different set of occupations due to changing societal norms.

[38]Borghans et al. (2006) report that increased demand for "people skills" resulted in an increase

Table 9: Impact of Attribute Bundles on Change in Employment Share

	Male		Female	
	1980-1990	1990-2000	1980-1990	1990-2000
Skill bundles				
Communication	-0.018	0.013	0.171*	0.196***
	(0.033)	(0.020)	(0.074)	(0.051)
Machine	-0.020	0.014	-0.038	-0.059
	(0.032)	(0.020)	(0.097)	(0.067)
Socio-technical	-0.041	0.040*	0.342***	0.204***
	(0.030)	(0.019)	(0.077)	(0.051)
Ability bundles				
Non-routine psychomotor	0.017	-0.003	0.542***	0.217**
	(0.034)	(0.020)	(0.092)	(0.065)
Cognitive	-0.034	0.034	0.112	0.182***
	(0.030)	(0.020)	(0.069)	(0.052)
Routine psychomotor	0.019	-0.040	0.129	-0.010
	(0.038)	(0.024)	(0.069)	(0.052)
Task bundles				
Gathering & processing	0.017	0.064**	-0.133	-0.025
	(0.032)	(0.020)	(0.073)	(0.052)
Coordinate, oversee, advise	-0.047	0.021	0.313***	0.274***
	(0.030)	(0.019)	(0.074)	(0.050)
Manual or technical	-0.012	0.020	0.239*	0.067
	(0.037)	(0.022)	(0.099)	(0.067)
Work context bundles				
Manual or hazardous	0.020	0.010	0.351*	0.141
	(0.033)	(0.019)	(0.164)	(0.114)
Professional interpersonal	0.011	0.084***	-0.060	0.089
	(0.031)	(0.019)	(0.001)	(0.000)
Service interpersonal	-0.020	-0.040	0.204**	0.163**
	(0.038)	(0.023)	(0.071)	(0.053)
Routine	-0.053	-0.049*	-0.159*	-0.152**
	(0.036)	(0.023)	(0.077)	(0.056)
Adjusted R-squared				
Skill attributes equation	0.008	0.007	0.160	0.159
Ability attributes equation	0.004	0.005	0.235	0.126
Task attributes equation	0.008	0.037	0.197	0.181
Work context equation	0.007	0.079	0.194	0.129

Notes: A separate equation is estimated for each attribute bundle. *** denotes significance at the .1% level or better, ** at the 1% level, and * at the 5% level. Employment shares are mulitplied by 100.

conjectures and are not examined directly in this study. Notice that socio-technical skills (scientists, engineers, accountants, some managers) are generally positively related to female wages and employment shares, but not males. Also notice that the relationship between female wage changes and socio-technical skills, coordinating-overseeing-advising tasks and service interpersonal work stagnates during the 1990s, perhaps reflecting an endogenous wage response to the female positive reallocation into those occupations.

5.2.2 Computerization and wage inequality

According to the computerization hypothesis, the ability to substitute computers for routine work done by labor should lower the wage for those occupations engaged in routine work. Similarly, occupations whose attributes are enhanced by computerization (i.e. non-routine cognitive tasks) should experience an increase in wages. The results are partially supportive of these implications but the results also uncover some patterns relating wage changes to occupation attributes that are either incompatible with the computerization hypothesis or that the computerization hypothesis fails to directly address.

First, while routine work is negatively associated with male wages in the 1980s (and employment share tends to be negatively related to routine work in both decades), during the 1990s routine work is positively associated with median occupation wages for both males and females. The rebound in wages for routine work occurs mostly in the lower portion of the occupation wage distribution for males but in the upper portion of occupation wage distribution for females. In the occupations that receive the highest scores for routine work, the average male median wage in 1990 is 2.7, the average wage at the 10^{th} percentile is 1.99 and 3.36 at the 90^{th} percentile. The same statistics for female wages are 2.31, 1.74, and 2.92, respectively.[39] Therefore, the increase returns to routine work in the 1990s could be driven

in demand for female labor.

[39]These are the 1990 averages of the log of hourly wages across the occupations scoring in the

by similar work across genders since female wages in the upper portion of their occupation distributions are close to male wages in the lower portion of their occupation distributions. Additionally, the attribute bundle routine psychomotor ability never shows any statistically significant relationship to wage changes in any part of the distribution and as shown above, there is little employment re-allocation away from these attributes. So, while the computerization hypothesis predicts falling returns to routine work, this occurs only for a set of routine attributes only during the 1980s and only for males.

Second, the wage changes associated with non-routine cognitive attributes display diversity in magnitude, timing and distributional placement. The general pattern in the relationship between wage changes and non-routine cognitive attributes across occupations is consistent with the computerization hypothesis. In particular, the attribute bundle "gathering and processing information" is the only bundle in this set to be associated with median wage increases in both the 1980s and the 1990s. However, the computerization hypothesis in its current state does not suggest why wage changes would occur throughout the occupation wage distribution initially and then impact mainly the upper portion of the occupation distribution in the following period. The change in the pattern of wage increases may arise from self-selection of workers following a change in relative wages. But why the wage changes are concentrated in the upper portion of the occupation wage distribution is not yet well represented within a theoretical model.

The results in this paper also show that the magnitude of wage increases varies substantially between non-routine cognitive attribute bundles. While a corollary to the computerization hypothesis is that tasks with greater complementarities to computerization should incur larger wage increases, there has been little discussion of which types of non-routine cognitive activities might expect the largest complementarities. The communication and professional interpersonal attribute bundles

top decile for routine work. The averages are calculated by weighting individual occupation wage percentiles by the occupation employment count in 1990.

are associated with the largest median wage increases in the male sample during the 1980s. (Recall that teachers, lawyers, professional sales, doctors, dentists and veterinarians top the occupations that score high in the communication attribute-bundle and professional sales, lawyers, and judges score high in the professional interpersonal bundle). The gathering and processing information bundle claims the largest effect on the 90^{th} percentile occupation wage during the 1990s. Furthermore, in the male sample, the attribute bundle service interpersonal has no impact on wage changes in the 1980s and is associated with wage declines at the 50^{th} and the 90^{th} percentiles in the 1990s. Occupations with high scores in this service interpersonal bundle are dominated by health-field professions and some supervisory occupations. Moreover, the attribute bundle socio-technical skills displays little relation to wage structure changes. Is it that computerization raises the productivity of sales and teaching occupations more than for health occupations? In any case, the computerization hypothesis, in its current state, does not directly address which types of non-routine cognitive skills might have the largest complementarity with computerization.

Third, to the extent that computerization results in machines substituting for labor in production, one would expect wages for attribute-bundles that complement machines (machine repairers, installers, maintenance, etc.) to rise. However, those attribute-bundles (machine skills and manual or technical work) are associated with male wage declines at the top of the occupation wage distribution during the 1980s and 1990s and further decreases at the bottom of the distribution during the 1990s.[40] The attribute bundle whose high scoring occupations are connected with non-routine manual work (non-routine psychomotor skills) is also associated with wage declines in the upper portion of the occupation wage distribution. Either automation has not produced an ancillary demand for labor to maintain the machines or the supply of workers to those occupations increased faster than demand. The latter is plausible

[40]The wage structure relationships are a bit different for females in these traditionally male-dominated occupations. While the relationship is a predominantly negative one (with the exception of the statistically insignificant coefficients on the manual or hazardous attribute-bundle), the female wage declines tend to occur in the lower and middle portions of the occupation wage distributions.

if production workers and machine operators switched into repair and maintenance roles.[41]

6 Conclusion

Previous research has documented significant employment shifts between occupation groups. This paper has shown that these employment shifts contribute little to the changes in wage inequality during the 1980s and 1990s. Instead, both between and within occupation wage changes (changes in wage structure) "explain" the bulk of changes in the wage distribution. The importance of within occupation wage distribution, the inability to distinguish the impact of changing task content on wages in different parts of the distribution, and the vagueness with regard to the degree of complementarity between computerization and different types of non-routine cognitive tasks are identified as empirically important elements to be added to the computerization model. Moreover, this paper has found that tasks that complement machines were associated with wage declines.

