Racing With and Against the Machine: Changes in Occupational Skill Composition in an Era of Rapid Technological Advance

Completed Research Paper

Frank MacCrory
MIT Sloan School of Management
77 Massachusetts Ave., Cambridge, MA
maccrory@mit.edu

George Westerman
MIT Sloan School of Management
77 Massachusetts Ave., Cambridge, MA
georgew@mit.edu

Yousef Alhammadi
Masdar Institute
Masdar City, Abu Dhabi, U.A.E.
yalhammadi@masdar.ac.ae

Erik Brynjolfsson
MIT Sloan School of Management
77 Massachusetts Ave., Cambridge, MA
erikb@mit.edu

Abstract

Rapid advances in digital technologies have profound implications for work. Many middle and low skill jobs have disappeared, contributing to increasing inequality, falling labor force participation and stagnating median incomes. We examine changes in the skill content of jobs from 2006-2014 using comprehensive data on occupational skill requirements of 674 occupations to understand the effects of recent changes in automation. We identify seven distinct skill categories empirically and explain over 62% of the variation in the data.

Consistent with theory, we find a significant reduction in skills that compete with machines, an increase in skills that complement machines, and an increase in skills where machines (thus far) have not made great in-roads. Complementarity across skills has increased, boosting the need for worker flexibility. The remarkable scale and scope of occupational skill changes that we document just since 2006 portend even bigger changes in coming years.

Keywords: Social issues, Skill-biased technical change, Complementarity, Empirical Research/Study, IT-enabled change, Job characteristics, Skills, Economic impacts, Econometric analyses, Employment, Inequality

Introduction

"There's never been a better time to be a worker with special skills or the right education, because these people can use technology to create and capture value. However, there's never been a worse time to be a worker with only 'ordinary' skills and abilities to offer, because computers, robots, and other digital technologies are acquiring these skills and abilities at an extraordinary rate."

–Brynjolfsson and McAfee (2014)

In the past decade, digital technologies have advanced tremendously. For instance, C-Path, a computational pathologist developed at Stanford, identified three new cancer markers that were never before recognized by humans. Apple's Siri can recognize human speech and respond to simple commands. Google showed that a driverless car can go hundreds of thousands of miles on ordinary highways. Rethink Robotics' Baxter can perform basic manual tasks at a fraction of the costs of human labor.[1]

The implications of these technologies for work and employment are profound. Many middle and low skill jobs have disappeared, contributing to increasing inequality, falling labor force participation and stagnating median incomes (Autor & Dorn, 2013). While there are a variety of explanations for these economic trends, an emerging consensus among economists is that technology -- particularly information technology that substitutes for routine work -- is an important driver. For instance, Jaimovich and Sui (2012) write that "a trend in routine-biased technological change can lead to job polarization that is concentrated in downturns, and recoveries from these recessions that are jobless."

In this paper, we examine the research question: how do recent changes in automation capabilities affect occupational skill composition? We answer the question by examining changes in the skill content of jobs between 2006 and 2014, using the United States government's most comprehensive data set of occupational skill requirements, the O*NET database (www.onetonline.org). Our theory is that substitution effects will remove some skills from occupations, complementarity effects will amplify other skills, and skills that are orthogonal will be amplified due to Baumol's Cost Disease (Baumol & Bowen, 1966).

We significantly broaden earlier research in two ways. First, we provide the most comprehensive quantitative evidence of what has happened in recent years across a large and well-documented set of occupations. In particular, no other papers have examined intensive changes in occupational skills in the years since 2008, during which new automation and communication innovations, such as the fast rise of mobile devices and social media, have had effects that vary substantially from efficiency-oriented technologies of the past.

Second, we identify an important set of new skill categories. Where prior research defined small numbers of skill categories a priori, we identify multiple orthogonal categories of skill empirically. These skill dimensions go beyond those identified in prior studies, and have the benefit of improving statistical inference. We are able to explain 75% of the variation in the importance of skill groups constructed in prior research as well as 62% to 69% of the variation in skill factors we derive directly from the O*NET data. The new skill categories also provide opportunities to examine the nature of skill-biased technical change in greater depth than past studies.

We find that skills that compete with machine capabilities, such as basic perception (*e.g.* vision) or supervising routine work, have been disappearing or changing. Meanwhile, skills that complement machinery, such as deductive reasoning and written expression, have become more important. This is also true to the residual of jobs where machines (thus far) have not made great in-roads, such as those that require interpersonal skills. Furthermore, our analysis suggests that complementarity across skills has changed, creating an increased need for workers to be flexible in their skill development. One striking example is that facility with technology has become such a common job requirement that it is no longer a major differentiator between jobs.

[1] For more details on these examples, and many others, see Brynjolfsson and McAfee (2014) and the many references therein.

Background

Previous research has linked technology advancement, particularly digital technologies, with changes in employment and productivity (see *e.g.* Acemoglu and Autor, 2011; Brynjolfsson and McAfee, 2014 and the studies citied therein). These effects have been reflected in metrics such as jobs created or lost, the nature of work, and changes in levels of GDP or productivity. In the United States since the late 1990s, increases in productivity have not been accompanied by an increase in the number of jobs created (Brynjolfsson and McAfee, 2011) as shown in Figure 1. This dynamic reflects a sharp break from the historical pattern.

