

The Changing Task Composition of the US Labor Market: An Update of Autor, Levy, and Murnane (2003)*

David H. Autor

Brendan Price

MIT and NBER

MIT

June 21, 2013

Introduction

A 2003 paper by Autor, Levy and Murnane (ALM), “The Skill Content of Recent Technological Change,” introduced an influential methodology for measuring and analyzing changes in the skill demands of jobs in the U.S. and other economies. Whereas conventional analyses had used the average educational levels of workers employed within occupations as a summary measure of skill demands in those occupations, ALM proposed drawing a distinction between skills and tasks. In their terminology, a task is a unit of work activity that produces output. A skill is a worker’s *stock* of capabilities for performing various tasks. Workers apply their skills to tasks in exchange for wages. ALM argue that distinguishing between skills and tasks permits a nuanced view of how advances in technologies, changes in skill supplies, and the shifting availability of trade and offshoring opportunities affect the division of labor between workers and machines, the set of tasks that workers perform, and ultimately, the skills demanded by their jobs.

ALM focus on three broad categories of tasks, which they argue are differently affected by ongoing computerization.¹ The first category encompasses so-called ‘routine’ tasks, which are

*The authors gratefully acknowledge financial support from the Hewlett Foundation and valuable input from Charles Fadel of the Center for Curriculum Redesign and Barbara Chow of the Hewlett Foundation.

¹A key paragraph from their paper summarizes the argument: “...(1) computer capital substitutes for workers in carrying out a limited and well-defined set of cognitive and manual activities, those that can be accomplished by following explicit rules (what we term “routine tasks”); and (2) that computer capital complements workers in carrying out problem-solving and complex communication activities (“nonroutine” tasks). Provided that routine and nonroutine tasks are imperfect substitutes, these observations imply measurable changes in the

job activities that are sufficiently well defined that they can be carried out successfully by either a computer executing a program or, alternatively, by a comparatively less-educated worker in a developing country who carries out the task with minimal discretion. Routine tasks are characteristic of many middle-skilled cognitive and production activities, such as bookkeeping, clerical work and repetitive production tasks. The core job tasks of these occupations in many cases follow precise, well-understood procedures. As computer and communication technologies improve in quality and decline in price, these routine tasks are increasingly codified in computer software and performed by machines or, alternatively, sent electronically to foreign worksites to be performed by comparatively low-wage workers. ALM further distinguish between routine *cognitive* tasks such as bookkeeping and data entry and routine *manual* tasks such as repetitive production and monitoring jobs performed on an assembly line. Subsequent work has tended to combine these two categories under the routine rubric.

ALM argue that as computers have taken over our routine tasks, they have boosted demand for workers who perform ‘nonroutine’ tasks that are complementary to the automated activities. What are these nonroutine tasks? They can be roughly divided into two major categories that happen to lie on opposite ends of the occupational skill distribution. On one side are so-called ‘abstract’ tasks, which require problem-solving, intuition, persuasion, and creativity. These tasks are characteristic of professional, managerial, technical and creative occupations, such as law, medicine, science, engineering, marketing and design. Workers who are most adept in these tasks typically have high levels of education and analytical capability, and they benefit from computers that facilitate the transmission, organization, and processing of information. ALM further distinguished between abstract tasks involving formal analytic skills (e.g., engineering and science) and those involving managerial and interpersonal skills. As with routine cognitive and manual tasks, subsequent work has tended to combine the two nonroutine cognitive measures (analytical and managerial) under a single heading of ‘abstract tasks.’

On the other side of the occupational skill spectrum from abstract tasks are so-called ‘manual’ tasks, which demand situational adaptability, visual and language recognition, and in-person interaction. Tasks like preparing a meal, driving a truck through city traffic, or cleaning a hotel room present mind-bogglingly complex challenges for software engineering. But from the human perspective, these manual tasks are straightforward, requiring primarily

task composition of jobs.”

innate abilities like dexterity, sightedness, and language recognition, and perhaps a modest amount of training.

A key contribution of the ALM paper was to document changes in labor input in these five task categories—routine cognitive, routine manual, nonroutine cognitive analytic, nonroutine cognitive interpersonal, and nonroutine manual, over nearly a five decade span from 1960 - 1998. Figure 1 of their paper, reproduced immediately below, found three patterns consistent with ALM’s reasoning: 1) labor input of routine cognitive and manual tasks, which had been rising in the 1960s and 1970s, went into sharp decline from the 1980s forward, consistent with growing substitution of computer capital for routine tasks; 2) labor input of nonroutine cognitive analytic and interpersonal tasks grew rapidly from 1980 forward, with some evidence of acceleration prior to earlier decade, consistent with a potential complementarity between computerization and demand for abstract tasks; and 3) the long-standing secular decline in nonroutine manual tasks, evident from at least 1960 forward, decelerated after 1990, consistent with the possibility that computerization was displacing labor from routine into manual task-intensive work.