The regression analysis in this paper has shown that communication skills, gathering and processing information and professional interpersonal work were associated with wage increases in both decades for both genders (along with service interpersonal work in the female sample). Regression analysis also showed that female labor re-allocation was positively correlated with the communication, coordinate, oversee and advise and interpersonal service attribute-bundles while male labor re-allocation was not well explained by the occupation attribute-bundles. To get "inside" these results a bit, Tables 10 and 11 list the ten occupations with the largest median wage gains and employment share gains in the 1980s and the 1990s.[42]

[41] AD argue that production workers and operators switched into low skill service occupation. The flow of these workers into repair and maintenance roles offers an additional channel for labor re-allocation.

[42] The employment shares are calculated from the base of this paper's sample that includes all workers in occupations with at least 100 workers in each census year. The Data Appendix offer slightly longer lists along with listing occupations by median wage and employment share declines.

Table 10: Occupations Ranked by Median Wage Changes

Male Sample 1980-1990		Male Sample 1990-2000	
Registered nurses	.265	Ushers	.784
Lawyers	.228	Recreation workers	.415
Respiratory therapists	.227	Broadcast equipment operators	.407
Licensed practical nurses	.210	Air traffic controllers	.391
Physicians	.201	Announcers	.329
Pharmacists	.176	Pharmacists	.289
Elevator installers and repairers	.139	Computer software developers	.284
Clergy and religious workers	.137	Art/entertainment performers	.263
Managers of properties and real estate	.136	Ships crews & marine engineers	.256
Postmasters and mail superintendents	.136	Musician or composer	.253
Female Sample 1980-1990		**Female Sample 1990-2000**	
Registered nurses	.265	Salespersons, n.e.c.	.426
Lawyers	.228	Pharmacists	.418
Respiratory therapists	.227	Welfare service aides	.399
Licensed practical nurses	.210	Eligibility clerks for government	.357
Physicians	.201	Art makers	.353
Pharmacists	.176	Computer software developers	.304
Elevator installers and repairers	.139	Material recording, etc. clerks	.300
Clergy and religious workers	.137	Retail sales clerks	.290
Managers of properties and real estate	.136	Recreation workers	.279
Postmasters and mail superintendents	.136	Sales demonstrators, etc.	.277

The numbers show the change in the log of the hourly median wage.

Table 11: Occupations Ranked by Employment Share Changes

Male Sample 1980-1990		Male Sample 1990-2000	
Supervisors & proprietors of sales	.0214	Retail sales clerks	.0190
Managers, nec	.0083	Computer systems analysts & scientists	.0142
Cooks, variously defined	.0043	Computer software developers	.0106
Computer software developers	.0039	Customer service representatives & related	.0068
Computer systems analysts scientists	.0028	Office supervisors	.0055
Gardeners and groundskeepers	.0022	Managers/specialists in mktg & related	.0040
Lawyers	.0021	Material recording & related clerks	.0033
Cashiers	.0021	Stock and inventory clerks	.0030
Supervisors of mechanics & repairers	.0021	Cooks, variously defined	.0028
Other law enforcement:	.0019	Police, detectives, & investigators	.0027
Female Sample 1980-1990		**Female Sample 1990-2000**	
Managers, nec	.0204	Retail sales clerks	.0190
Supervisors & proprietors of sales	.0156	Customer service reps & related	.0188
Accountants and auditors	.0085	Office supervisors	.0144
Management support occupations	.0066	Computer systems analysts &scientists	.0082
Customer service reps & related	.0055	Managers/specialists in mrktg & related	.0066
Registered nurses	.0039	Personnel & related specialists	.0059
Financial managers	.0035	Health aides, except nursing	.0058
Health technologists & technicians, nec	.0034	Child care workers	.0049
Other financial specialists	.0034	Dental lab & medical appliance techs	.0049
Teacher's aides	.0033	Vocational and educational counselors	.0045

Employment shares are the actual change multiplied by 100.

The patterns that stand out from both the regression-based task analysis and examining the occupations with large employment share changes indicate that while labor has consistently migrated to occupations that directly work with computers, male reallocation more generally occurred over a diverse set of occupations while female labor tended to migrate into occupations that require communication and interpersonal skills.

During the 1980s, health and real-estate related occupations and lawyers enjoyed some of the largest wage gains for both males and females. In the 1990s the occupations with large median wage gains were a much more diverse group, indicating why the explanatory power of the wage regressions for the 1990s is lower than for the 1980s. For both males and females pharmacists, recreation and art jobs, and computer software developers incur large median wage gains.

Analyzing the data at the occupation level and through the lens of occupation attributes, as done in this paper, has confirmed the relevance of the non-routine cognitive attributes. However, it has also recognized that the returns to those non-routine cognitive skills are concentrated within occupations that may or may not be the most affected by computerization. Moreover, the results show that it is the returns to these attributes in the upper portion of the occupation distribution that have partially driven wage structure changes in the 1990s. As a whole the results imply that explanations for the pattern of wage inequality should focus more on the impact of wage dispersion within occupations, the relevance of specific types of non-routine cognitive attributes, the falling return to labor that complements machines and the relative insensitivity of male employment to changing attribute demand.

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Data Appendix (not intended for publication in its entirety)

Data description

The data come from the 1% Integrated Public Use Microfiles of the decennial census data. The sample includes workers between the ages of 16 and 64 with wage and salary income who worked at least 40 weeks in previous and usually worked at least 35 hours per week in the previous year. Wages were converted to hourly rates by dividing annual wage and salary income by total hours worked. The latter is the product of the number of weeks worked that year and usual hours worked per week. Hourly wages were converted to real values using the PCE index. Following the practice in related papers, outliers were trimmed from the data and top-coded values for annual income were multiplied by 1.45. All of the results reported in this paper eliminate hourly observations less than $2.80 in 2000 dollars and hourly observations exceeding 1/35th of top-coded value of weekly earnings. (As done in Autor, Katz and Kearney (2009).) Most of the results are also duplicated using a less stringent trimming rule as in Lemieux (2006), where hourly wages less than $2.12 and greater than $212.50 in 2000 dollars are dropped. The results were similar using the alternative trimming strategy. In estimation results and when calculating summary statistics, the sample is weighted by the product of census sample weights and hours usually worked.

The data sample was limited to include only occupations with at least 100 observations in each decennial year 1980, 1990 and 2000, yielding 264 occupations in the male sample and 183 occupations in the female sample. The occupation categories are based on the census variable OCC1990 which narrows the original 1990 classification from 514 occupation categories to 389 OCC1990 categories and then reassigns other census year categories to the OCC1990 scheme.[43]

[43]The crosswalk is available at: http://usa.ipums.org/usa/volii/occ_ind.shtml. In the data set, some modifications to the OCC1990 variable were implemented to increase consistency.

Top-coding adjustment within occupations

The share of top-coded observations by occupation is generally quite small. Table A1 below shows the number of occupations out of the 264 male occupations with at least 100 observations in all years with 10%, 5% and 2% of their observations top-coded. Physicians are the only occupation with an unusually large share of top-coded observations: 16% in 1980, 20% in 1990, and 27% in 2000.

Table A1: Number of occupations

	1980	1990	2000
At least 10% of observations top-coded	1	1	1
At least 5% of observations top-coded	1	2	3
At least 2% of observations top-coded	3	5	14
With any top-coded observations	68	99	114

of the truncated sample

The mean and variance of the wage for any occupation with top-coded observations was calculated by assuming that the log of wages within occupations are normally distributed with mean, μ, and variance, σ^2. Let $\Phi(\cdot)$ and $\phi(\cdot)$denote the cdf and the pdf of the normal distribution, respectively, and a the value of the wage at the truncation point. The estimated population mean and variance are given by:

$$E\left[w\right] = \hat{\mu} - \sigma\lambda(\alpha)$$

$$Var(w) = \hat{\sigma}^2\left[1 - \delta(\alpha)\right]$$

where$\alpha = \frac{a-\mu}{\sigma}$ $\lambda(\alpha) = \frac{-\phi(\alpha)}{\Phi(\alpha)}$, $\delta(\alpha) = \frac{\lambda(\alpha)}{\lambda(\alpha)-\alpha}$, $\hat{\mu}$is the sample mean and $\hat{\sigma^2}$is the sample variance of the truncated sample, respectively. To recover the population mean and variance from the truncated sample, first calculate the proportion of top-coded wage in the occupation (x) and use this information to recover $\alpha = \Phi^{-1}(1-x)$.