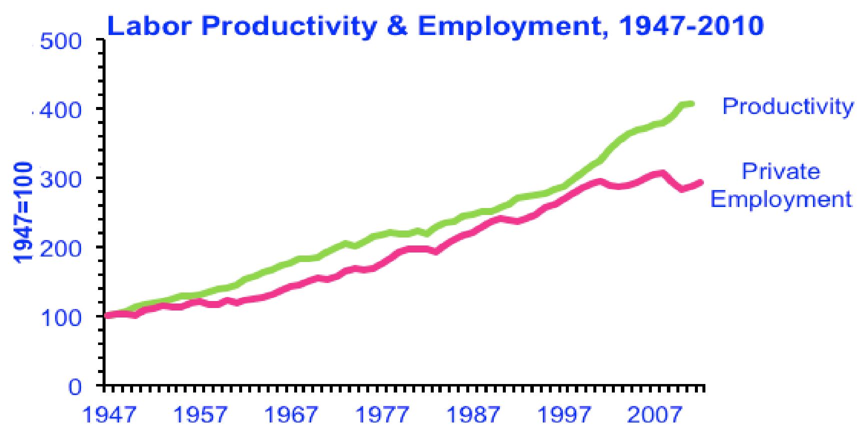

Figure 1: Productivity and Employment have become decoupled in the United States (Brynjolfsson & McAfee, 2011)

Digital tools can now perform an increasing variety of human tasks with high levels of technical skill. In particular, automation of more and more tasks creates challenges for job creation. Brynjolfsson and McAfee (2011, 2014) describe how recent digital technologies are reducing the demand for many types of labor while creating enormous opportunities for wealth creation by others. One reflection of this change is the simultaneous increase in both job openings and unemployment relative to the early 2000s (Elsby *et al.*, 2010). Job openings and unemployment are usually negatively correlated. This suggests that the types of skills now demanded by employers do not match up with those of the existing labor force (Katz, 2010). As technology changes, there is a growing need to update lagging skills and institutions to be able to race with machines, and not against them.

Occupational skill categories

In assessing the impact of automation on employment levels, it is beneficial to segment the workforce into skill categories. Several studies in the literature provide useful frameworks.

Routine tasks have been described by Autor, Levy and Murnane (2003) (hereafter ALM) as "job activities that are sufficiently well defined that they can be carried out successfully by either a computer executing a program or … a less-educated worker." Such tasks may be manual or cognitive, and they tend to appear in occupations such as bookkeeping and assembly-line work. Acemoglu and Autor (2011) (hereafter AA) describe these tasks as "low-skill occupations" for a machine. So what occupations are "high-skill" for machines? The evidence suggests several categories, including non-routine job tasks that involve situational awareness, creativity and human interaction.

Non-routine tasks can be segmented into two major categories: a) abstract tasks requiring problem solving, intuition, persuasion, high levels of education and analytical capability, *e.g.,* giving legal advice or designing an engine; and b) manual tasks requiring situational adaptability, visual and language recognition, and in-person interactions, *e.g.*, bathing a patient or styling hair. Many of these tasks have been difficult to automate as noted by Moravec (1988). They have not (yet) been mastered by machines.

Elliot (2014) surveyed articles in the Artificial Intelligence and Robotics fields from 2002-2012 and categorized the capabilities of advanced technologies and robots into four broader human capability areas, defined a priori by the authors: *language, reasoning, vision* and *movement*. Frey and Osborne (2013) state that "Engineering Bottlenecks" create three categories of labor inputs that are not susceptible to automation in the near future: *Perception and Manipulation Tasks*, *Creative Intelligence Tasks* and *Social Intelligence Tasks*.[2]

These categorizations have been useful initial steps for understanding the nature of skill-biased technical change. However, they tend to be defined a priori, and are thus limited by the assumptions inherent in logical inference. They also are non-orthogonal, leading to potential biases in estimation using the categories. Furthermore, a handful of very specific categories can capture neither the full breadth of occupations in the labor market nor the varied economic impact of biased technical change across a variety of human skills and capabilities.

Intensive vs. Extensive Change

Prior work has focused on changes in the *extensive margin* of occupational skill demand. That is, researchers created skill categories and then assessed past or possible future changes in demand for jobs that contained those categories. Fewer studies examine changes on the *intensive margin*, or the ways in which technology is changing the composition of jobs themselves.[3] Yet we know that technology is fundamentally altering their nature as noted by ALM.

Elliot (2014) called for a more "systematic and frequent (once or twice each decade) review to compare "the full range of IT and robotics capabilities with the full range of capabilities used in different occupations." Large-scale empirical work in this area is still in the exploratory stage, and to our knowledge our study is the first to undertake the type of systematic review urged by Elliot.

Theoretical Development

In this study, we dig deeper into the question of how technology is transforming jobs. We ask the research question: how do recent changes in automation capabilities affect occupational skill composition?

Griliches (1969) was among the first to posit that capital equipment would be skill biased and that it would complement some skills more than others. For instance, consider an economy in which each worker contributes two distinct types of labor (skills), and for the moment consider each worker's endowment in each skill to be exogenous (or more precisely, predetermined). These skills are used with an employer's capital to produce a single good with a modified translog production function as shown in (1).

$$\ln(Y)=\ln(A_t)+\beta_1\ln(L_1)+\beta_2\ln(L_2)+\beta_3\ln(K)+\beta_4\ln(L_1)\ln(L_2)+\beta_5\ln(L_1)\ln(K)+\beta_6\ln(L_2)\ln(K) \quad (1)$$

where Y is output, and L_1 and L_2 are two types of labor, K is capital input, and A_t is a technology parameter, which advances over time.

As the unit price of capital changes over time, the effect on labor demand will be stronger for skills that have higher magnitude interactions with capital. Cheaper capital (K) makes labor L_1 more valuable if β_5 is positive due to complementarity and less valuable if β_5 is negative due to substitutability. The same effect is present between β_6 and L_2. Likewise, our specification allows different types of labor to be complements or substitutes. When we expand our model to an economy with N skills, the market prices for some of them may be affected indirectly through complementarity with other skills. Furthermore, it is possible that the nature of technology will change over time, which can increase or decrease the complementarities.

[2] A clear divergence or "polarization" of growth in employment and wages of occupations was observed by many studies including Autor, Katz and Kearney (2006) and AA. Frey and Osborne (2013) predict 47% of the US employees are at "high risk" of losing their jobs due to advanced technologies.

[3] ALM used a priori measures of a few non-orthogonal skill categories to examine intensive changes. AA build a model that includes intensive changes, but empirically examine only extensive changes through 2008.