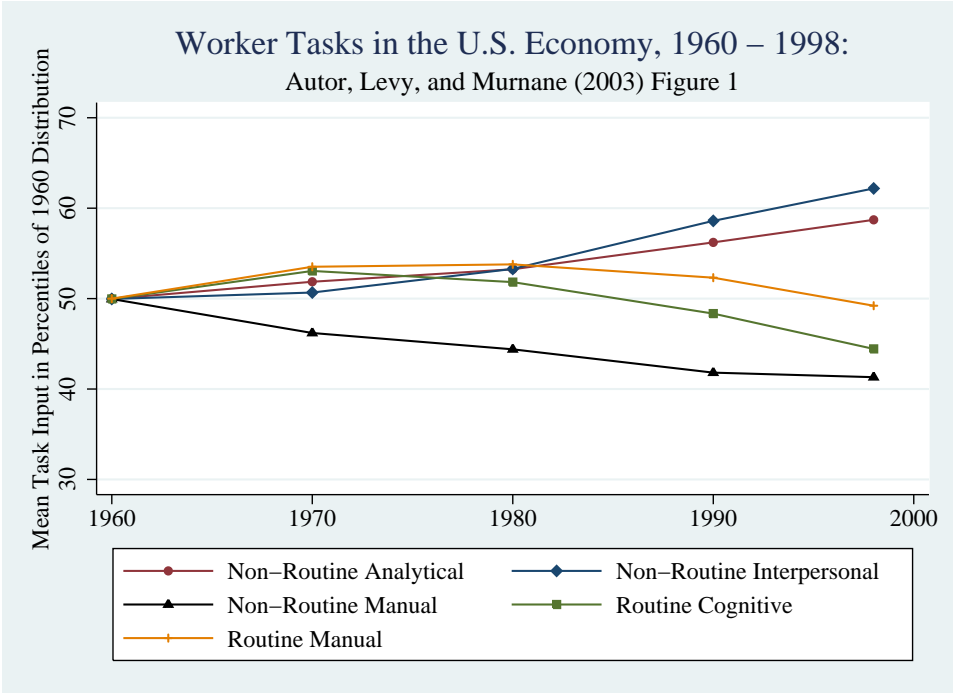


Figure 1. Autor, Levy and Murnane (2003) Figure I

While the ALM analysis has proved influential for both economic research and policy discussion, the trends that ALM identified using data current through 1998 have not been

systematically extended since their paper was published a decade ago. As Nobel Laureate Paul Samuelson once said, “If you must forecast, forecast often,” and ten years is a long time between forecasts. This memo and accompany data work updates and extends to the year 2009 the ALM task analysis. We first carefully recreate their original data work, suitably modifying their procedures to accommodate later revisions to the data sources on employment by occupation on which ALM drew.² We then extend ALM’s time series data to describe changes in the labor input of job tasks in the U.S. economy through the year 2010. The next section of this memo describes the results of this exercise, while the subsequent section offers potential interpretations of the updated findings. The Data Appendix thoroughly documents the procedures used to construct and analyze the data.

Results

Table 1 displays the original and updated values of the ALM measures of trend in task inputs in the U.S. economy between 1960 and 1998 (ALM original) and 1960 and 2009 (updated data). Because task values taken from the Dictionary of Occupational Titles variables do not have a cardinal scale, we follow ALM in transforming the DOT measures into percentile values corresponding to their rank in the 1960 distribution of task input. All of our outcome measures may therefore be interpreted as levels or changes in task input relative to the 1960 task distribution, measured in “centiles.” By construction, the overall level of input of each task in 1960 is equal to the mean and median across task centiles in 1960 (which is 50.0). Figure 2 plots these replicated and extended values, while Appendix Figures 1 through 3 plot the original and replicated value of each task scale alongside one another to assess comparability.³

²These include the Census of Populations, Current Population Survey, and the American Community Survey, which, though not used in ALM’s original work, became an important primary source for data on employment and occupations for the years 2005 forward.

³Comparability is overall quite good. Revisions to the historical data (1960 through 1998) that were needed to accommodate subsequent (post-ALM) revisions to the Census occupation coding scheme starting in 2000 introduce modest discrepancies from the original results. These discrepancies are visible in the 1970, 1980 and 1990 columns of Table 1 but do not appear substantively significant.

Table 1. Trends in Task Input in the U.S. Economy, 1960 - 2009
 Updated Values 1960 - 2009, and Comparison with ALM 2003 for 1960-1998

	1960	1970	1980	1990	2000/1998 Update/ALM	2006	2009
A. Non-Routine Analytical							
Update	50.0	51.5	57.5	60.8	64.2	63.3	63.9
ALM	50.0	51.9	53.2	56.2	58.7		
G. Non-Routine Interpersonal							
Update	50.0	49.9	57.9	62.4	66.4	66.1	66.7
ALM	50.0	50.7	53.3	58.6	62.2		
C. Routine Cognitive							
Update	50.0	53.2	51.2	46.9	42.6	41.0	39.5
ALM	50.0	53.1	51.8	48.3	44.4		
D. Routine Manual							
Update	50.0	55.3	54.9	52.6	47.6	46.0	45.2
ALM	50.0	53.5	53.8	52.3	49.2		
E. Non-Routine Manual							
Update	50.0	47.0	45.2	43.0	42.5	43.8	43.1
ALM	50.0	46.2	44.4	41.8	41.3		

Notes: In the column marked "1998/2000," ALM use 1998 values, and the Update reports 2000 values.

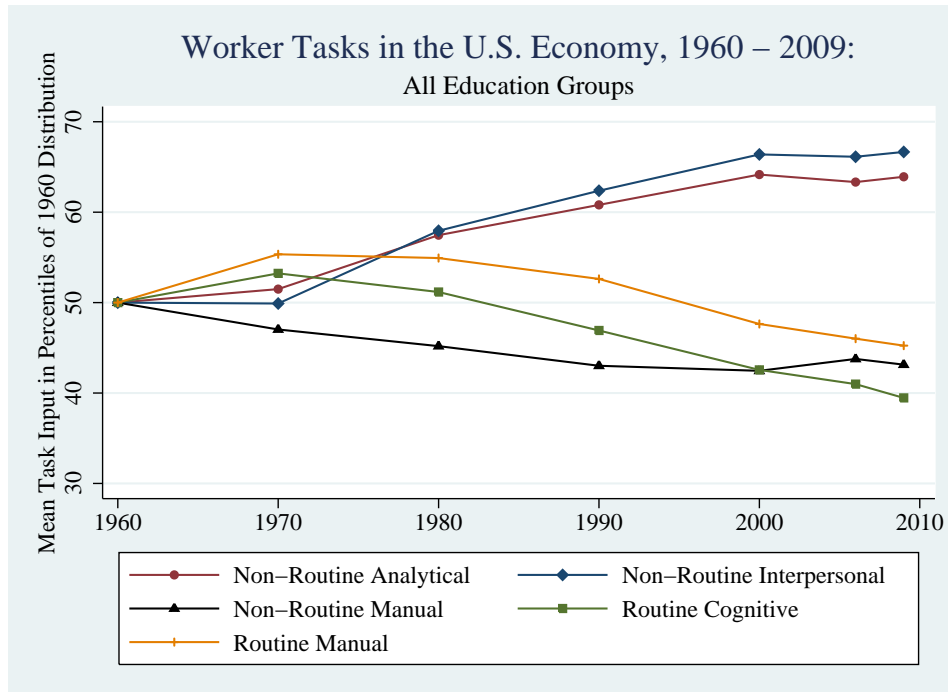


Figure 2. Replication and Extension of ALM Figure 1: 1960 - 2009

Of three major trends originally identified by ALM, the extended data series strongly confirms two of them, and offers surprising evidence on a third. The first trend that is strongly

