

THE SKILL CONTENT OF JOBS AND THE EVOLUTION OF THE WAGE STRUCTURE[†]

This Job is “Getting Old”: Measuring Changes in Job Opportunities using Occupational Age Structure

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One of the most remarkable developments in the US labor market of the past two and a half decades has been the rapid, simultaneous growth of employment in both the highest- and lowest-skilled jobs. This phenomenon is depicted in Figure 1, which plots changes in the share of aggregate hours worked at each percentile of the occupational skill distribution over the period 1980 through 2005. These skill percentiles are constructed by ranking occupations according to their mean hourly wages in 1980 and grouping them into 100 bins, each comprising 1 percent of 1980 employment.¹ The pronounced U-shape of Figure 1 underscores that employment growth over this 25-year period has been disproportionate in the top and bottom of the occupational skill distribution. Occupations that were in the lowest and highest deciles of the 1980 distribution grew in relative size by 10 to 25 percent between 1980 and 2005, while occu-

pations in the second through sixth deciles contracted.² This hollowing out, or “polarization,” of the occupational employment distribution is not unique to the United States. Using harmonized European Union Labour Force Survey data, Maarten Goos, Alan Manning, and Anna Salomons (2008) find that in 14 of 16 European countries for which data are available, high-paying occupations expanded relative to middle-wage occupations in the 1990s and 2000s, and in all 16 countries, low-paying occupations expanded relative to middle-wage occupations.

A leading explanation for the hollowing out of the occupation distribution in industrial countries is that nonneutral technical change, augmented by offshoring, is eroding demand for middle-skilled “routine” cognitive and manual activities, such as bookkeeping, clerical work, and repetitive production tasks (Daron Acemoglu 1999; Autor, Frank Levy, and Richard J. Murnane 2003, “ALM” hereafter; Autor, Lawrence F. Katz, and Melissa S. Kearney 2006; Alan Blinder 2007; Goos and Manning 2007; Autor and Dorn 2008).³ Because the core job tasks of these occupations follow precise, well-understood procedures, they are increasingly codified in computer software and performed by machines or, alternatively, offshored over computer networks to foreign work sites. This displacement of routine job tasks raises relative demand for nonroutine tasks in which workers hold a comparative advantage over

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¹ All analyses in the paper use data from the 1980, 1990, and 2000 census IPUMS and the 2005 American Community Survey (ACS). Samples are limited to workers age 16 through 64 in the prior year, and all calculations are weighted by labor supply, equal to the product of the census sampling weight, weeks worked in the prior year, and usual weekly hours. We group occupations into a balanced panel of 330 harmonized census occupation categories encompassing all of US employment from 1980 through 2005.

² The series in Figure 1 is smoothed with a locally weighted regression using a bandwidth of 0.8. Results are extremely similar if we use the 2000 census IPUMS in place of the 2005 ACS.

³ See also Manning (2004), and Francesca Mazzolari and Giuseppe Ragusa (2008) for an alternative hypothesis attributing the growth of low-skill employment to marketization of household production.

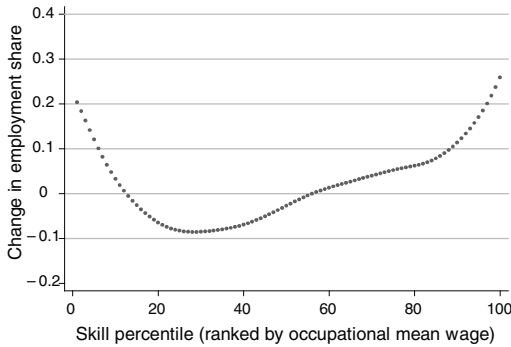


FIGURE 1. SMOOTHED CHANGES IN EMPLOYMENT SHARE BY OCCUPATIONAL SKILL PERCENTILE, 1980–2005

current technology, in particular “abstract” tasks requiring problem-solving, creativity, or complex interpersonal interactions (e.g., attorneys, scientists, managers), and “manual” tasks requiring, variously, situational adaptability, visual and language recognition, and in-person interactions (e.g., janitors and cleaners, home health aides, beauticians, construction laborers, security personnel, and motor vehicle operators). Notably, these two categories of nonroutine tasks lie at opposite ends of the skill distribution: abstract tasks are the core activity of professional specialty and technical occupations, while manual tasks are most intensive in personal service, transportation, construction, and operative occupations. Thus, displacement of occupations intensive in routine tasks and growth of occupations intensive in nonroutine tasks may give rise to the U-shaped pattern of job growth visible in Figure 1.