Labor market reactions to technological progress can be along either the extensive or intensive margins. Extensive margin changes may lead to a reduction in how many people perform a manufacturing job while intensive changes may lead to a redefinition of the job. For example, the introduction of computerized machining tools radically changed the content of the "machinist" job from an emphasis on hand-eye coordination and steadiness to an emphasis on engineering and design, all without changing the job's name (Kemp & Clegg, 1987).

The O*NET database is designed to document these changes in the skill-content of jobs. We can measure these changes within a particular job by estimating the importance of skill n at time t as a function of all skills' importance at a prior point t-1.

$$L_{n,t} = \beta_0 + \beta_1 L_{1,t-1} + \beta_2 L_{2,t-1} + \beta_3 L_{3,t-1} + \beta_4 L_{4,t-1} \ldots + \varepsilon \qquad (2)$$

If technological change exhibits no skill bias, then we would see β_0 ... $\beta_{n-1} = 0$, $\beta_n = 1$ and β_{n+1} … $\beta_N = 0$. If technological change is skill biased then it will not affect all skills equally; some skills will be more amenable to technological substitution than others.

Skill substitution

AML, AA and Jaimovich and Sui (2012) each documented a "hollowing out" of extensive demand for middle-level skills such as coordination and routine document processing. Lower-skilled manual work and higher skilled cognitive work, especially non-routine work, was less affected because technology could not yet substitute for those skills.

Even in the presence of labor market adjustments on the extensive margin, we expect substitution effects in intensive skill demand. As technology substitutes for skills within occupations, we should see a redesign of jobs to rebalance the tasks performed by machines and humans. Technology advances at different rates for different types of skills, and those rates should have differential effects for occupations that rely on the different skills. This differential effect allows us to make the following hypotheses:

Manual skills. Past automation has replaced routine manual tasks and can be expected to continue to do so (AA, ALM). Meanwhile, technology advances now allow computers to do several manual tasks that are non-routine. Google's autonomous car and Rethink robotics' Baxter are two examples of relatively difficult manual tasks that can now be performed by computers. Factory automation is transforming many other jobs, from painting automobiles to sorting mail to picking products in warehouses.

For a fixed wage level, the improved price performance of technology in manual tasks should lead to a substitution effect, reducing the manual content of many occupations, distinct from any extensive effects on demand for those occupations.

***H1:** The importance of "manual" skills within jobs has decreased over time.*

Perception. An important recent change in technological capability has been in the area of perception. There have been remarkable advances in robotic vision and perception that would have been the domain of science fiction ten or twenty years ago. For instance, computers are now are able to understand speech in ways they never could before. In the words of Tom Mitchell, who heads Machine Learning at Carnegie Mellon University, "we are at the beginning of a ten-year period where we're going to transition from computers that can't understand language to a point where computers can understand quite a bit about language" (Markoff, 2011). Similarly, computer vision capabilities have advanced rapidly for tasks such as distinguishing objects, understanding writing, and identifying production defects on assembly lines.

Following reasoning in ALM and AA, where automation's routine capabilities substituted for routine occupations, automation's new capability to perform perception activities may lead to similar changes in occupations where perception is important. Thus we expect a substitution of technology for labor in occupations that relied on routine human perception, particularly in cases that favor the machines' inherent advantage of consistent performance over long periods without breaks.

***H2**: The importance of "perception" skills within jobs has decreased over time.*

Non-substitutable skills

Although computers have made strong advances in many manual or perception-related tasks, they have made less progress in others. Minsky (1986) argues that the most difficult human skills to automate are those that are unconscious: "In general, we're least aware of what our minds do best…we're more aware of simple processes that don't work well than of complex ones that work flawlessly."

One important area in which computers still trail humans is interpersonal interaction. The Turing Test, which examines whether computers can fool people into thinking they are real in a blinded conversation, has only recently been challenged (McCoy, 2014).[4] More complex interpersonal interactions, such as those in sales, customer service, and supervision, remain the domain of human workers.

We can expect that occupations will shift toward those skills in which humans have a relative advantage over machines. Machines have demonstrated limited ability to perform interpersonal tasks, and human customers have a preference for interacting with other humans (Walker *et al.*, 2002). Therefore,

H3: *The importance of "interpersonal" skills within jobs has increased over time.*

Skill complementarity

While technology can substitute for labor in many occupations, it can augment human skills in others. Computerized systems are making workers, from call centers to factories, more productive. Digital tools provide graphic artists and product designers with the ability to work more quickly and flexibly than ever before. Workflow and collaboration tools improve coordination and knowledge sharing among workers. At the high end of the skill distribution, medical diagnostics, electronic medical records, and technology-assisted surgery are improving physician productivity and patient outcomes.

As technology substitutes for some skills, it can also serve as a complement that increases the need for, and the productivity of, skills that computers cannot yet perform. In addition, technology may be able to remove the need for humans to perform some parts of an occupation, while making them more effective at what remains. Therefore, even in occupations that historically were not considered "technology-related" (for example, salesperson or machinist), the ability to use technology where appropriate would become increasingly important.

H4: *The importance of workers' facility with technology has increased over time.*

Finally, we can expect that skills resistant to automation will not be rebalanced across jobs at random, but rather that certain sets of skills will be observed to appear together. Although these complementarities probably always existed, we can expect that newly-automated skills will make it efficient to combine skills into jobs in new ways.

H5: *Technological progress will affect the apparent complementarities among skills. That is, the pattern of correlations among the skills that are important within jobs will change over time.*

To test these hypotheses, we employ detailed data about the skill content of jobs in 2006 and 2014. These data allow us to explore new insights into distinct dimensions of skill and the ways in which they change over time. The ideal experiment to test this theory would be to forbid any change in the proportion of people working in each occupation (that is, hold all extensive changes to zero) and observe the changing importance of skills within jobs over time. However, the actual economy can accommodate some change in skill demand by adjusting employment levels for different occupations. Even with this limitation, by analyzing changes in the skill content of occupations in a time of rapid technological change, we expect to document significant changes in the importance of several skill categories in American occupations.