confirmed by the data is the continual decline in labor input of routine tasks in the U.S. economy. Between the end of the ALM sample and the year 2009, routine cognitive task input fell at approximately three centiles per decade—consistent with the rate observed between 1980 and 1998. The ongoing fall in routine cognitive task input between 1980 and 2009 follows a three centile *rise* in routine cognitive task input between 1960 and 1970, and then a modest decline between 1970 and 1980. Labor input of routine manual tasks follows a similar trend. It rises between 1960 and 1970, modestly reverses direction between 1970 and 1980, and then falls more rapidly between 1980 and 2009, with perhaps a slight deceleration in the most recent decade. Thus, trends in both measures of routine task input echo and amplify the pattern identified by ALM.

The second major trend strongly confirmed by the updated data is the reversal of the long-standing secular decline in nonroutine manual tasks, which was evident from at least 1960 forward. In the time window visible to ALM, the secular decline of nonroutine manual tasks had decelerated in the final eight years of their sample (1990 through 1998) but had not reversed direction. The updated data reveal that input of nonroutine manual tasks in fact did rise modestly after 2000. This finding is consistent with the predictions of the ALM framework, and is also consistent with Autor and Dorn’s (forthcoming) subsequent work on employment polarization.

The third pattern notable pattern, which is not expected from the ALM analysis, is that input of nonroutine cognitive tasks appears to slow substantially after 2000. Both nonroutine analytical and nonroutine interpersonal tasks modestly *decline* between 2000 and 2006 and then rebound slightly to 2009. At the end of the period, analytical task input was very slightly below its 2000 level and interpersonal task input was very slightly above its 2000 level.

While unexpected based on the analysis in ALM, the apparent leveling off of nonroutine cognitive task input in the U.S. economy is consistent with patterns noted by Acemoglu and Autor (2011) and discussed in detail by Beaudry, Green and Sand (2013). This unanticipated pattern merits further study.

Table 2. Trends in Task Input in the U.S. Economy, Overall and by Sex, 1960 - 2009

	1960	1970	1980	1990	2000	2006	2009
A. Non-Routine Analytical							
Both Sexes	50.0	51.5	57.5	60.8	64.2	63.3	63.9
Men Only	53.6	55.6	60.4	61.7	64.3	62.8	63.5
Women Only	37.1	40.3	50.0	57.2	61.5	61.6	61.9
B. Non-Routine Interpersonal							
Both Sexes	50.0	49.9	57.9	62.4	66.4	66.1	66.7
Men Only	57.5	59.9	65.4	66.0	68.5	67.9	68.6
Women Only	26.3	26.3	42.7	54.9	61.2	61.5	61.9
C. Routine Cognitive							
Both Sexes	50.0	53.2	51.2	46.9	42.6	41.0	39.5
Men Only	47.9	50.0	46.9	44.8	42.8	41.8	40.3
Women Only	52.9	57.7	56.6	48.3	40.6	38.2	36.9
D. Routine Manual							
Both Sexes	50.0	55.3	54.9	52.6	47.6	46.0	45.2
Men Only	42.3	45.2	43.2	42.1	39.0	37.4	36.2
Women Only	68.7	74.7	73.7	66.4	58.2	56.4	55.6
E. Non-Routine Manual							
Both Sexes	50.0	47.0	45.2	43.0	42.5	43.8	43.1
Men Only	55.7	53.9	53.8	52.8	52.4	53.8	52.6
Women Only	31.2	30.0	27.9	26.8	26.7	28.0	29.1
F. Non-Routine Cognitive Composite							
Both Sexes	50.0	50.7	57.9	61.9	65.8	65.2	65.8
Men Only	55.5	57.8	63.4	64.5	67.4	66.3	67.1
Women Only	31.4	32.8	45.7	55.7	61.2	61.3	61.7
G. Routine Composite							
Both Sexes	50.0	54.0	52.6	48.5	43.7	42.0	40.6
Men Only	46.3	48.7	45.9	44.0	41.6	40.3	38.6
Women Only	57.4	62.9	62.4	53.5	45.2	42.9	41.7

Notes: Non-routine cognitive composite measure in row (F) is a simple average of non-routine cognitive analytic and interpersonal scales. Routine composite measure in row (G) is a simple average of routine cognitive and routine manual scales.

Table 2, and the accompanying Figures 3 through 7, provide a detailed comparison of levels and trends in task input by gender.⁴ Though not a focus of ALM's analysis, these figures document remarkable gender differences in the evolution of task input. In 1960, average male input of nonroutine cognitive tasks greatly exceeded that of males. In nonroutine cognitive tasks, this gap was 25 centiles, and in nonroutine interpersonal tasks, it was 30 percentiles.

⁴Rows F and G of Table 2 also summarize composite measures of routine tasks and nonroutine analytic tasks. The nonroutine cognitive composite measure in row F is a simple average of nonroutine cognitive analytic and interpersonal scales. The routine composite measure in row G is a simple average of routine cognitive and routine manual scales.

Over the next four decades, these gaps closed substantially. While male input of nonroutine cognitive tasks rose by approximately 10 centiles in both analytical and interpersonal task categories, female input rose by 24 percentiles in analytical tasks and 35 percentiles in interpersonal tasks. By the close of the sample, the male-female gap in analytic tasks had shrunk to two centiles, and the gap in interpersonal tasks had shrunk to seven centiles.