The value of α then allows the calculation of $\lambda(\alpha)$ and then $\delta(\alpha)$.

Consistent occupation codes

Meyers and Osborne (2005) describe the reclassification of other decennial year occupation schemes to a set of occupation based on their 1990 occupation classification. The codes used in this paper are slightly modified versions of the consistent occupation codes developed by Meyers and Osborne. All of the changes made to the Meyers and Osborne classification merge two more of the 1990 occupation codes into a combined category, dropping the original code(s) and creating new codes. A few 2000 occupations were not properly assigned into the Meyers and Osborne classification and some of these were incorporated into the new coding. Additional details are available upon request.

Attribute bundles from O*NET

The consistent occupation classifications from the census data were matched to the O*NET classifications by using (1) the cross-walk between the SOC occupation codes listed in O*NET and 2000 census occupation codes and (2) the cross-walk between the 2000 and 1990 census occupation codes. When occupations from O*NET had to be combined to fit into the 1990 consistent occupation codes, the weights from the cross-walks provided the weighting scheme for combining the O*NET data into one value for any given occupation. Additional details are available upon request.

The number of factors estimated for each subset of the O*NET data was determined by beginning with the number of eigenvalues greater than unity and estimating that number of factors. If the last factor produced no heavy loadings on any individual attribute, that factor was dropped and the estimated number of factors was reduced by one. This process continued until each estimated factor contained heavy loadings on a some individual attributes. In most instances this procedure began with 5-8 factors which were then reduced to three factors from the skill, ability and work activities subsets and four factors from the work context subset. The reduced number of factors also corresponded to the point where the next factor would add very little to the cumulative explained variance. The cumulative variance explained by the chosen factors was 60% for work context subset, 67% for the work activities subset, 70% for the skills subset and 72% for the ability subset. Tables A2a, A2b, and A2c below lists the specific attributes from each of the four O*NET subsets and the factor loadings on each attribute. The highlighting indicates the "heavy" loadings on each factor. Table A3 lists the occupations with the highest scores for each factor and Table A4 displays the correlation coefficients between the attribute bundles. The remaining tables (A5-A10) offer more detailed lists of occupation rankings by employment share and median wage changes.

Table A2a: Attributes and factor loadings

Skill attributes	factor loadings (1)	(2)	(3)	Ability attributes	factor loadings (1)	(2)	(3)
Reading Comprehension	0.827	0.061	0.148	Oral Comprehension	-0.341	0.800	-0.249
Active Listening	0.876	-0.031	-0.033	Written Comprehension	-0.445	0.809	0.010
Writing	0.857	-0.103	0.113	Oral Expression	-0.346	0.790	-0.327
Speaking	0.885	-0.146	-0.035	Written Expression	-0.450	0.781	-0.117
Mathematics	0.472	0.315	0.168	Fluency of Ideas	-0.179	0.818	0.081
Science	0.374	0.525	0.330	Originality	-0.166	0.796	0.084
Critical Thinking	0.862	0.131	0.248	Problem Sensitivity	0.014	0.865	-0.084
Active Learning	0.860	0.257	0.173	Deductive Reasoning	-0.235	0.878	-0.014
Learning Strategies	0.752	0.278	0.028	Inductive Reasoning	-0.184	0.880	-0.005
Monitoring	0.827	0.064	0.291	Information Ordering	-0.169	0.773	0.179
Social Perceptiveness	0.791	-0.302	-0.045	Category Flexibility	-0.209	0.776	0.317
Coordination	0.730	0.233	0.213	Mathematical Reasoning	-0.319	0.682	0.179
Persuasion	0.885	-0.095	0.076	Number Facility	-0.186	0.607	0.224
Negotiation	0.860	-0.156	0.122	Memorization	-0.055	0.795	-0.055
Instructing	0.690	0.270	0.118	Speed of Closure	0.156	0.815	0.199
Service Orientation	0.728	-0.148	-0.101	Flexibility of Closure	0.207	0.711	0.459
Complex Problem Solving	0.745	0.287	0.366	Perceptual Speed	0.348	0.493	0.572
Operations Analysis	0.609	0.550	0.110	Spatial Orientation	0.860	0.012	-0.013
Technology Design	0.368	0.723	0.306	Visualization	0.391	0.427	0.548
Equipment Selection	0.195	0.900	0.002	Selective Attention	0.319	0.659	0.237
Installation	0.026	0.888	0.061	Time Sharing	0.380	0.669	-0.065
Programming	0.237	0.381	0.458	Arm-Hand Steadiness	0.645	-0.243	0.565
Operation Monitoring	-0.235	0.606	0.531	Manual Dexterity	0.661	-0.311	0.520
Operation and Control	-0.183	0.700	0.391	Finger Dexterity	0.443	0.060	0.743
Equipment Maintenance	-0.235	0.891	0.060	Control Precision	0.696	-0.185	0.556
Troubleshooting	0.068	0.848	0.342	Multilimb Coordination	0.816	-0.291	0.330
Repairing	-0.200	0.901	0.080	Response Orientation	0.877	-0.097	0.253
Quality Control Analysis	0.177	0.545	0.529	Rate Control	0.787	-0.198	0.400
Judgment U Decision Making	0.791	0.111	0.334	Reaction Time	0.835	-0.149	0.320
Systems Analysis	0.300	0.358	0.783	Wrist-Finger Speed	0.430	-0.205	0.569
Systems Evaluation	0.413	0.267	0.746	Speed of Limb Movement	0.859	-0.269	0.126
Time Management	0.858	0.063	0.077	Static Strength	0.843	-0.307	0.190
Management of Financial Res.	0.709	0.027	0.161	Explosive Strength	0.646	-0.092	-0.066
Management of Material Res.	0.473	0.458	0.273	Dynamic Strength	0.839	-0.298	0.196
Management of Personnel Res.	0.662	-0.031	0.310	Trunk Strength	0.743	-0.369	0.179
				Stamina	0.825	-0.340	0.062
				Extent Flexibility	0.807	-0.359	0.225
				Dynamic Flexibility	0.566	-0.308	0.089
				Gross Body Coordination	0.833	-0.309	0.042
				Gross Body Equilibrium	0.856	-0.166	0.122
				Near Vision	-0.180	0.671	0.374

Skill bundles: (1) Communication, (2) Machine skills, (3) Socio-technical skills

Ability bundles (1) Non-routine psychomotor, (2) Cognitive, (3) Routine psychomotor

Table A2a: Attributes and factor loadings (continued)

Ability attributes (cont'd)	**factor loadings**		
	(1)	**(2)**	**(3)**
Far Vision	0.567	0.428	0.253
Visual Color Discrimination	0.508	0.282	0.633
Night Vision	0.853	0.012	-0.001
Peripheral Vision	0.889	-0.017	-0.014
Depth Perception	0.767	0.042	0.396
Glare Sensitivity	0.850	-0.020	0.058
Hearing Sensitivity	0.604	0.266	0.466
Auditory Attention	0.624	0.267	0.288
Sound Localization	0.847	0.047	0.091
Speech Recognition	-0.308	0.718	-0.286
Speech Clarity	-0.296	0.750	-0.370

Skill bundles: (1) Communication, (2) Machine skills, (3) Socio-tech

Ability bundles (1) Non-routine psychomotor, (2) Cognitive, (3) Routine psychomotor