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[4] Turing is not the first to make this claim. Philosophers considering the nature of consciousness have encountered the question in previous centuries. For example, in 1637 René Descartes wrote: "[W]e can easily understand a machine's being constituted so that it can utter words, and even emit some responses to action on it of a corporeal kind…But it never happens that it arranges its speech in various ways, in order to reply appropriately to everything that may be said in its presence, as even the lowest type of man can do." (Descartes, 1637)

Data and Methods

The labor market features firms that demand skills, workers who supply skills, and technological progress that changes the productivity of each skill. AA proposed an example of an empirical approach to estimate the wage and employment effects of technological progress, allowing technological progress to affect different job types differently. Their study investigates the wages that specific types of skills attract in the labor market (as detailed in the Appendix), whereas we focus on the types of skills required to perform a job.

We gathered occupational skill data from the O*NET database (www.onetonline.org). This database, compiled by the US Department of Labor, provides empirical data on the content of 974 representative occupations in the US economy. The database includes information about characteristics of the job itself (*e.g*., typical tasks, level of responsibility, and exposure to hazards) and the people who perform the job (*e.g*., abilities, skills and interests). Of the information available through O*NET, we use *Abilities*, *Generalized Work Activities,* and *Skills* to characterize jobs. The scales reflect highly trained labor experts' assessments of the importance of each skill to each occupation.

Each year, data is updated for approximately 10%-15% of the occupations in O*Net. The current set of skill descriptors has been in use since 2006. In the intervening eight years 78.5% of the occupations had their skill data fully updated. Partial updates occur as well; all of the 674 occupations with full data in 2006 were at least partially updated as of 2014.

To compare our results with AA, we initially reconstructed their variables[5] using data from 2006 and 2014. These variables are normalized to mean zero and standard deviation one. Interestingly, when we performed a factor analysis of AA's variables, we found they loaded on a single underlying factor that can be interpreted as a continuum of routine to non-routine content. Although AA's six factors are logically distinct *a priori*, the complementarities between certain combinations of these factors are so strong that they cannot be distinguished from one another statistically. This method, characteristic of important early stages of theory development in the field, can introduce a potential bias into estimation methods.

In a departure from past research practice, we chose to identify orthogonal skill dimensions empirically, rather than use a priori categorizations. Identifying orthogonal dimensions allows us to assess independent effects of each dimension, without being affected by estimation bias inherent in working with correlated constructs. We performed principal component factor analysis on all Abilities, Generalized Work Activities and Skills characteristics in the O*NET dataset separately for 2006 and 2014. To maintain comparability with AA, we used the importance measures for Abilities, rather than skill level measures. We retained items that loaded on any factor with an absolute value of 0.6 or higher after varimax rotation, and retained any factor that had at least three items loading on it. We dropped all other items. We then iterated the procedure until all remaining items loaded on one or more factors.

This procedure extracted seven distinct factors in O*NET for 2006, and five factors for 2014. After varimax rotation, these factors are mutually orthogonal and normalized within a year, eliminating any potential issues from correlated dependent variables. Under the null hypothesis of no within-job changes, calculating the 2006 factor scores with 2014 data (or vice versa) would also produce orthogonal distributions statistically indistinguishable from mean zero and standard deviation one.

Our analysis identified the following seven O*NET factors in 2006 in decreasing order of discriminatory power.

1. **Manual:** Dynamic strength, Gross body coordination, Handling physical objects, Manual dexterity, Speed of limb movement, Stamina
2. **Equipment:** Equipment Maintenance, Installation, Operation Monitoring, Repairing, Systems analysis, Troubleshooting
3. **Supervision:** Coordinate others' work, Develop/build teams, Guide/motivate subordinates, Manage financial resources, Monitor resources, Schedule work or activities

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[5] The O*NET characteristics defining these variables are described in AA's Data Appendix. A Stata script for translating raw O*NET data into their variables is available at http://economics.mit.edu/faculty/dautor/data

4. **Perception:** Category flexibility, Far vision, Perceptual speed, Selective attention, Speed of closure, Visual color discrimination
5. **Interpersonal:** Adaptability, Assisting or caring for others, Cooperation, Dependability, Service orientation, Stress tolerance
6. **Initiative:** Achievement, Independence, Initiative, Innovation, Persistence
7. **Vehicle Operation:** Operate vehicles, Night vision, Peripheral vision, Sound localization, Spatial orientation

We repeated the analysis in 2014, and identified the following five O*NET factors in decreasing order of discriminatory power:

1. **Cognitive:** Complex problem solving, Critical thinking, Deductive reasoning, Oral comprehension, Speed of Closure, Written expression
2. **Manual:** Equipment Maintenance, Finger dexterity, Handling physical objects, Multi-limb coordination, Reaction time, Visual color discrimination
3. **Supervision:** Coordinate others' work, Develop/build teams, Guide/motivate subordinates, Manage financial resources, Monitor resources, Schedule work or activities
4. **Interpersonal:** Adaptability, Assisting or caring for others, Cooperation, Dependability, Service orientation, Stress tolerance
5. **Initiative:** Achievement, Independence, Initiative, Innovation, Persistence

Note that while the *Initiative*, *Interpersonal* and *Supervision* factors retain largely the same skills in both periods, the skills associated with the *Manual* factor have changed between 2006 and 2014. The *Manual* factors in 2006 and 2014 both focus on coordination, dexterity and speed in handling physical objects. However, compared to 2006, the *Manual* factor in 2014 reflects an increased emphasis on physical abilities for using and maintaining machinery and a reduced emphasis on abilities related to strength and stamina.

Since the same factor analysis procedure produced different numbers of factors in each year, it is readily apparent that significant within-job changes – changes on the intensive margin – occurred in the O*NET data during our sample period. In the next section, we explore the nature of these changes.