An important, unstudied question raised by this pattern of nonneutral occupational change is: where do the routine workers go? In particular, as middle-skill routine occupations decline, which age and skill groups move upward in the occupational distribution toward high-skill, nonroutine jobs, and which groups gravitate downward toward the lower tail of nonroutine occupations? Analyzing this process of occupational change offers insights into the shifting opportunity set faced by workers at different age and education levels.

Our analysis relies on a simple and, to our knowledge, novel approach for measuring how changing job opportunities affect worker re-allocation across occupations. The idea of this approach is that because workers develop occupation-specific human capital as they gain work experience, skill

specificity makes the costs of occupational mobility higher for older than younger workers. When an occupation declines, therefore, older workers will face an incentive not to exit the occupation while younger workers will face an incentive not to enter. Moreover, firms may react to changing demands for occupations by hiring young workers into growing occupations and curtailing such hiring into contracting jobs. These suppositions imply that occupations will “get old” as their employment declines—that is, the mean age of an occupation’s workforce will rise.

The plan of the paper is as follows. We first offer a simple “proof of concept” to demonstrate the tight empirical link between declines in an occupation’s employment and increases in the mean age of its workforce. The balance of the paper then applies this tool to the study of local labor markets to assess how shifts in occupational structure have affected the job composition of young and old workers at different education levels between 1980 and 2005.

I. Are Middle-Skill Jobs Getting Old?

We first document the robust relationship between changes in occupational size and shifts in the age distribution of the occupation’s workforce. Table 1 reports simple bivariate regressions of the form:

$$(1) \quad \Delta Y_j = \alpha + \beta_1 \Delta E_j + \varepsilon_j,$$

where Y_j is the mean age of workers in occupation j or the share of workers in that occupation who fall into a given age bracket, E is the share of an occupation in total employment in a given year, and the Δ operator denotes the change in a variable over the time interval 1980 to 2005.

The average age of the working population rose by 3.3 years during 1980 through 2005, reflecting the aging of the baby boom cohorts. Occupations that contracted over this period aged substantially faster than average. Column 1 of the first panel shows that occupations that contracted by 1 percentage point as a share of aggregate employment between 1980 and 2005 gained in age by an additional 0.78 years relative to the mean. Columns 2 through 4 show that, as hypothesized, age increases in contracting occupations are driven by a falling employment share of young workers and rising employment shares of prime age and older workers.

TABLE 1—PREDICTING CHANGES IN THE AGE STRUCTURE OF OCCUPATIONS 1980–2005 USING CHANGES IN OCCUPATION SIZE AND INITIAL ROUTINE TASK -INTENSITY

Independent variable	Δ Mean age (1)	Δ Share of workers in age bracket		
		Young 16–29 (2)	Prime 30–54 (3)	Older 55–64 (4)
<i>Panel A: OLS model 1</i>				
Δ Occupation's share of total employment (percentage points)	–0.78*** (0.18)	0.027*** (0.006)	–0.020*** (0.005)	–0.007* (0.003)
<i>Panel B: OLS model 2</i>				
Occupation's routine task intensity in 1980	0.55 *** (0.11)	–0.015*** (0.003)	0.004 (0.003)	0.011*** (0.002)
<i>Panel C: OLS model 3</i>				
Occupation's routine task intensity in 1980	0.50*** (0.10)	–0.013*** (0.003)	0.003 (0.003)	0.010*** (0.002)
Δ Occupation's share of total employment (percentage points)	–0.66*** (0.18)	0.023*** (0.006)	–0.019*** (0.005)	–0.004 (0.003)
<i>Panel D: Descriptive statistics</i>				
Mean	3.25	–0.128	0.120	0.008
Standard deviation	(1.99)	(0.065)	(0.057)	(0.036)

Notes: $N = 330$ harmonized occupations. Each column of panels A, B, and C corresponds to a separate OLS regression of the outcome variable at the top of the column on tabulated control variables and a constant. Standard errors are in parentheses. Models are weighted by occupational shares in total hours worked in 1980.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

Figure 2 plots smoothed changes in the mean age of workers by occupational skill percentile between 1980 and 2005. This figure shows a distinct inverted U-shape that is a near mirror image of changes in occupational employment shares depicted in Figure 1. Occupations in the bottom and top two deciles of the skill distribution aged by roughly two years between 1980 and 2005, which is substantially *below* the overall average of 3.3 years. Occupations in the second through sixth skill deciles gained approximately four years on average. Thus, over the last 25 years, middle-skill jobs have gotten old.