Table A2b: Attributes and factor loadings

Task attributes	factor loadings		
	(1)	(2)	(3)
Getting Information	0.802	0.316	-0.163
Monitor Processes, Materials, or Surroundings	0.506	0.296	0.548
Identifying Objects, Actions, and Events	0.641	0.288	0.215
Inspecting Equipment, Structures, or Material	0.045	0.047	0.896
Estimating the Quantifiable Characteristics of Products, Events, or Information	0.556	0.246	0.501
Judging the Qualities of Things, Services, or People	0.466	0.600	0.094
Processing Information	0.891	0.163	-0.131
Evaluating Information to Determine Compliance with Standards	0.673	0.327	0.135
Analyzing Data or Information	0.901	0.238	-0.051
Making Decisions and Solving Problems	0.727	0.493	0.094
Thinking Creatively	0.581	0.430	-0.034
Updating and Using Relevant Knowledge	0.829	0.286	-0.005
Developing Objectives and Strategies	0.602	0.628	-0.085
Scheduling Work and Activities	0.574	0.608	-0.068
Organizing, Planning, and Prioritizing Work	0.665	0.475	-0.137
Performing General Physical Activities	-0.396	0.051	0.784
Handling and Moving Objects	-0.410	-0.077	0.788
Controlling Machines and Processes	-0.102	-0.113	0.871
Operating Vehicles, Mechanized Devices, or Equipment	-0.145	0.060	0.764
Interacting With Computers	0.778	0.100	-0.342
Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment	0.324	0.046	0.605
Repairing and Maintaining Mechanical Equipment	-0.085	-0.067	0.880
Repairing and Maintaining Electronic Equipment	0.184	-0.064	0.727
Documenting/Recording Information	0.757	0.232	-0.095
Interpreting the Meaning of Information for Others	0.793	0.395	-0.141
Communicating with Supervisors, Peers, or Subordinates	0.646	0.449	-0.038
Communicating with Persons Outside Organization	0.513	0.497	-0.408
Establishing and Maintaining Interpersonal Relationships	0.459	0.610	-0.339
Assisting and Caring for Others	-0.049	0.568	0.010
Selling or Influencing Others	0.251	0.564	-0.276
Resolving Conflicts and Negotiating with Others	0.278	0.775	-0.296
Performing for or Working Directly with the Public	-0.077	0.545	-0.351
Coordinating the Work and Activities of Others	0.352	0.760	0.112
Developing and Building Teams	0.329	0.807	0.014
Training and Teaching Others	0.321	0.717	0.236
Guiding, Directing, and Motivating Subordinates	0.275	0.853	0.082
Coaching and Developing Others	0.192	0.862	0.079
Provide Consultation and Advice to Others	0.559	0.649	-0.041
Performing Administrative Activities	0.497	0.486	-0.368
Staffing Organizational Units	0.262	0.796	-0.059
Monitoring and Controlling Resources	0.400	0.637	0.080

(1) Gathering & processing information bundle, (2) Coordinate, oversee or advise others bundle

(3) Manual or technical activities bundle

Table A2c: Attributes and factor loadings

Work context attributes	factor loadings			
	(1)	(2)	(3)	(4)
Public Speaking	-0.250	0.358	0.371	-0.286
Telephone	-0.202	0.673	0.457	-0.032
Electronic Mail	-0.397	0.750	0.160	0.039
Letters and Memos	-0.254	0.733	0.395	0.006
Face-to-Face Discussions	0.101	0.339	0.562	0.104
Contact With Others	-0.200	0.180	0.754	0.090
Work With Work Group or Team	0.026	0.133	0.657	0.140
Deal With External Customers	-0.293	0.352	0.582	-0.108
Coordinate or Lead Others	0.097	0.287	0.563	0.017
Responsible for Others' Health and Safety	0.639	-0.220	0.405	0.036
Responsibility for Outcomes and Results	0.343	0.206	0.452	0.132
Frequency of Conflict Situations	-0.136	0.230	0.707	0.025
Deal With Unpleasant or Angry People	-0.173	-0.062	0.698	0.082
Deal With Physically Aggressive People	-0.007	-0.078	0.610	-0.159
Indoors, Environmentally Controlled	-0.595	0.163	0.317	0.186
Indoors, Not Environmentally Controlled	0.785	-0.071	-0.142	-0.018
Outdoors, Exposed to Weather	0.776	0.138	0.021	-0.279
Outdoors, Under Cover	0.748	0.139	0.075	-0.229
In an Open Vehicle or Equipment	0.801	-0.058	-0.135	-0.012
In an Enclosed Vehicle or Equipment	0.651	0.384	0.018	-0.189
Physical Proximity	0.054	-0.432	0.610	0.046
Sounds, Noise Levels Are Distracting or Uncomfortable	0.655	-0.270	-0.016	0.288
Very Hot or Cold Temperatures	0.868	-0.146	-0.075	-0.080
Extremely Bright or Inadequate Lighting	0.834	-0.115	0.061	0.034
Exposed to Contaminants	0.763	-0.402	0.008	0.167
Cramped Work Space, Awkward Positions	0.822	-0.236	0.047	0.099
Exposed to Whole Body Vibration	0.750	-0.014	-0.085	0.012
Exposed to Radiation	0.120	-0.144	0.389	0.196
Exposed to Disease or Infections	-0.030	-0.263	0.565	-0.106
Exposed to High Places	0.829	-0.009	-0.032	0.035
Exposed to Hazardous Conditions	0.758	-0.184	-0.020	0.153
Exposed to Hazardous Equipment	0.830	-0.246	-0.179	0.178
Exposed to Minor Burns, Cuts, Bites, or Stings	0.738	-0.459	-0.023	-0.013
Spend Time Sitting	-0.450	0.724	0.019	0.292
Spend Time Standing	0.436	-0.740	0.129	-0.140
Spend Time Climbing Ladders, Scaffolds, or Poles	0.770	-0.048	-0.030	-0.032
Spend Time Walking and Running	0.476	-0.668	0.167	-0.166
Spend Time Kneeling, Crouching, Stooping, or Crawling	0.686	-0.425	0.031	-0.095
Spend Time Keeping or Regaining Balance	0.724	-0.401	0.042	-0.079
Spend Time Using Hands to Handle, Control, or Feel Objects, Tools, or Controls	0.493	-0.524	-0.122	0.356

(1) Manual or hazardous work, (2) Interpersonal: professional, (3) Interpersonal: service, (4) Routine work

Table A2c: Attributes and factor loadings (continued)

Work context attributes	factor loadings			
	(1)	**(2)**	**(3)**	**(4)**
Spend Time Bending or Twisting the Body	0.646	-0.641	0.025	0.105
Spend Time Making Repetitive Motions	0.110	-0.549	-0.106	0.463
Wear Common Protective or Safety Equipment	0.746	-0.368	-0.073	0.148
Wear Specialized Protective or Safety Equipment	0.709	-0.203	0.119	0.129
Consequence of Error	0.473	0.134	0.322	0.382
Impact of Decisions on Co-workers or Company Results	0.182	0.473	0.546	0.315
Frequency of Decision Making	0.162	0.375	0.583	0.280
Freedom to Make Decisions	0.180	0.586	0.346	0.033
Degree of Automation	-0.165	0.091	0.011	0.613
Importance of Being Exact or Accurate	-0.020	0.232	0.270	0.715
Importance of Repeating Same Tasks	-0.169	0.097	0.176	0.649
Structured versus Unstructured Work	0.016	0.620	0.283	0.033
Level of Competition	0.177	0.412	0.149	0.190
Time Pressure	0.209	0.189	0.123	0.524
Pace Determined by Speed of Equipment	0.440	-0.435	-0.264	0.458

(1) Manual or hazardous work, (2) Interpersonal: professional, (3) Interpersonal: service, (4) Routine work