Results

Our analysis explores the nature of intensive changes in occupational skill demand -- how the skill content of jobs has evolved over time as a result of skill biased technical change. All of our results are net of any extensive margin adjustments in the labor market, which would bias our results toward zero. As a result, our findings are conservative and thus measure a lower bound for actual intensive-margin changes.

Changes in AA skill constructs over time

To measure the intensive changes within jobs, we wish to look at the importance of skills within a job at different points in time. In principle, equation (2) can be estimated using all of the skills from O*NET, but there are three important limitations. First, O*NET has many dimensions of skill per job. Second, we expect that many of the skills' importance ratings will be correlated, introducing significant instability into our parameter estimates. Third, the large number of parameter estimates would be difficult to interpret. We avoid these limitations by aggregating skills into a manageable number of variables.

We begin our analysis by identifying intensive changes using AA's variables. We calculated AA's variables for 2006 and also 2014. Model I in Table 1 uses Ordinary Least Squares (OLS) to estimate equation (2) for the same occupations. Each row uses an AA-defined 2006 variable as a regressor for the 2014 variable identified in the column. Because the factor scores are normalized (i.e. Z scores), the coefficient can be interpreted as the response of the dependent variable, measured in standard deviations, to a one-standard deviation increase in the explanatory variable. As expected, each AA construct in 2006 is a strong predictor of that same construct in 2014. This is evident from the high coefficients and significant levels on the diagonal.

In addition, each construct also influences at least one other construct. Positive coefficients indicate that the two constructs have gained stronger covariance over time, due to complementarities increasing between those constructs. For example, Model I(f) shows that a job that has one standard deviation higher than average importance for *Routine Cognitive* skills in 2006 has 0.123 standard deviations higher than average importance for *Nonroutine Manual Interpersonal* skills in 2014. However, Model I(c) shows that the same job would require less *Manual Routine* than before.

Table 1: Changes in Job Characteristics – Constructs from Acemoglu & Autor (2010)

	Model I(a)	Model I(b)	Model I(c)	Model I(d)	Model I(e)	Model I(f)
	NR Cognitive Analytical '14	NR Cognitive Interpers. '14	Routine Cognitive '14	Routine Manual '14	NR Manual Physical '14	NR Manual Interpers. '14
NR Cognitive Analytical '06	0.885*** (0.028)	0.051 (0.035)	-0.034 (0.037)	-0.130*** (0.023)	-0.069*** (0.020)	-0.098** (0.038)
NR Cognitive Interpersonal '06	-0.046 (0.031)	0.825*** (0.039)	-0.037 (0.041)	0.020 (0.025)	0.013 (0.022)	0.337*** (0.042)
Routine Cognitive '06	0.013 (0.021)	-0.019 (0.026)	0.762*** (0.027)	0.002 (0.017)	-0.057*** (0.015)	0.123*** (0.029)
Routine Manual '06	-0.123*** (0.031)	-0.069* (0.040)	0.082** (0.041)	0.728*** (0.026)	0.031 (0.023)	-0.314*** (0.043)
NR Manual Physical '06	-0.074*** (0.026)	-0.039 (0.033)	-0.054 (0.035)	0.117*** (0.022)	0.879*** (0.019)	-0.043 (0.036)
NR Manual Interpersonal '06	-0.012 (0.026)	0.082** (0.034)	-0.023 (0.035)	-0.063*** (0.022)	-0.035* (0.019)	0.479*** (0.036)
(Intercept)	-0.195*** (0.018)	-0.256*** (0.023)	0.052** (0.024)	0.028* (0.015)	0.037*** (0.013)	-0.106*** (0.025)
R^2	0.796	0.672	0.659	0.863	0.897	0.613

Note: *N* = 674. * indicates p<0.10 ** indicates p<0.05 *** indicates p<0.01. "NR" = "nonroutine"

Note: *Each dependent variable is an AA factor score of an occupation calculated with 2014 data, and the independent variables are AA factor scores for that same occupation calculated with 2006 data.*

Changes in the importance of critical skills

The analysis above is very useful to understand the ways in which skills of different types have increased or decreased in importance over time, using AA's skill categories. However, as we described above, the dependent variables are highly correlated, confounding this analysis somewhat.[6]

To mitigate this problem, we defined a set of skill dimensions which are orthogonal by construction for each year, using principal component factor analysis. This analysis avoids issues in correlated constructs. It also allows us to identify important dimensions of skill from the data rather than choosing among different a priori classifications of skill that have face validity but may not be empirically distinct. We can also discover new dimensions that may not have been investigated in earlier research.

To do this analysis, we developed new skill factors for 2006 and 2014 independently, as described in the Data and Methods section. We also calculated hybrid factors for 2014 using the 2006-defined factor loadings on 2014 data. This allows us to conduct comparisons across time in two ways.

Model II in Table 2 follows the same format as Table 1, using different data. Rows represent the 2006 factors as explanatory variables (the $L_{n,t-1}$'s from equation (2)), and the dependent variable in each columns is a factor recalculated with data from 2014. As before, the unit of measure is standard deviations, since all variables are Z scores.

The results in Table 2 follow a similar pattern as Table 1: each factor in 2006 is a strong predictor of that factor in 2014, but each factor also significantly influences two to four others. Since the variables are

[6] In some cases, Seemingly Unrelated Regression (SUR) can extract information from the correlation between error terms to improve the interpretability of the coefficients. Unfortunately, an SUR system using the same explanatory variables for each equation produces precisely the same results as independent OLS regressions. None of our variables are appropriate to put in one equation without also belonging in all of the other equations.

mutually orthogonal in the base year of 2006, the coefficients in this specification can now be interpreted as factors tending to covary more or less in 2014 than they did in 2006. With the suggestive evidence in Table 1 and the stronger evidence in Table 2, we find that Hypothesis 5 is supported.