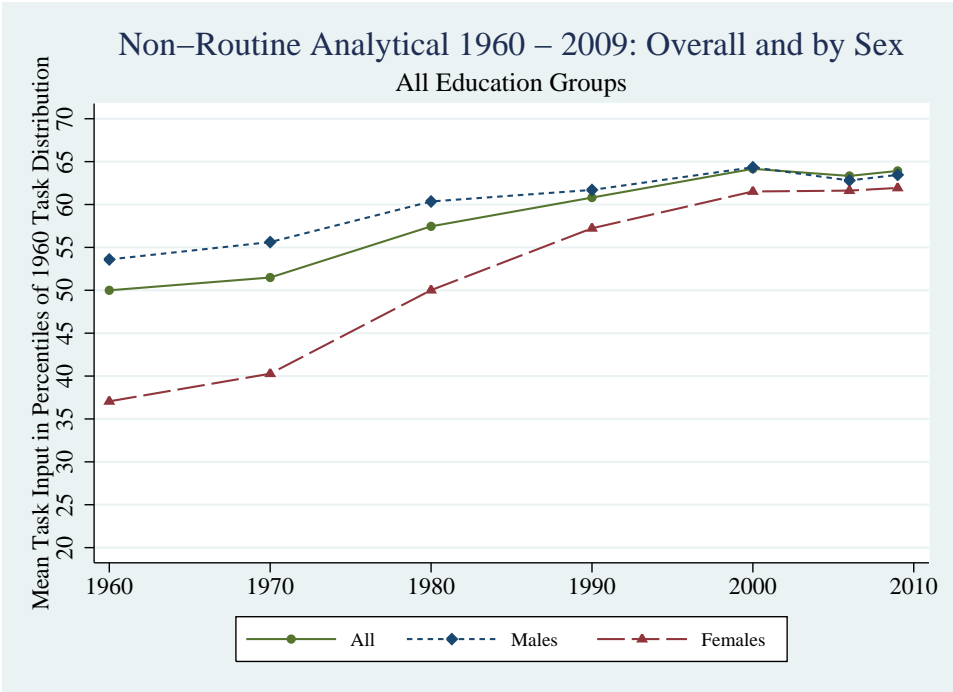


Figure 3. Nonroutine Analytical Tasks: Levels and Changes by Sex

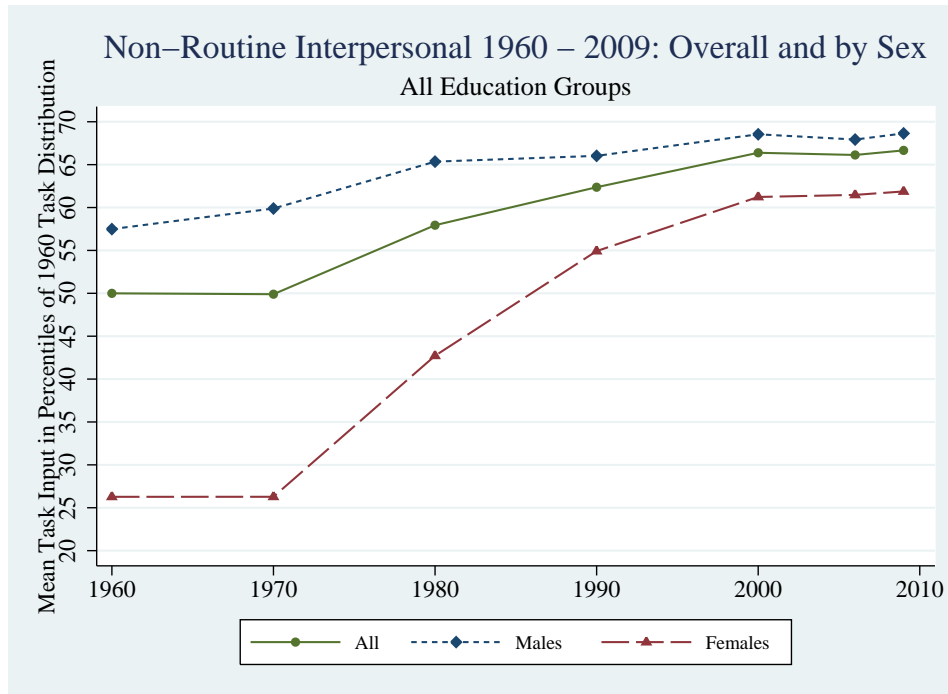


Figure 4. Nonroutine Interpersonal Tasks: Levels and Changes by Sex

The gender-specific trends in routine task input are equally dramatic. In 1960, female input of routine cognitive tasks was five centiles above that of males. This gap *rose* to seven centiles between 1960 and 1970, and held roughly constant for another decade. Then, between 1980 and 2009, female routine cognitive task input fell by 20 centiles while male routine cognitive task input fell by only 7 centiles. At the end of the period, female routine cognitive task input was 15 centiles below its 1960 starting point, and 3 centiles below that of males. In net, the gender pattern in routine cognitive tasks had been reversed over three decades. Trends in routine manual task input tell a similar qualitative story, though they are not as pronounced. Routine manual task input rose among both males and females between 1960 and 1970, then was roughly constant between 1970 and 1980. After 1980, it commenced a three decade decline. At the start of the period, female task input in routine manual tasks was 69 centiles versus 42 centiles among males. By the close of the period, these levels had fallen to 56 and 36 percentiles respectively. By implication, the gender gap in routine manual tasks had fallen from 27 to 20 centiles.