Table A3a: Occupations with highest factor scores in skill attribute bundles

Communication	Machine skills	Socio-technical skills
Secondary school teachers	Repairers of electrical eqpt, n.e.c.	Locomotive operators
HS/College subject teachers	Machinery maintenance	Civil engineers
Managers in education & related	Industrial machinery repairers	Managers in medicine and health
Judges	Heavy & farm eqpt mechanics	Aerospace engineer
Biological scientists	Repairers, hh appliances & tools	Accountants and auditors
Primary school teachers	Elevator installers and repairers	Human res & labor relations mgrs
Lawyers	Millwrights	Airplane pilots and navigators
Sales engineers	Data processing repairers	Construction inspectors
Physicians	Automobile mechanics	Geologists
Aerospace engineer	Patternmakers and model makers	Chemical engineers
Teachers , n.e.c.	Farmers (owners and tenants)	Funeral directors
Veterinarians	Boilermakers	Registered nurses
Vocational and educ counselors	Drillers of oil wells	Electrical engineer
Dentists	Tool and die makers and die setters	Physicists and astronomers
Salespersons, n.e.c.	Plasterers	Management analysts
Librarians	Miners	Farm managers, except hortcult
Therapists, n.e.c.	Construction & survey helpers	Licensed practical nurses
Financial managers	Precision makers, repairers, & smiths	Chemists
Paving & related eqpt opratrs	Fire fight, prevention, inspection	Supervisors of mechanics & repairer
Social workers	Repairers, industrial elect eqpt	Engineers, nec
Recreation workers	Repairers, mech controls & valves	Sales engineers
Supervisors of guards	Assemblers of electrical equipment	Water, sewage treatment plant oper
Financial services sales	Aircraft mechanics	Oper & systems researchers/analysts
Economists, & related researchers	Grinding, abrading, & polishing	Machinists
Art/entertainment performers	Lathe, milling, & turning mach op.	Metallurgical and materials engineer
Architects	Other plant and system operators	Assemblers of electrical equipment
Mgrs in marketing & related	Printing machine operators	Agricultural and food scientists
Plant & system operators	Bus, truck, engine mechanics	Chemical technicians
Clergy and religious workers	Farm managers, except hortcult	Winding/twisting textile/apparel ope
Insurance adjusters, examiners, etc.	Slicing and cutting machine operators	Bakers
Designers	Fishers, hunters, and kindred	Misc textile machine operators
Police, detectives, and related	Supervisors of agric occupations	Health technologists/technicians nec
Supervisors & proprietors sales	Crushing, grinding, mixing workers	Biological scientists
Management analysts	Heating, air cond, & refrig mechanic	Computer scientists & syst analysts
Postmasters and mail superintendents	Sales engineers	Other plant and system operators
Insurance sales occupations	Roofers and slaters	Managers in education and related
Physicists and astronomers	Computer software developers	Nursing aides, orderlies, attendants
Office supervisors	Plumbers, pipe fitters &steamfitters	Crushing, grinding, mixing & blendi
Production supervisors or foremen	Management analysts	Electricians
Actors, directors, producers	Dentists	Power plant operators
Chemists	Telecom & line installers & repairers	engineering technicians
Musician or composer	Crane, derrick, winch & hoist operators	Dispatchers
Engineers not elsewhere classified	Drafters	Computer software developers

* Table lists top 42 occupations. Remainder available on author's website. Some occupation categories abbreviated.

Table A3b: Occupations with highest factor scores in ability attribute bundles

Non-routine psychomotor	Cognitive	psychomotor - fine
Fire fighting, prevention, inspection	Air traffic controllers	Dental lab & med appliance techn
Taxi cab drivers and chauffeurs	Physicists and astronomers	Precision makers/ repairers
Miners	Actors, directors, producers	Clinical lab techngists/technicians
Construction trades, n.e.c.	Physicians	Textile sewing machine operators
Ship crews and marine engineers	Aerospace engineer	Mechanics and repairers, n.e.c.
Excavating & loading mach oper	Civil engineers	Data entry keyers
Parking lot attendants	Mechanical engineers	tailors, dressmakers & sewers
Airplane pilots and navigators	managers, nec	Winding/twisting textile/apparel ope
construction & survey helpers	Lawyers	Surveyors, cartographers, related
Other mining occupations	Veterinarians	Art makers: painters, sculptors, craft
Supervisors of guards	Drafters	Typesetters & related
Truck, delivery, and tractor drivers	Dentists	Drafters
Railroad conductors & yardmasters	Airplane pilots and navigators	Upholsterers
Heating, air cond, refiger mechanics	Mgrs/specialists: marketing & related	Pressing machine oper (clothing)
Bus drivers	Sales engineers	Packers, fillers, and wrappers
Drillers of oil wells	Biological scientists	Misc textile machine operators
Farmers (owners and tenants)	Registered nurses	Cabinetmakers & bench carpenters
Packers, fillers, and wrappers	Supervisors of guards	Aircraft mechanics
Industrial machinery repairers	Financial managers	Machinists
Structural metal workers	Inspectors and compliance officers	Physicians
Electricians	Supervisors of mechanics/repairers	Hairdressers and cosmetologists
Crane, derrick, winch, hoist oper	Judges	Butchers and meat cutters
Paving, surfacing, tamping eqpt oper	Engineers not elsewhere classified	Administrative support jobs, n.e.c.
Garbage & recyclable collectors	Chemical engineers	Repairers of electrical eqpt, nec
Masons, tilers, and carpet installers	Librarians	Chemical engineers
Roofers and slaters	Clinical lab technologists/technicians	Health techngists/ technicians nec
Messengers	Respiratory therapists	Repairers of household appliances
Grinding, abrading, & polishing	Hum resources/labor relations mgrs	Designers
Misc material moving occupations	Managers: medicine/health	Photographic process workers
Insulation workers	Mgrs in education & related	Assemblers of electrical equipment
Fishers, hunters, and kindred	Geologists	Metallurgical/materials engineers
Bus, truck, engine mechanics	Accountants and auditors	Bakers
Carpenters	Office supervisors	Slicing /cutting machine oper
Electric power installers /repairers	Production supervisors or foremen	Typists
Pest control occupations	Correspondence and order clerks	Photographers
Separating, filtering machine oper	Customer service reps & related	Industrial machinery repairers
Millwrights	Salespersons, n.e.c.	Printing machine operators
Woodworking machine operators	Teachers , n.e.c.	Small engine repairers
Construction laborers	Agricultural and food scientists	Painters, hand & machine operators
Oper engineers: constrction eqpt	Biological technicians	Molders, and casting machine oper
Plasterers	Industrial engineers	Mail clerks outside of post office
Telecom /line installers/repairers	Oper/systems research/analysts	Drillers of earth
Farm workers	Insurance sales occupations	File clerks

* Table lists top 42 occupations. Remainder available on author's website.

Table A3c: Occupations with highest factor scores in task attribute bundles

athering and processing information	Coordinate, oversee or advise others	Manual & technical activities
Geologists	Managers of medicine and health	Miners
Engineers nec	Art/entertnmnt performers & related	Elevator installers and repairers
Electrical engineer	Managers in education and related	Boilermakers
Physicists and astronomers	Supervisors of guards	Other mining occupations
Administrative support jobs, nec	Dentists	Power plant operators
Aerospace engineer	Supervisors personal service jobs nec	Aircraft mechanics
Biological scientists	Supervisors: mechanics/repairers	Millwrights
Computer/peripheral equipment oper	Human resources/labor relations mgrs	Machinery maintenance occupations
Chemical engineers	Office supervisors	Crane, derrick, winch, hoist oper
Clinical lab technlgsts/technicians	Production supervisors or foremen	Insulation workers
Metallurgical/materials engineers	Mgrs /specialists: marketing & related	Repairers industrial electrical eqpt
Biological technicians	Plant/syst oper, stationary engineers	Industrial machinery repairers
Computer software developers	Supervisors: agricultural	Extruding/forming machine operators
Surveyors, cartographers, related	Funeral directors	Electric power installers/repairers
Inspectors & compliance officers	Actors, directors, producers	Grinding, abrading, buffing, polishing
Mechanical engineers	Supervisors: motor vehicle transport	Packers, fillers, and wrappers
Real estate sales occupations	Managers, nec	Other plant and system operators
Economists, market researchers	Personal service occupations, nec	Slicing/cutting machine operators
Air traffic controllers	Supervisors of construction work	Electricians
Pharmacists	Farm managers	Ship crews and marine engineers
Chemists	Therapists, nec	Cabinetmakers and bench carpenters
Financial services sales occupations	Designers	Heavy & farm equipment mechanics
Editors and reporters	Financial managers	Heating, air, and refiger mechanics
Architects	Paving, surfacing equipment oper	Bus, truck, and engine mechanics
Lawyers	Recreation workers	Fire fighting, prevention, inspection
Actors, directors, producers	Fire fighting, prevention, inspection	Telecom/line installers/repairers
Management analysts	Clergy and religious workers	Separating, filtering machine oper
Civil engineers	Primary school teachers	Clinical lab technlgsts/technicians
Sales engineers	Teachers , nec	Health technlgsts/technicians, nec
Computer systems analysts/scientists	Pest control occupations	Printing machine operators
Agricultural and food scientists	Electric power installers/repairers	Sawing machine operators/sawyers
Chemical technicians	Postmasters/mail superintendents	Respiratory therapists
Power plant operators	Vocational/educational counselors	Water/sewage treatment plant oper
Industrial engineers	Supervisors/proprietors sales	Drillers of oil wells
Technical writers	Insulation workers	Machinists
Drafters	Secondary school teachers	Farmers (owners and tenants)
Repairers of industrial elect eqpt	HS/college subject teachers	Farm managers
Insurance adjstrs, examiners & related	Registered nurses	Lathe, milling, turning mach oper
Broadcast equipment operators	Respiratory therapists	Tin/coppersmiths, sheet metal wrkrs
Accountants and auditors	Pharmacists	Machine feeders and offbearers
Physicians	Auto body repairers	Carpenters
Personnel/labor relations specialists	Sales engineers	Supervisors of construction work
Salespersons, n.e.c.	Civil engineers	Automobile mechanics

* Table lists top 42 occupations. Remainder available on author's website.