II. Are Routine Task-Intensive Jobs Getting Old?

If routine tasks are indeed being supplanted by computerization and offshoring, then employment declines should be concentrated in occupations that are specialized in such tasks. The year 1980 is a particularly apt starting point for gauging the effects of workplace computerization. National Income and Product Accounts (NIPA) data show that the share of computer hardware

and software in all US private nonresidential capital investment hovered at approximately 4 percent from 1970 to 1978, and then rose steeply at approximately three-quarters of a percentage point *per year* through the year 2000.⁴ Thus, occupations concentrated in routine tasks would be predicted by our hypothesis to experience sharp contractions from 1980 going forward.

To assess this hypothesis using occupational age structure as above, we draw on occupation level data assembled by ALM, who merge job data on task requirements—manual, routine and abstract—from the fourth edition of the US Department of Labor's *Dictionary of Occupational Titles* (US Department of Labor 1977) to their corresponding census occupation classifications. For each occupation j , we form an index of routine task-intensity, RTI_j :

$$(2) \quad RTI_j = \ln(\hat{R}_{j,1980}/\hat{M}_{j,1980}),$$

⁴ Authors' calculations using NIPA data (US Department of Commerce 2002).

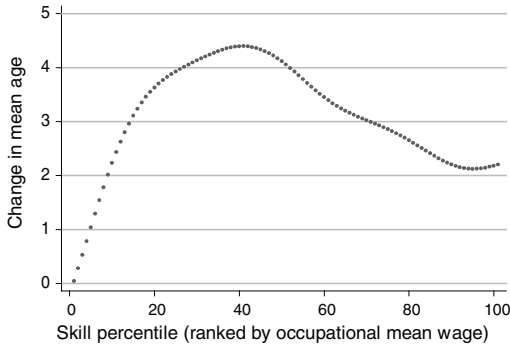


FIGURE 2. SMOOTHED CHANGES IN MEAN WORKER AGE BY OCCUPATIONAL SKILL PERCENTILE, 1980–2005

where \hat{R} and \hat{M} are, respectively, the intensity of routine and manual task input in each occupation in 1980, measured on a 0 to 10 scale. This measure is rising in the relative importance of routine tasks within an occupation and falling in the relative importance of manual tasks. Since *RTI* does not have a cardinal scale, we standardize it with a mean of zero and an employment weighted, cross-occupation standard deviation of unity in 1980.

This simple measure appears to capture well the job categories that motivate our conceptual framework. Among the 10 most routine task-intensive occupations in our sample of 330, 6 are clerical and accounting occupations and several others represent repetitive physical motion activities. Among the 10 least routine task intensive occupations, 4 are in-person service occupations, while the remainder involve driving motor vehicles.⁵

To test the link between routine task-intensity and changes in age structure, we estimate a variant of equation (1) in which the *RTI* measure is included as a predictor of changes in occupational age structure. The second and third panels of Table 1 show that this variable is highly significant in all specifications. Occupations that in 1980 were one standard deviation above the mean of routine intensity gain 0.6 years of age relative to the mean over the next 25 years. This age gain is driven by declining relative employment of young workers in routine task-intensive occupations, and by rising relative employment

of older workers, particularly those age 55 to 64. The third panel of Table 1 shows that the predictive relationship between routine intensity and occupation aging is quite robust to controlling for contemporaneous changes in occupations' employment shares—though of course the employment shares of routine task-intensive occupations fall significantly in this period.

Thus, like middle-skill occupations, routine task-intensive occupations are getting old. This finding reflects the fact that middle-skill occupations are also disproportionately routine task-intensive.

III. Where Do the Routine Workers Go?

We now exploit the robust predictive relationship between occupational decline and occupational aging to study how the decline of routine occupations affects the opportunity set of workers at different age and skill levels. Specifically, we ask which *nonroutine* jobs absorb young and older workers as routine task-intensive occupations are displaced.

For this analysis, we shift the unit of observation from changes in age structure within occupations to changes in the age composition of employment within local labor markets, following an approach developed by Christopher L. Smith (2008). Based on the results above, we anticipate that local labor markets that were specialized in routine task-intensive occupations at the start of the sample period should have experienced a differential contraction of middle-skill jobs over the subsequent 25 years. We use this cross-market variation in (expected) occupational declines to analyze the effect of the thinning of the ranks of middle-skill occupations on the occupational distribution of young and old workers.