Changes in prevalence of skills across occupations

Of particular interest are the intercept terms. For each and every one of the seven factors, a job with mean importance for all skills in 2006 would be significantly different from the mean in 2014. Note that a negative value for the intercept represents a skill that is *more* important in 2014 than in 2006 because the "average" 2006 occupation would be considered "below average" in 2014. In particular, the average occupation in 2014 involves significantly fewer *Manual*-related skills and *Perception*-related skills, supporting Hypotheses 1 and 2. On the other hand, occupations in 2014 demand more *Interpersonal*- and *Equipment*-related skills than the average occupation in 2006, supporting Hypotheses 3 and 4.

Changes in what skills differentiate jobs from one another

Next, we investigate the difference in skill dimensions between 2006 and 2014. Recall that, in addition to empirically identifying skill dimensions in 2006, we also did so for 2014. The process generated different factors for each year. This substantial difference represents a shift in the nature of, and complementarities between, skills demanded across occupations over the eight year period. In other words, different clusters of skills are moving together now than in the past, due to changes in tasks performed by humans and machines.

In Table 3 we use an occupation's seven "2006 factors" using 2006 data to predict the same occupation's five "2014 factors" using 2014 data. The results indicate that the job skills identified as important in 2006 are still important in 2014, but the seven factors have coalesced into five. As some tasks are taken over by automation, complementarities among the tasks remaining for humans have become more pronounced, lending further support to Hypothesis 5. For example, although the average 2014 job is more demanding of *Equipment* skills (that is, facility with technology) than the average 2006 job, *Equipment* skills themselves have ceased to be a distinct job characteristic.

Table 2: Changes in Job Characteristics – Consistent Factors

	Model II(a) Manual '14	Model II(b) Supervision '14	Model II(c) Equipment '14	Model II(d) Perception '14	Model II(e) Interpers. '14	Model II(f) Initiative '14	Model II(g) Vehicle Op. '14
Manual '06	0.902*** (0.013)	-0.027 (0.023)	0.154*** (0.017)	-0.014 (0.019)	0.044** (0.019)	-0.051** (0.022)	0.011 (0.018)
Supervision '06	-0.015 (0.013)	0.742*** (0.023)	-0.066*** (0.017)	0.029 (0.019)	0.044** (0.019)	0.043* (0.023)	0.049*** (0.018)
Equipment '06	0.057*** (0.013)	0.064*** (0.023)	0.666*** (0.017)	0.193*** (0.019)	-0.130*** (0.019)	0.042* (0.022)	-0.012 (0.018)
Perception '06	-0.052*** (0.013)	-0.013 (0.023)	0.143*** (0.017)	0.443*** (0.019)	0.094*** (0.019)	-0.020 (0.022)	0.034* (0.018)
Interpers. '06	0.007 (0.013)	0.080*** (0.023)	-0.061*** (0.017)	0.029 (0.019)	0.774*** (0.019)	-0.057** (0.022)	-0.070*** (0.018)
Initiative '06	-0.076*** (0.013)	0.029 (0.023)	-0.026 (0.017)	-0.006 (0.019)	-0.065*** (0.019)	0.714*** (0.022)	0.045** (0.018)
Vehicle Op. '06	0.009 (0.013)	-0.027 (0.023)	0.083*** (0.017)	0.004 (0.019)	-0.011 (0.019)	-0.050** (0.022)	0.859*** (0.018)
(Intercept)	0.115*** (0.013)	0.444*** (0.023)	-1.261*** (0.017)	0.519*** (0.019)	-0.424*** (0.019)	0.146*** (0.022)	-0.087*** (0.018)
R^2	0.878	0.619	0.720	0.497	0.720	0.608	0.773

Note: N = 674. * indicates p<0.10 ** indicates p<0.05 *** indicates p<0.01.

***Note:** Independent variables are factor scores for occupations in 2006. Each dependent variable is a score of occupations calculated by applying factor weights from 2006 to 2014 data. Note that in this specification, a negative intercept represents an increase in the factor's importance for the mean 2014 occupation relative to the mean 2006 occupation.*

Table 3: Changes in Job Characteristics – Contemporary Factors					
	Model III(a)	Model III(b)	Model III(c)	Model III(d)	Model III(e)
	Cognitive '14	Manual '14	Interpersonal '14	Supervision '14	Initiative '14
Manual '06	-0.433*** (0.026)	0.602*** (0.016)	0.151*** (0.020)	0.092*** (0.027)	-0.025 (0.028)
Supervision '06	0.239*** (0.026)	0.001 (0.016)	0.104*** (0.020)	0.702*** (0.027)	0.057** (0.028)
Equipment '06	0.151*** (0.026)	0.578*** (0.016)	-0.189*** (0.020)	0.046* (0.027)	0.133*** (0.028)
Perception '06	0.341*** (0.026)	0.239*** (0.016)	0.086*** (0.020)	-0.091*** (0.027)	-0.103*** (0.028)
Interpers. '06	0.015 (0.026)	-0.066*** (0.016)	0.783*** (0.020)	0.061** (0.027)	-0.043 (0.028)
Initiative '06	0.311*** (0.026)	-0.050*** (0.016)	-0.070*** (0.020)	-0.047* (0.027)	0.698*** (0.028)
Vehicle Op. '06	0.096*** (0.026)	0.294*** (0.016)	-0.062*** (0.020)	-0.046* (0.027)	-0.115*** (0.028)
(Intercept)	-0.032 (0.026)	-0.086*** (0.016)	0.072*** (0.020)	-0.050* (0.027)	-0.018 (0.028)
R^2	0.529	0.839	0.728	0.513	0.512

Note: N = 674. * indicates p<0.10 ** indicates p<0.05 *** indicates p<0.01.