Table A3d: Occupations with highest factor scores in work context attribute bundles

manual/hazardous work	Interpersonal/professional
Heating, air conditioning, and refigeration mechanics	Financial services sales occupations
Millwrights	Lawyers
Bus, truck, and stationary engine mechanics	Architects
Elevator installers and repairers	Real estate sales occupations
Crane, derrick, winch, and hoist operators	Salespersons, n.e.c.
Electric power installers and repairers	Insurance sales occupations
Roofers and slaters	Financial managers
Drillers of oil wells	Paving, surfacing, and tamping equipment operators
Other mining occupations	Geologists
Electricians	Managers in education and related fields
Heavy equipment and farm equipment mechanics	Actors, directors, producers
Fire fighting, prevention, and inspection	Judges
Boilermakers	Musician or composer
Telecom and line installers and repairers	Civil engineers
Ship crews and marine engineers	Metallurgical and materials engineers
Concrete and cement workers	Engineers not elsewhere classified
Carpenters	Administrative support jobs, n.e.c.
Drillers of earth	Economists, market researchers, and survey researchers
Repairers of mechanical controls and valves	Construction inspectors
Water and sewage treatment plant operators	Editors and reporters
Miners	Advertising and related sales jobs
Machinery maintenance occupations	Supervisors of mechanics and repairers
Repairers of household appliances and power tools	Airplane pilots and navigators
Automobile mechanics	Chemical engineers
Misc material moving occupations	Farmers (owners and tenants)
Plasterers	Accountants and auditors
Supervisors of agricultural occupations	Human resources and labor relations managers
Railroad conductors and yardmasters	Police, detectives, and private investigators
Separating, filtering, and clarifying machine operators	Physicists and astronomers
Painters, construction and maintenance	Power plant operators
Supervisors of construction work	Farm managers, except for horticultural farms
Pest control occupations	Operations and systems researchers and analysts
Locomotive operators (engineers and firemen)	Mechanical engineers
Operating engineers of construction equipment	Supervisors and proprietors of sales jobs
Truck, delivery, and tractor drivers	Sales engineers
Power plant operators	Managers/specialists marketing, & public relations
Glaziers	Plant and system operators, stationary engineers
Farmers (owners and tenants)	Surveyors, cartographers scientists and technicians
Auto body repairers	Aerospace engineer
Other plant and system operators	managers, nec
Furnace, kiln, and oven operators, apart from food	Insurance adjusters, examiners, and investigators
tinsmiths, coppersmiths & sheet metal workers	Electrical engineer
Industrial machinery repairers	Interviewers, enumerators, and surveyors

* Table lists top 42 occupations. Remainder available on author's website.

Table A3e: Occupations with highest factor scores in work context attribute bundles

Interpersonal/service	Routine
Radiologic tech specialists	Telephone operators
Supervisors of guards	Dentists
Licensed practical nurses	Air traffic controllers
Veterinarians	Crane, derrick, winch, and hoist operators
Physicians	Legal assistants, paralegals, legal support, etc
Registered nurses	Slicing and cutting machine operators
Dentists	Extruding and forming machine operators
Nursing aides, orderlies, and attendants	Typesetters, compositors, photoengravers,lithographers
Supervisors of personal service jobs, n.e.c.	Dental laboratory and medical appliance technicians
Health technologists and technicians, n.e.c.	Computer and peripheral equipment operators
Primary school teachers	Broadcast equipment operators
Teachers , n.e.c.	Dispatchers
Supervisors of cleaning and building service	Miners
Therapists, n.e.c.	Data entry keyers
Postmasters and mail superintendents	Postal clerks, excluding mail carriers
Funeral directors	Woodworking machine operators
Guards, watchmen, doorkeepers	Surveyors, cartographers cientists and technicians
Respiratory therapists	Interviewers, enumerators, and surveyors
Managers of medicine and health occupations	Molders, and casting machine operators
Social workers	Lathe, milling, and turning machine operatives
Judges	Packers, fillers, and wrappers
Health aides, except nursing	Bookkeepers and accounting and auditing clerks
Personal service occupations, nec	Inspectors and compliance officers
Protective services, n.e.c.	Salespersons, nec
Fire fighting, prevention, and inspection	Machinists
Recreation facility attendants	Insurance adjusters, examiners, and investigators
Recreation workers	Drafters
Broadcast equipment operators	Winding and twisting textile/apparel operatives
Waiter/waitress	Painters, hand & machine operators
Clinical laboratory technologies and technicians	Printing machine operators
Managers of properties and real estate	Sawing machine operators and sawyers
Pharmacists	Other financial specialists
Air traffic controllers	Hotel clerks
Baggage porters	Assemblers of electrical equipment
managers, nec	Bill and account collectors
Vocational and educational counselors	Personnel, HR, training, and labor relations specialists
Supervisors of mechanics and repairers	Technical writers
Bartenders	Textile sewing machine operators
Plasterers	Tool and die makers and die setters
Supervisors of motor vehicle transportation	Patternmakers and model makers
engineering technicians	Tailors, dressmakers & sewers
Supervisors and proprietors of sales jobs	Batch food makers
Parking lot attendants	Furnace, kiln, and oven operators, apart from food

* Table lists top 42 occupations. Remainder available on author's website.

Table A4: Correlation coefficients between attribute bundles

			skf1	skf3	abf2	waf1	waf2	wcf2	wcf3	skf2	waf3	wcf1	abf1	abf3	wcf4
non-routine cognitive	communication	skf1	1.000												
	socio-tech	skf3	0.017	1.000											
	cognitive	abf2	0.706	0.302	1.000										
	gathering/proc	waf1	0.569	0.413	0.701	1.000									
	coordinate, etc	waf2	0.475	0.075	0.437	0.020	1.000								
	interp: prof	wcf2	0.588	0.186	0.590	0.611	0.219	1.000							
	interp: serv	wcf3	0.452	-0.031	0.447	0.124	0.570	0.010	1.000						
complements machines	machine skills	skf2	-0.004	0.026	0.020	0.088	-0.166	-0.074	-0.201	1.000					
	manual/tech	waf3	-0.334	0.295	-0.018	-0.005	0.002	-0.278	-0.045	0.670	1.000				
physical	manual/hazard	wcf1	-0.257	0.124	-0.016	-0.137	0.077	-0.009	0.002	0.559	0.774	1.000			
non-routine	on-routine psychomot	abf1	-0.312	0.006	-0.004	-0.322	0.153	-0.284	0.144	0.398	0.713	0.782	1.000		
routine	routine psychomotor	abf3	-0.189	0.246	0.002	0.200	-0.327	-0.160	-0.339	0.453	0.437	0.140	0.011	1.000	
routine	routine	wcf4	-0.022	0.177	0.152	0.357	-0.302	0.000	0.007	0.226	0.185	0.002	-0.078	0.458	1.000