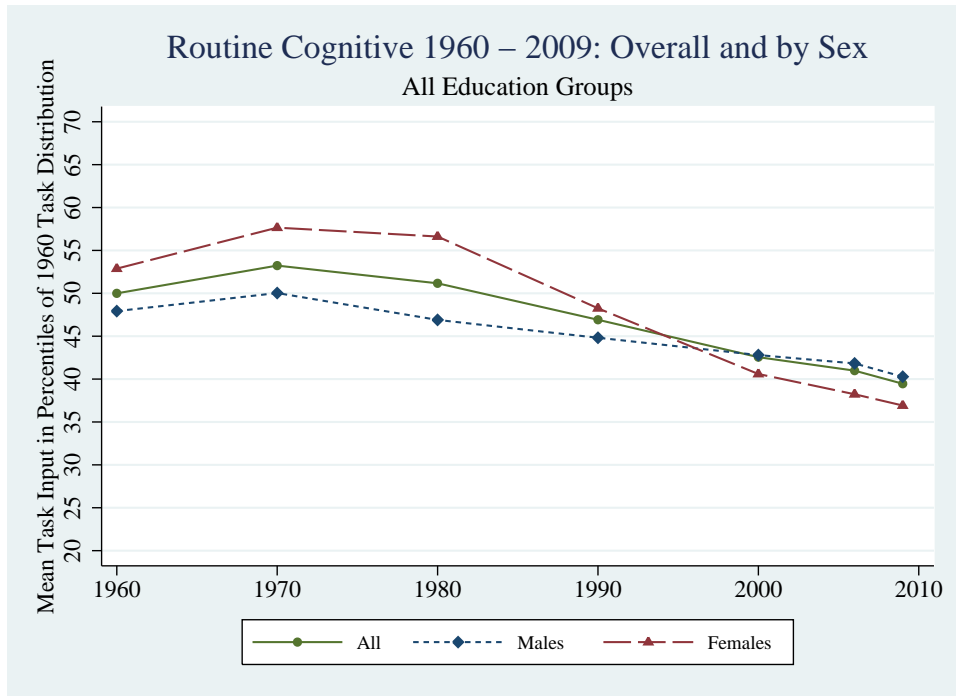


Figure 5. Routine Cognitive Tasks: Levels and Changes by Sex

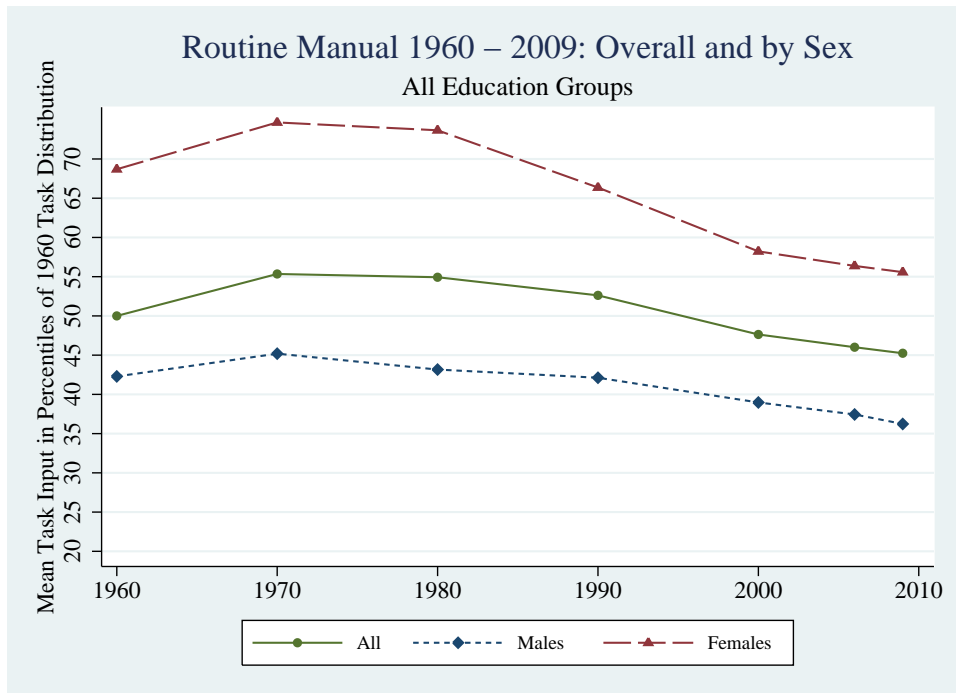


Figure 6. Routine Manual Tasks: Levels and Changes by Sex

The gender trends in nonroutine manual task input show the smallest movements in both relative and absolute terms. At both the start and end of the sample, males were employed in substantially more nonroutine manual task-intensive occupations than females. In 1960, the male-female gap in nonroutine manual task input was 24 centiles, and that gap was essentially unchanged in 2009. Both sexes saw a gradual decline in nonroutine manual tasks input between 1960 and 1990, a plateau between 1990 and 2000, and then an *increase* between 2000 and 2009.