Note: *Each dependent variable is a factor score of an occupation in 2014. The independent variables are the factor scores for that same job in 2006, using independent factor analysis in 2006 and 2014.*

Discussion

Our analysis digs deeply into the nature of intensive change in skill demand across occupations. Figure 2 allows us to see these effects as they emerge from Model II. An occupation that had mean scores for all factors in 2006 (and therefore values of zero for all independent variables) would not have scores at the mean in 2014 because the labor market has changed. This "average 2006 occupation" would have significantly above-average scores for *Perception* and *Supervision* in 2014 as well as significantly below-average scores for *Equipment* and *Interpersonal*.

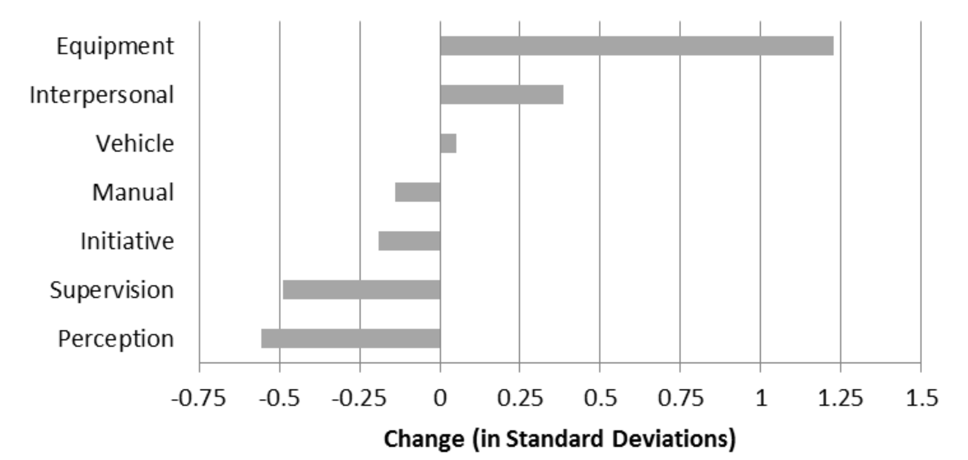

Figure 2: Average Factor Shifts between 2006 and 2014

Note: *Values are the additive inverses of the intercepts from Model II. Positive values in this figure indicate that average occupational requirements are higher for that skill factor in 2014 than in 2006.*

Differential effects of technology on skills are leading to different mechanisms of adjustment in occupational skill composition. Human workers have three choices in how to compete in an era of fast-moving technology:

- Racing against the machine: Machines take over skills that were formerly done by humans (substitution of new technologies for labor).
- Racing with the machine: Machines complement human skills, amplifying the ability of humans to do work (complementarity between new technologies and labor).
- Running a different race: Occupations remain that focus on skills that computers have not yet significantly affected, allowing these jobs to remain largely unchanged (no net substitution or complementarity between new technologies and labor).

Racing against the machine

Racing against the machine pits humans against technology in a competition where machines can increasingly substitute for skills that were previously the sole domain of humans. *Perception* and *Supervision* show a positive intercept in Model II (negative value in Figure 2). This means that, on average, occupations require less of these skills in 2014 than they did in 2006.

Perception:

The data are consistent with the hypothesis that perception is becoming less of a human task and more of a machine task. The automated voice response unit is an example of how computers have substituted for humans in jobs requiring perception – in this case the ability to hear sounds such as voices, distinguish signal from noise, decode the language, and then respond in appropriate language. While voice response began in very routine transactional environments and very constrained contexts, voice recognition capabilities have advanced rapidly in recent years. Companies like Verizon and United Airlines routinely rely on automated voice response systems for millions of customer interactions. It is conceivable that, in not too many years, voice response systems may be handling the majority of all phone transactions that human agents currently conduct. Perhaps one of the most surprising examples of an occupation for which *Perception* has decreased in importance is speech pathologists. In this occupation, the importance of *Perception* dropped from 2.895 in 2006 to 1.638 in 2014.

Automated perception is not limited to voice. For years, machines have sorted a large fraction of the mail entering post offices, or checks entering banks. In recent years, machines have rapidly moved from these highly constrained visual contexts to more difficult and variable jobs. For example, machines increasingly perform roles in quality control on production lines. They extend from "clean" and standardized environments like chip manufacturing to more variable contexts such as fruit sorting. They bring to these new environments another advantage they traditionally enjoyed over human perception: the ability to conduct the same tests over and over again, for hours at a time, without getting tired or needing a break.

Our data analysis reveals that these are not isolated examples. The intercept term of 0.519 on *Perception* shows the magnitude of the decline in demand for these skills among human workers. The average occupation in 2014 requires a half-standard-deviation less of the *Perception* skill in 2014 than in 2006.

Supervision:

The findings for *Supervision* highlight an interesting trend that we have not previously seen in the research literature. As technology takes on routine work, there is a concomitant reduction in the need for people to supervise routine work. Individuals who managed teams of people doing routine work have moved from telling people to do things to telling machines to do them. For example, architects traditionally coordinated the work of several draftsmen but now use CAD software tools. In essence, architects playing this role have moved from being supervisors to machine operators.

Self-organization is another technology-enabled trend that reduces the prevalence of supervisory skills across occupations. The *Supervision* factor includes items related to scheduling work and activities, coordinating work and activities, staffing units, and monitoring or controlling resources. In recent years, technology has enabled workers to conduct their own organizing without supervisory intervention. Email, online meeting tools, and online storage enable people to collaborate at will, without having to request resources or schedule meetings through supervisors. This disintermediation is not limited to peers within an organization; the same technology enables customers to summon Uber cars without interacting with a human dispatcher.

As with *Perception*, our analysis reveals that these examples reflect a larger trend across occupations. The intercept term of 0.444 on *Supervision* shows the magnitude of the decline in demand for this set of skills.

Racing with the machine

As shown above, racing *against* the machine entails performing tasks for which computers increasingly possess a competitive advantage. But this is not the only option. Humans can race *with* the machine, doing more than they ever could before by collaborating -- rather than competing -- with machines.