Table A5a: Male occupations by employment changes 1980-1990

Largest employment gains		Largest employment losses	
Supervisors & proprietors of sales	.0214	Production supervisors or foremen	-.0149
Managers, nec	.0083	Machine operators nec	-.0088
Cooks, variously defined	.0043	Managers/specialists in marketing	-.0046
Computer software developers	.0039	Industrial machinery repairers	-.0042
Computer systems analysts scientists	.0028	welders, solderers & metal cutters	.0035
Gardeners and groundskeepers	.0022	Office supervisors	-.0033
Lawyers	.0021	laborers in freight, stock or materials	-.0033
Cashiers	.0021	Lathe & related operatives	-.0028
Supervisors of mechanics & repairers	.0021	Farm workers	-.0027
Other law enforcement:	.0019	Automobile mechanics	-.0026
construction laborers	.0019	Truck, delivery, and tractor drivers	-.0023
Bus, truck, & related mechanics	.0018	Grinding, etc. workers	-.0022
Teachers , nec	.0017	Misc material moving occupations	-.0022
Operations & systems analysts	.0017	Secondary school teachers	-.0021
Guards, watchmen, doorkeepers	.0017	Telecom &line installers & repairers	-.0021
Aircraft mechanics	.0016	Janitors	-.0021
Managers of properties and real estate	.0016	Packers and packagers by hand	-.0015
Electrical engineer	.0016	Crane, etc. operators	-.0015
Airplane pilots and navigators	.0015	Tool and die makers and die setters	-.0014
Financial services sales occupations	.0014	Production inspectors, etc.	-.0014
Health technologists & technicians, nec	.0013	Carpenters	-.0013
Designers	.0012	Furnace, kiln, and oven operators	-.0013
Physicians	.0012	Insurance sales occupations	-.0012
Accountants and auditors	.0011	Butchers and meat cutters	-.0012
Management support occupations	.0011	Plumbers, pipe fitters, & steamfitters	-.0012

Table A5b: Female occupations by employment changes 1980-1990

Largest employment gains		**Largest employment losses**	
Managers, nec	.0204	Secretaries	-.0261
Supervisors & proprietors of sales	.0156	General office clerks	-.0124
Accountants and auditors	.0085	Bookkeepers accounting clerks	-.0117
Management support occupations	.0066	Machine operators nec	-.0085
Customer service reps & related	.0055	Textile sewing machine operators	-.0078
Registered nurses	.0039	Assemblers of electrical equipment	-.0067
Financial managers	.0035	Waiter/waitress	-.0061
Health technologists & technicians, nec	.0034	Typists	-.0057
Other financial specialists	.0034	Packers and packagers by hand	-.0054
Teacher's aides	.0033	Secondary school teachers	-.0052
Managers in education and related fields	.0033	Telephone operators	-.0042
Primary school teachers	.0027	Office supervisors	-.0041
Insurance adjusters & related	.0027	Bank tellers	-.0036
Legal assistants, etc	.0026	Child care workers	-.0035
Administrative support jobs, nec	.0026	production inspectors, etc.	-.0034
Lawyers	.0025	Production supervisors or foremen	-.0032
Computer software developers	.0025	Correspondence and order clerks	-.0030
Managers of properties and real estate	.0023	Health aides, except nursing	-.0030
Transportation ticket agents	.0023	Licensed practical nurses	-.0029
Managers/specialists in marketing, etc	.0023	Salespersons, nec	-.0027

Table A6a: Male occupations by employment changes 1990-2000

Largest employment gains		**Largest employment losses**	
Retail sales clerks	.0190	Salespersons, nec	-.0198
Computer systems analysts & scientists	.0142	Managers, nec	-.0188
Computer software developers	.0106	Laborers in freight, stock or materials	-.0082
Customer service representatives & related	.0068	Janitors	-.0045
Office supervisors	.0055	Production supervisors or foremen	-.0040
Managers/specialists in mktg & related	.0040	Assemblers of electrical equipment	-.0030
Material recording & related clerks	.0033	Shipping and receiving clerks	-.0030
Stock and inventory clerks	.0030	Computer & eqpt operators	-.0029
Cooks, variously defined	.0028	Engineering technicians	-.0028
Police, detectives, &investigators	.0027	Insurance sales occupations	-.0025
Management analysts	.0025	Repairers of industrial electrical eqpt	-.0023
Industrial machinery repairers	.0025	Electrical engineer	-.0021
Machine operators, nec	.0022	Supervisors/ proprietors of sales	-.0021
Supervisors of motor vehicle transport	.0021	Postal clerks, excl mail carriers	-.0020
Secondary and college subject teachers	.0020	Machinists	-.0019
Telecom and line installers and repairers	.0020	Garage, service station	-.0018
Mechanical engineers	.0018	Drafters	-.0017
Gardeners and groundskeepers	.0016	Construction trades, n.e.c.	-.0016
Data processing, etc. repairers	.0015	Printing machine operators	-.0015
Personnel & related specialists	.0015	Guards, watchmen, doorkeepers	-.0014
Supervisors of mechanics and repairers	.0014	Misc material moving occupations	-.0014
Vocational and educational counselors	.0014	Operations and systems r analysts	-.0012
Operating engineers of construction eqpt	.0013	Mechanics and repairers, n.e.c.	-.0012
Other financial specialists	.0013	Carpenters	-.0012
Waiter/waitress	.0012	Plant, system operators, & related	-.0012

Table A6b: Female occupations by employment changes 1990-2000

Largest employment gains		**Largest employment losses**	
Retail sales clerks	.0190	Managers, nec	-.0232
Customer service reps & related	.0188	Salespersons, nec	-.0211
Office supervisors	.0144	Secretaries	-.0173
Computer systems analysts &scientists	.0082	Typists	-.0083
Managers/specialists in mrktg & related	.0066	Textile sewing machine operators	-.0071
Personnel & related specialists	.0059	Computer & equipment operators	-.0067
Health aides, except nursing	.0058	Bookkeepers and accounting clerks	-.0065
Child care workers	.0049	Cashiers	-.0057
Dental lab & medical appliance techs	.0049	Assemblers of electrical equipment	-.0052
Vocational and educational counselors	.0045	laborers in freight, stock or materials	-.0051
Legal assistants & related	.0040	Management support occupations	-.0043
Financial managers	.0039	Health technologists/technicians, nec	-.0038
Secondary & college subject teachers	.0037	General office clerks	-.0035
Teacher's aides	.0033	Janitors	-.0035
Supervisors/ proprietors of sales	.0033	Bank tellers	-.0031
Welfare service aides	.0029	Administrative support jobs, n.e.c.	-.0028
Computer software developers	.0027	Data entry keyers	-.0025
Human resources managers	.0027	Production inspectors, testers, etc.	-.0023
Financial records processing	.0026	Nursing aides, orderlies, attendants	-.0022
Registered nurses	.0026	Waiter/waitress	-.0020

Table A7a: Male occupations by median wage changes 1980-1990

Largest median wage gains		Largest median wage losses	
Registered nurses	.265	Telephone operators	-.488
Lawyers	.228	File clerks	-.349
Respiratory therapists	.227	Packers, fillers, and wrappers	-.311
Licensed practical nurses	.210	Data entry keyers	-.310
Physicians	.201	Ship crews and marine engineers	-.283
Pharmacists	.176	Butchers and meat cutters	-.282
Elevator installers and repairers	.139	Transportation ticket agents	-.280
Clergy and religious workers	.137	Cashiers	-.271
Managers of properties and real estate	.136	Air traffic controllers	-.265
Postmasters and mail superintendents	.136	Broadcast equipment operators	-.236
Batch food makers	.128	Airplane pilots and navigators	-.235
Radiological tech specialists	.125	Management support occupations	-.233
Financial managers	.121	Aircraft mechanics	-.230
Messengers	.118	Weighers, measurers, and checkers	-.205
Funeral directors	.115	Vehicle washers & equipment cleaners	-.204
Primary school teachers	.112	Dispatchers	-.200
Pressing machine operators (clothing)	.112	Ushers	-.178
Judges	.108	Other mining occupations	-.176
Managers/specialists in mktg & related	.106	Hand molders & shapers, excl jewelers	-.168
Vocational and educational counselors	.106	Recreation workers	-.165
Secondary school teachers	.102	Structural metal workers	-.162
Computer software developers	.096	Packers and packagers by hand	-.160
Foresters and conservation scientists	.095	Crane, derrick, winch, hoist operators	-.154
Construction inspectors	.091	Personnel, HR, etc. specialists	-.154
Power plant operators	.091	Paving, surfacing, etc eqpt operators	-.151

The numbers show the change in the log of the hourly median wage.