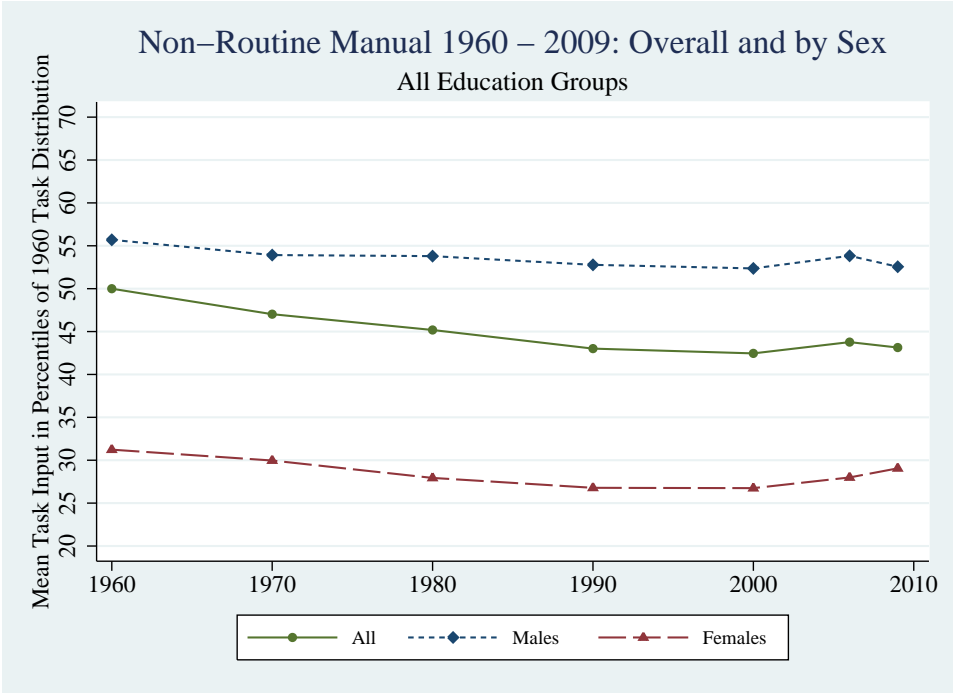


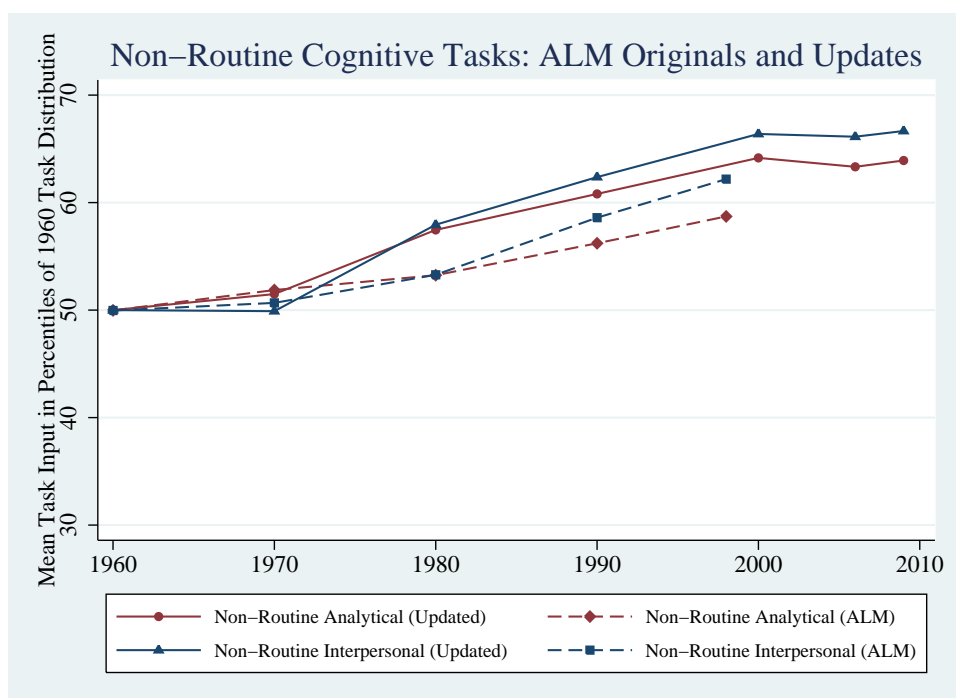
Figure 7. Nonroutine Manual Tasks: Levels and Changes by Sex

In net, the results by gender are fully consistent with the pooled gender results in their decade-by-decade direction, in the sharp fall in routine task input after 1980, and in the trend reversal in nonroutine manual task inputs after 1990. The key distinction is that women have seen sharper overall changes in task allocation, with vast gains in their employment in nonroutine cognitive tasks and even sharper falls in their employment in routine tasks—particularly routine cognitive tasks. These observations echo recent work by Black and Spitz-Oener (2010) and Autor and Wasserman (2013), who document differentially rapid movement of women out of 'middle skill' routine task-intensive occupations and into 'high skill' nonroutine cognitive task-intensive occupations.

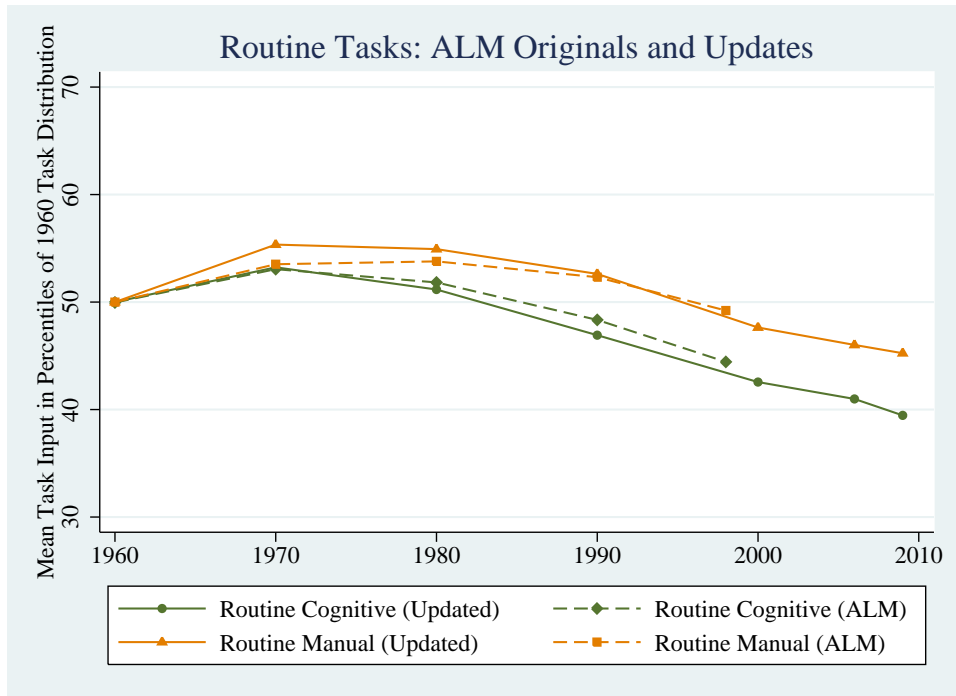
Conclusions

The updated analysis of trends in labor input of job tasks in the U.S. economy, following ALM's 2003 paper, presents two key confirmations of the original ALM analysis and offers one significant puzzle—the plateauing of nonroutine cognitive task input in both analytic and interpersonal tasks after 2000. Further in-depth analysis of the proximate and ultimate sources of this plateau is warranted.