As a time-consistent measure of local labor markets, we implement the concept of Commuting Zones (“CZs”), developed by Charles M. Tolbert and Molly Sizer (1996), who used commuting data from the 1990 census to identify clusters of counties—i.e., CZs—that exhibit strong commuting ties within clusters but weak commuting across clusters. Our analysis uses 722 CZs that cover the entire mainland of the United States, including metropolitan and rural areas.⁶

⁵ Additional details on the Routine Task Intensity measure are found in Autor and Dorn (2008), who develop this measure using the ALM data.

⁶ Commuting zones have two advantages over other geographic units typically used for analysis of local labor

To measure cross-market variation in employment in routine task-intensive occupations, we apply a simple binary approach to distinguish routine and nonroutine occupations. We classify as routine those occupations that fall in the top third of the employment-weighted distribution of the *RTI* measure in 1980. Using this classification, we then assign to each commuting zone k a routine employment share measure (RSH_{kt}) equal to the fraction of CZ employment at the start of a decade that falls in routine task-intensive occupations. The mean of this measure in 1980 is, by construction, equal to 0.33. The population weighted 80/20 percentile difference in routine employment share is 10 percentage points.

Putting these pieces together, we estimate in Table 2 a set of OLS stacked first-difference models for CZ level changes in occupational employment by age and education:

$$(3) \quad \Delta Y_{ak\tau} = \alpha_{\tau} + \beta_2 RSH_{kt} + \omega_{ak}\tau,$$

where ΔY is ten times the annual change in an outcome measure for age-education group a in commuting zone k over the five- or ten-year time interval τ , RSH is the routine employment share in the CZ at the start of the time interval, and α is a vector of time dummies.

Estimates of equation (3) produce a number of striking results. Panel A of Table 2 shows that, as predicted, CZs that were initially specialized in routine task-intensive occupations saw substantial declines in the share of workers employed in these occupations between 1980 and 2005. These declines are evident at all age levels, but they are uniformly larger for younger than older workers. Interestingly, the decline in routine employment is greater for noncollege workers (high school or lower education) than for college workers (at least one year of college). A potential explanation for this pattern is that less educated workers in routine task-intensive occupations perform a disproportionate share of the routine tasks, and thus are differentially subject to displacement.

Which occupations absorb workers from these different age brackets as routine task-intensive jobs in a CZ contract? To form a simple accounting, we use occupational wage data from 1980 to

evenly divide the two-thirds of employment classified as nonroutine into two occupation clusters containing equal shares of 1980 employment, one cluster containing low-wage occupations and the other high-wage occupations. Notably, these occupational clusters roughly correspond to the two nonroutine task categories defined above (i.e., abstract and manual). The high-skill nonroutine cluster is largely composed of professional specialty and technical occupations, with mean log hourly wages that are 30 percent above the routine occupation mean. The low-skill nonroutine group is largely composed of low-education service, labor, and operative occupations, with mean log hourly wages 25 percent below the routine occupation mean.

Panels B and C of Table 2 show that relative declines in routine occupation employment within CZs are primarily offset by relative employment gains in *low-skill* nonroutine occupations—jobs that are significantly less skill-intensive and lower paying than the routine occupations that are displaced. Among the three age brackets we consider, only young workers age 16 to 29 gain in employment in high-skill nonroutine occupations. Both the prime age and older age groups gain employment in low-skill nonroutine occupations. Moreover, even among the young, employment gains in high-skill nonroutine occupations are less than half as large as gains in low-skill nonroutine occupations. Clearly, the hollowing out of employment in initially routine task-intensive local labor markets primarily generates a movement of employment into low-skill, nonroutine jobs.

When we drill down on these occupational shifts by education group, however, it is immediately apparent that declines in routine employment have decidedly nonneutral impacts across education groups and across age groups within an education level. The second row of Table 2 shows that college workers in initially routine task-intensive labor markets gain employment in both high- and low-skill nonroutine jobs. But the gains in high-skill nonroutine employment are concentrated among the young and almost entirely absent among the old. Thus, the bulk of the differential decline in routine employment among young college workers in these labor markets is offset by gains in high-skill nonroutine employment. Among prime-age and older workers, however, offsetting employment gains are found mostly in low-skill nonroutine jobs. Thus, it appears that the

markets: they are based primarily on economic geography rather than incidental factors such as minimum population or state boundaries; and they cover the entire United States (see Autor and Dorn 2008 for details).

opportunity for high-education workers to reallocate upward depends greatly on age.

The final row of Table 2 portrays an even less encouraging picture for noncollege workers. For this skill group, the entire differential decline in routine employment in routine task-intensive CZs is absorbed by increased low-skill, non-routine employment. Moreover, while young noncollege workers roughly hold their ground in high-skill, nonroutine occupations, prime age and older noncollege workers differentially lose employment in these jobs and gain in employment in low-skill, nonroutine jobs.