Table A7b: Female occupations by median wage changes 1980-1990

Largest median wage gains		**Largest median wage losses**	
Physicians	.359	Sales demonstrators, etc.	-.289
Respiratory therapists	.328	Transportation ticket agents	-.244
Carpenters	.306	Bookbinders	-.224
Lawyers	.295	Health record tech specialists	-.167
Pharmacists	.285	Kindergarten &earlier teachers	-.136
Managers/specialists in mktg & related	.281	Cashiers	-.129
Art/entertainment performers &related	.278	Butchers and meat cutters	-.114
Industrial engineers	.273	Management support occupations	-.092
Actors, directors, producers	.270	Vehicle washers & equipment cleaners	-.090
Photographers	.251	Packers and packagers by hand	-.087
Welfare service aides	.245	Eligibility clerks -government	-.081
Financial managers	.241	Food counter & fountain workers	-.080
Registered nurses	.238	Slicing and cutting machine operators	-.079
Engineers not elsewhere classified	.232	Public transport attendants, inspectors	-.078
Special education teachers	.221	Janitors	-.077
Chemical technicians	.218	Bakers	-.071
Financial services sales occupations	.214	teacher's aides	-.069
construction laborers	.209	Child care workers	-.067
Computer software developers	.201	Misc textile machine operators	-.062
Radiological tech specialists	.201	Cooks, variously defined	-.060

The numbers show the change in the log of the hourly median wage.

Table A8a: Male occupations by median wage changes 1990-2000

Largest median wage gains		**Largest median wage losses**	
Ushers	.784	Correspondence and order clerks	-.275
Recreation workers	.415	Vocational & educational counselors	-.237
Broadcast equipment operators	.407	Pressing machine operators (clothing)	-.209
Air traffic controllers	.391	Telephone operators	-.150
Announcers	.329	Construction trades, nec	-.147
Pharmacists	.289	Typesetters, & related	-.135
Computer software developers	.284	Drywall installers	-.135
Art/entertainment performers	.263	Locomotive operators	-.124
Ships crews & marine engineers	.256	Telecom and line installers, repairers	-.122
Musician or composer	.253	Barbers	-.114
Retail sales clerks	.248	Plasterers	-.111
Typists	.243	data processing, etc. repairers	-.110
Psychologists	.241	Railroad conductors and yardmasters	-.094
Physicians	.239	Door-to-door & street sales	-.093
Financial records processing	.237	Other mining occupations	-.088
Precision makers, repairers, & smiths	.233	production helpers	-.085
Interviewers & related	.225	Stock and inventory clerks	-.083
Salespersons, n.e.c.	.220	Customer service reps, & related	-.083
Librarians	.214	Computer systems analysts & scientists	-.082
Health technologists, technicians nec	.199	Shipping and receiving clerks	-.080
Art makers	.196	Heavy and farm equipment mechanics	-.067
Baggage porters	.187	Structural metal workers	-.067
Bartenders	.184	Fishers, hunters, and kindred	-.065
Library assistants	.184	Office supervisors	-.063
Child care workers	.180	Electric power installers and repairers	-.058

The numbers show the change in the log of the hourly median wage.

Table A8b: Female occupations by median wage changes 1990-2000

Largest median wage gains		**Largest median wage losses**	
Salespersons, n.e.c.	.426	Vocational and educational counselors	-.125
Pharmacists	.418	Correspondence and order clerks	-.120
Welfare service aides	.399	Postmasters and mail superintendents	-.110
Eligibility clerks for government	.357	Shipping and receiving clerks	-.056
Art makers	.353	Telephone operators	-.018
Computer software developers	.304	Photographers	-.009
Material recording, etc. clerks	.300	Computer systems analysts & scientists	-.007
Retail sales clerks	.290	Public transport attendants, inspectors	-.005
Recreation workers	.279	Taxi cab drivers and chauffeurs	-.002
Sales demonstrators, etc.	.277	Punching and stamping press operatives	-.001
Psychologists	.245	Dental lab and medical appliance techs	.002
Librarians	.236	Packers and packagers by hand	.002
Kindergarten & earlier teachers	.230	Photographic process workers	.004
Electricians	.226	Stock and inventory clerks	.005
Advertising and related sales jobs	.224	Precision makers, repairers, and smiths	.008
Dental hygienists	.221	Misc food prep workers	.008
Management analysts	.216	Mail carriers for postal service	.016
Musician or composer	.216	Door-to-door sales, etc.	.020
Managers of medicine and health jobs	.213	Pressing machine operators (clothing)	.021
Managers, nec	.211	Guards, watchmen, doorkeepers	.021

The numbers show the change in the log of the hourly median wage.

Table A10a: Male occupations by employment changes 1980-2000

Largest employment gains		**Largest employment losses**	
Retail sales clerks	0.0195	Salespersons, nec	-0.0193
Supervisors of sales jobs	0.0194	Production supervisors	-0.0189
Computer systems analysts & scientists	0.0169	Laborers in freight, etc.	-0.0114
Computer software developers	0.0145	Managers, nec.	-0.0105
Cooks	0.0074	Machine operators, nec	-0.0066
Gardeners & groundskeepers	0.0070	Janitors	-0.0065
Management analysts	0.0038	Welders, solderers, & metal cutters	-0.0046
Supervisors of mechanics & repairers	0.0035	Insurances sales	-0.0037
Stock & inventory clerks	0.0034	Farm workers	-0.0037
Police, detectives & private investigators	0.0030	Lathe, milling & turning machine oper.	-0.0036
Supervisors of motor vehicle transport	0.0029	Miscellaneous material moving	-0.0036
Other law enforcement	0.0029	Truck, delivery & tractor drivers	-0.0031
Material recording, scheduling, etc clerks	0.0028	Shipping and receiving clerks	-0.0030
Lawyers	0.0028	Garage & service station workers	-0.0029
Other financial specialists	0.0026	Assemblers of electrical equipment	-0.0029
Office supervisors	0.0022	Automobile mechanics	-0.0028
Data processing & ATM repair	0.0022	Grinding, abrading, buffing, etc.	-0.0028
Waiter	0.0022	Carpenters	-0.0025
Bus, truck, stationary engine mechanic	0.0022	Drafters	-0.0025
Registered nurse	0.0022	Machinists	-0.0022

Employment share changes are actual multiplied by 100.

Table A10b: Female occupations by employment changes 1980-2000

Largest employment gains		**Largest employment losses**	
Customer service reps & related	0.0243	Secretaries	-0.0434
Retail sales clerks	0.0195	Salespersons, nec	-0.0239
Supervisors of sales jobs	0.0188	Bookkeepers & related	-0.0181
Accountants and auditors	0.0106	General office clerks	-0.0159
Computer systems analysts & scientists	0.0104	Textile sewing machine operators	-0.0149
Office supervisors	0.0103	Typists	-0.0140
Managers & specialists in marketing	0.0089	Assemblers of electrical equipment	-0.0118
Financial managers	0.0074	Machine operators, nec	-0.0084
Personnel, HR, training, & labor relations	0.0070	Waitress	-0.0081
Legal assistants & related	0.0067	Bank tellers	-0.0067
Teacher aides	0.0066	Packers & packagers by hand	-0.0064
Registered nurses	0.0064	Telephone operators	-0.0061
Managers in education & related	0.0052	Computer operators	-.0059
Computer software developers	0.0052	Production inspectors, testers, etc	-.0058
Insurance adjusters & related	0.0050	Cashiers	-.0053
Dental lab & medical technicians	0.0049	Correspondence & order clerks	-.0049
Vocational & education counselors	0.0047	Laborers in freight, stock, etc.	-.0043
High school and college subject teachers	.0041	Secondary school teachers	-.0035
Managers in medicine & health	.0041	Production supervisors	-.0030

Employment share changes are actual multiplied by 100.