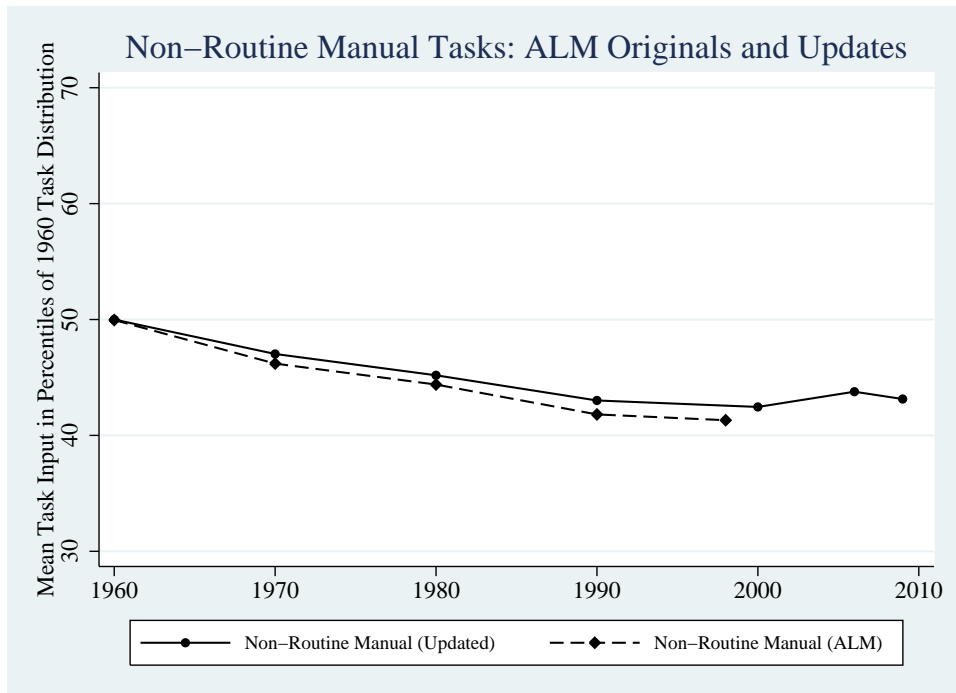
Appendix Figures



Appendix Figure 1. Comparison of Trends in Nonroutine Cognitive Tasks: Original and Updated



Appendix Figure 2. Comparison of Trends in Routine Tasks: Original and Updated



Appendix Figure 3. Comparison of Trends in Nonroutine Manual Tasks: Original and Updated

Data Appendix

The results above document changes in the average task content of US jobs between 1960 and 2010. Our basic procedure is to construct a representative sample of workers for each time period, assign each worker a set of task scores on the basis of his or her occupation, and average these task scores across workers, weighting workers by the amount of labor they supply. As a benchmark, we express changes in task content in terms of the 1960 distribution of task inputs. This appendix describes each of these steps in detail.

Constructing the Employment Samples

We estimate changes in the occupational, demographic, and industrial composition of the workforce using samples from the 1960, 1970, 1980, 1990, and 2000 Integrated Public Use Microdata Series Census extracts (IPUMS, Ruggles et al. 2010), together with the IPUMS American Community Survey (ACS) extracts for the years 2005-2010. To obtain adequate sample sizes, we pool the ACS samples into two three-year samples spanning 2005-2007 and 2008-2010. We restrict each sample to non-institutionalized, employed individuals between the ages of 18 and 64. We further exclude members of the armed forces, unpaid family workers, and workers whose occupation is unreported. Observations are weighted by full-time equivalent hours of labor supply, which is the product of the individual Census sampling weights, weeks worked during the previous year, and usual hours worked per week.⁵

Our procedure requires us to assign workers to education and industry categories that are consistent over time. To attain comparable educational categories across the redefinition of the Census Bureau's education variable introduced in the 1990 Census, we use the method proposed by Jaeger (1997). In the 1960, 1970, and 1980 Census samples, we define high school dropouts as those with fewer than twelve years of completed schooling; high school graduates as those having twelve years of completed schooling; some college attendees as those with any schooling beyond twelve years (completed or not) and fewer than sixteen completed years; and college plus graduates as those with sixteen or more years of completed schooling. In the

⁵The exact value of weeks worked is reported in the 1980, 1990, and 2000 Censuses and in the 2005-2007 ACS. Weeks worked are reported only in intervals (1-13 weeks, 14-26 weeks, etc.) in the 1960, 1970, and 2008-2010 samples. For the 1960 and 1970 samples, we impute weeks worked in each interval as the average number of weeks worked by individuals in the 1980 sample who fall into the corresponding interval. Similarly, we use average weeks worked in the 2005-2007 sample to impute values for the 2008-2010 sample. Since usual hours worked per week are also reported in intervals in the 1960 and 1970 samples, we adopt an analogous procedure to impute hours worked for individuals in these samples.

1990 and 2000 Census samples and the two ACS samples, we define high school dropouts as those with fewer than twelve years of completed schooling; high school graduates as those with either twelve completed years of schooling or a high school diploma or GED; some college as those with some college or holding an associate’s degree; and college plus as those with a B.A. or higher.

The industry classifications used in the Census and ACS have changed repeatedly since 1960. To obtain a consistent set of industry codes, we first use the IPUMS “ind1990” variable to convert workers in the post-1990 samples into 1990 Census industry codes. We then assign workers in all samples to a consistent set of 142 detailed industries using the crosswalk from Autor, Katz, and Kearney (AKK, 1998), which is applicable to the 1960, 1970, 1980, and 1990 Census industry codes. To ensure adequate sample sizes in each period, we combine a small number of closely related industries, resulting in a final set of 130 detailed industries.

Selecting Task Measures from the Dictionary of Occupational Titles

Our data on job task requirements come from the 1977 edition of the Dictionary of Occupational Titles (DOT). Our use of DOT measures of task inputs replicates the choices in ALM. To identify variables that best approximate our task constructs, ALM reduced the DOT variables to a relevant subset using DOT textual definitions, means of DOT measures by occupation from 1970, and detailed examples of DOT evaluations from the Handbook for Analyzing Jobs. They selected two variables to measure nonroutine cognitive tasks, one to capture interactive, communication, and managerial skills and the other to capture analytic reasoning skills. The first codes the extent to which occupations involve Direction, Control, and Planning of activities (DCP). It takes on consistently high values in occupations requiring managerial and interpersonal tasks. The second variable, GEDMATH, measures quantitative reasoning requirements. For routine cognitive tasks, we employ the variable STS, which measures adaptability to work requiring Set limits, Tolerances, or Standards. As a measure of routine manual activity, they selected the variable FINGDEX, an abbreviation for Finger Dexterity. The composite “routine” task measure reported in some tables and figures is computed by taking the unweighted average of STS and FINGDEX. To measure nonroutine manual task requirements, we employ the variable EYEHAND, an abbreviation for Eye-Hand-Foot coordination.

We have also performed robustness checks using analogous variables taken from the O*NET database.