In summary, the occupational structure of college workers in routine task-intensive labor markets is hollowing out, with movement of workers toward both tails. The occupational structure of noncollege workers, however, is shifting uniformly leftward toward lower-paying, nonroutine jobs. This leftward shift is most pronounced for older age groups.

These patterns are quite robust. Although the models in Table 2 include only time dummies and implicitly, CZ effects (recall that these are first-difference models), the qualitative pattern of results is little changed when the model is augmented with state fixed effects and detailed controls for the initial human capital, demographic, and industrial structure of commuting zones (A supplementary table is available from the authors.)

IV. Conclusion

Aggregate employment has shifted over the last 25 years against middle-skill, routine task-intensive work and toward the tails of the occupational skill distribution. Occupations at both tails are appropriately labeled as nonroutine, but they differ greatly in skill and pay. The right-hand tail of the distribution encompasses high-skill, nonroutine occupations that typically require capabilities in problem-solving, abstract reasoning, and decision making. The left-hand tail encompasses low-skill nonroutine occupations that demand basic human adaptability but little in the way of formal training. The contraction of routine occupations is therefore likely to have different impacts on workers across age and skill groups, depending on their ability to move upward toward high-skill, nonroutine jobs or, conversely, downward toward low-skill, nonroutine jobs.

By comparing local labor markets that, due to initial differences in concentration in routine

task-intensive activities in 1980, are subject to differing degrees of occupational change over the subsequent 25 years, we find that contractions of routine employment within local markets disproportionately raise the share of workers employed in low-skill, nonroutine jobs. In fact, only the youngest category of workers exhibits both downward and upward occupational reallocation; for other age groups, movement is entirely downward. Highly educated workers are clearly better prepared to adapt to changing occupational opportunities, and thus it is to be expected that college-educated workers are reallocating upward as well as downward. But the degree of upward reallocation is strongly negatively correlated with age: while young college workers are gaining employment in high-skill, nonroutine occupations, older college workers are increasingly found in low-skill, nonroutine work.

These secular shifts of age and education groups across occupational categories provide only a preliminary sense of what may potentially be learned from changing occupational age structures. We focus here on changes in occupational structure within age groups, but do not address how changes in aggregate job composition shape the progression of birth cohorts across occupations as they age. Our ongoing work suggests that the simple tools used above hold some promise for exploring these questions.

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TABLE 2—PREDICTING CHANGES IN THE ALLOCATION OF AGE GROUPS ACROSS OCCUPATIONS USING INITIAL COMMUTING ZONE EMPLOYMENT SHARES IN ROUTINE INTENSIVE OCCUPATIONS, 1980–2005

Coefficient on (share of routine occupations ₋₁) for skill group below	Occupation's share of age bracket		
	Young, 16–29	Prime, 30–54	Older, 55–64
<i>Panel A: Routine-intensive occupations</i>			
All workers	–0.31*** (0.02)	–0.21*** (0.01)	–0.25*** (0.03)
College workers	–0.18*** (0.03)	–0.11*** (0.01)	–0.12*** (0.03)
Noncollege workers	–0.46*** (0.04)	–0.28*** (0.03)	–0.23*** (0.05)
<i>Panel B: High-skill nonroutine occupations</i>			
All workers	0.10*** (0.02)	–0.01 (0.02)	–0.06** (0.03)
College workers	0.15*** (0.03)	0.03 (0.02)	–0.03 (0.03)
Noncollege workers	0.04 (0.03)	–0.09*** (0.02)	–0.19*** (0.04)
<i>Panel C: Low-skill nonroutine occupations</i>			
All workers	0.21*** (0.03)	0.22*** (0.02)	0.31*** (0.04)
College workers	0.03 (0.03)	0.08*** (0.02)	0.15*** (0.03)
Noncollege workers	0.42*** (0.04)	0.37*** (0.03)	0.42*** (0.05)

Notes: $N = 2,166$ (3 time periods \times 722 commuting zones). Robust standard errors in parentheses are clustered on state. Each cell corresponds to a separate stacked first-difference model. Models are weighted by start of period commuting zone share of national population and contain a constant and two time dummies. College workers are those with at least some college education. Occupations are classified as routine task-intensive if they fall in the top third of the employment-weighted distribution of the routine-intensity measure in 1980. Nonroutine occupations are classified as high-skill if they fall in the top half of the employment-weighted distribution of mean wages in nonroutine occupations in 1980, and are classified as low-skill otherwise.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

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