Computing Task Means for Each Occupation

We assign task scores to each worker on the basis of his or her reported Census Occupation Category (COC). The chief challenge in doing so is that the system of occupation codes changed several times over the sample period. In this section, we explain how we estimated mean task inputs for each round of the occupation codes.

To compute DOT task means for 1970 COC occupations, we used the April 1971 Current Population Survey (CPS) Monthly File issued by the National Academy of Sciences (1981) in which experts assigned individual DOT occupation codes and associated DOT measures to each of 60,441 workers. Because Census occupation categories are significantly coarser than DOT occupation categories, the 411 1970 census occupation codes represented in the 1971 CPS were assigned a total of 3,886 unique 1977 DOT occupations. We used the CPS sampling weights to calculate means of each DOT task measure by occupation. Because the gender distribution of DOT occupations differs substantially within COC occupation cells, we performed this exercise separately by gender. In cases where a COC cell contained exclusively males or females, we assigned the cell mean to both genders. This provided a set of 822 DOT occupation means by 1970 COC and gender.

To generate DOT means for 1960 occupations, we developed a crosswalk from the 1970 to 1960 COC occupational classification schemes using information in Priebe and Greene (1972). Our crosswalk provides a set of 211 consistent 1960–1970 occupations representing the lowest common level of aggregation needed to obtain a consistent series. We applied the 1970 COC means to our 1970 Census sample by occupation and gender and calculated weighted gender-occupation means across the 211 consistent 1960–1970 occupational categories.

It was not possible to develop a bridging crosswalk between 1970 and 1980 COC occupations due to the substantial differences between these classifications. Instead, we employed a Census sample prepared for the Committee on Occupational Classification and Analysis chaired by Donald Treiman and provided to ALM by Michael Handel. This file contains 122,141 observations from the 1980 Census that are individually dual-coded with both 1970 and 1980 COC occupation codes based on occupational and other demographic information

supplied by Census respondents. To calculate DOT means by 1980 occupation, we merged the 1970 COC-DOT means (above) to the Treiman file by gender and 1970 COC occupation, achieving a 97 percent match rate. We appended to the Treiman file consistent occupation codes for the years 1980 and 1990 developed by Autor, Katz, and Krueger (1998), and calculated weighted means of each DOT measure within occupation/gender categories. This yielded DOT means by gender for each of 485 occupations.

To determine changes in task content from 1990 through 2010, we converted the COC occupations in the 1990 and 2000 Census samples and the two ACS samples into a consistent set of occupation codes using a crosswalk developed by Autor and Dorn (forthcoming). We calculated weighted means of each DOT measure for each such occupation code.

A handful of uncommon occupations cannot be merged with the task measures and must be excluded from the analysis. These occupations account for a negligible fraction of total labor supply (less than 0.5% in all periods).

Expressing Task Changes in Terms of the 1960 Task Distribution

The procedure described above enables us to compute the change in DOT task means between each pair of consecutive samples (1960 to 1970, 1970 to 1980, etc.). Starting with 1960 task means, we cumulate these pairwise changes to obtain task means for each sample period. We perform this computation separately for each of 1,040 industry-education-gender cells: 130 industries \times two genders \times four education levels (high school dropout, high school graduate, some college, and college graduate).⁶

As a point of comparison, we express changes in task inputs relative to the 1960 task distribution. To convert DOT measures into percentiles of the 1960 distribution, we used 1977 DOT task measures paired to the 1960 Census to form an employment-weighted empirical cumulative distribution function of task input for each task measure across each of the industry-education-gender cells. We inverted this empirical distribution to obtain baseline percentile values for each task measure. In each post-1960 sample period, we assigned industry-education-gender cells to percentiles of the 1960 task distribution on the basis of our estimated task means. Finally, to obtain aggregate measures of task content for each period, we average over

⁶All 1,040 cells contain a non-zero amount of labor supply from 1970 onward. In 1960, seven of the 1,040 cells are empty; however, our methodology is not invalidated by the presence of empty cells.

the 1,040 cells, weighting them by full-time equivalent hours of labor supply.⁷

References

Acemoglu, Daron, and Autor, David H. 2011. Skills, Tasks and Technologies: Implications for Employment and Earnings. *Handbook of Labor Economics*, 4(11), 1043–1171.

Autor, David, and David Dorn. forthcoming. "The Growth of Low Skill Service Jobs and the Polarization of the U.S. Labor Market." *American Economic Review*.

Autor, David H., Frank Levy, and Richard J. Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." *The Quarterly Journal of Economics*, 118(4): 1279-1333.

Autor, David H., Lawrence F. Katz, and Alan B. Krueger. 1998. "Computing Inequality: Have Computers Changed the Labor Market?" *The Quarterly Journal of Economics*, 113(4): 1169-1213.

Autor, David H. and Melanie Wasserman. 2013. *Wayward Sons: The Emerging Gender Gap in Labor Markets and Education*. Third Way, Washington DC.

Beaudry, Paul, David A. Green and Benjamin Sand. 2013. "The Great Reversal in the Demand for Skill and Cognitive Tasks." NBER Working Paper No. 18901, March.

Jaeger, David A. 1997. "Reconciling the Old and New Census Bureau Education Questions: Recommendations for Researchers." *Journal of Business and Economics Statistics*, 15: 300-309.

National Academy of Science, Committee on Occupational Classification and Analysis. 1981. "Fourth Edition Dictionary of DOT Scores for 1970 Census Categories," ICPSR Document No. 7845, Ann Arbor, MI.

Priebe, J. A., J. Heinkel, and S. Greene. 1972. "1970 Occupation and Industry Classifications in Terms of their 1960 Occupation and Industry Elements," Census Bureau Technical Paper No. 26.

Steven Ruggles, J. Trent Alexander, Katie Genadek, Ronald Goeken, Matthew B. Schroeder, and Matthew Sobek. 2010. *Integrated Public Use Microdata Series: Version 5.0* [Machine-

⁷A limitation of this methodology is that DOT values after 1960 may potentially lie outside the support of the 1960 distribution, leading to truncation. In practice, this issue affects at most 6 percent of the distribution of each task in any year. Where the analysis is restricted to men only, this issue affects at most 7 percent of the distribution; where it is restricted to women, this issue affects at most 11 percent of the distribution.

readable database]. Minneapolis: University of Minnesota.