Equipment:

In the race against the machine described above, some of the people who formerly supervised humans now have machines that do the job of the humans. In essence, these supervisors have become equipment operators. But what has happened to the equipment operator skills of 2006? The *Equipment* skill shows clear signs of augmentation rather than substitution. In fact, this skill has become important across such a broad cross-section of occupations that it is no longer a skill characteristic that distinguishes among occupations. In the intervening years, it became part of many jobs, rather than being specific to some.

For example, tax preparers now have programs to assist with their calculations, enabling them to do work faster and more accurately than before. Placing advertisements is now a largely technology-assisted job, with equipment such as Google tools doing many routine tasks while also providing performance information to help marketers make better choices about where to run ads. These occupations are not traditionally categorized as "technology" jobs, yet a facility with technology has become essential for people to function in them.

The intercept term of -1.261 on *Equipment* shows the magnitude of the increase in demand for this set of skills among human workers. The typical 2014 occupation calls for more than a standard deviation more of these skills than 2006 occupations did.

Running a different race

Some skills are neither running with nor against the machine. These are skills in which computers have not yet made serious inroads. In recent years, occupations high in these skills have been largely unchanged. In Table 2, the most prominent example of running a different race is *Interpersonal* skills.

Interpersonal:

For the time being, demand for interpersonal skills has been growing, as reflected in the -0.424 coefficient on *Interpersonal* in Table 2. To date, computers have not been able to develop the interpersonal skills required in sales, childcare, or nursing. While computers can process information well, including an increasing variety of visual and auditory information as noted above, they are less able to show social orientation, interpersonal cooperation, adaptability, or concern for others in the way humans can.

But even here one can imagine machines making progress. Machines currently in the research stage can detect stress in the voice of a customer who calls a call center, and then prompt a supervisor to intervene before the customer becomes irate (Hernandez et al., 2011). Other algorithms can detect depression by monitoring mobile phones – how often an individual calls others, uses specific apps, or moves around – often before the individual himself knows he is depressed (Chu, 2009).

There are other factors that we also identified as being important in both 2006 and 2014, such as *Initiative*. The intercepts on these factors have not changed as much as the others. Given their lower explanatory power and explanatory significance than the larger factors, we will not seek to interpret the smaller changes they have undergone at this point. However, they highlight avenues for future analysis.

Changing Complementarities between Skills

In the Data and Methods section we described our procedure for identifying the underlying dimensions that differentiate occupations from one another in ways that previous research in skill-biased technical change has not. Using this procedure separately on the 2006 and 2014 data, we found a distinctly different set of dimensions in each period. Despite the relatively small eight year span, the intervening major recession and concomitant restructuring of many firms and industries created an opportunity for (surviving) organizations to redesign jobs to take advantage of emerging complementarities. Simultaneously, technology began a rapid advance along many dimensions such as perception, unstructured data analysis, coordination, and mass collaboration that went well beyond pure automation of routine tasks.

Model II lets us look at changes in extent of a skill on average, while Model III gives us insight into changes in complementarities among skills. While occupations continue to be defined by approximately eighty skill items, the clusters of skills (principal component factors) that differentiate between occupations in 2014 are **not** the same ones as in 2006. This represents a notable shift in the underlying structure of occupations in a very short period of time.

Of the seven dimensions that differentiated occupations in 2006, *Initiative*, *Interpersonal* and *Supervision* are still relevant in 2014. A new correlation pattern in the skills related to the *Equipment*, *Manual*, *Perception* and *Vehicle Operation* dimensions have reconfigured these skills into one new dimension in 2014, *Cognitive,* and a partially reformulated one, *Manual*.

Brynjolfsson and Milgrom (2013) state that this type of increased correlation can be evidence of complementarities (their "correlation test"). Many machine operators need to understand, diagnose and optimize their tools much more than in the past. Employers of workers as varied as logging machine operators, social workers, and print binding workers now have higher expectations in relation to the *Cognitive* dimension in 2014, whereas only a subset of those skills were considered relevant in 2006.

This malleability of dimensions indicates that specialization in certain skills may be detrimental for human workers in the long term. In the past, hyper-specialization on equipment could have been a differentiating role. However, such specialization may be less useful now. *Equipment* skills have become more broadly applicable across occupations almost to the point of being hygiene factors. This does not mean that all hyper-specialization loses value, since specializing in newly-differentiating skills such as *Cognitive* or growing skills such as *Interpersonal* can still be a successful strategy.

Table 3 also reveals another trend – the drive toward workers needing more flexibility. For any given skill one can think of, some computer scientist somewhere may already be trying to develop an algorithm to do it. So, workers – especially those with many years left in their careers -- need to stay flexible in focusing on new skills or finding occupations with new complementarities.

Conclusion

Perhaps the most important challenge facing advanced economies today is the economic dislocation reflected in falling median wages and labor force participation, even as productivity levels and overall GDP continue to rise. In part, these disruptions reflect the fact that rapid advances in technology, especially information systems and digital technologies, have made it possible to automate many human tasks, while augmenting others. These changes are reflected not only in specific occupations, but also in the broader pattern of the skill content of work in the U.S. economy.

Recently, technology has moved beyond automation to cognition, with the ability to replace or augment human skills of different types. The differential improvements in technology's capabilities have changed the types of jobs that are threatened by automation. Formerly laborers and factory workers were threatened, but now lawyers and journalists are. While the much of the prior research on skill-biased technical change has focused on a single dimension of more- or less-skilled work, the actual effects of technology are much more varied, affecting at least five distinct dimensions of skills. Moreover, the effects vary over time, which can explain the notable changes we document between 2006 and 2014.

While there has been ample speculation about the nature of the skill changes engendered by technology, careful measurement is the lifeblood of science. To our knowledge, we are the first researchers to measure, comprehensively and quantitatively, the significant skill content changes within jobs since 2006, using the largest and most comprehensive data set of job characteristics available (O*NET). Furthermore, we identified seven orthogonal skill groupings – including some novel dimensions -- that characterize over 600 occupations in the United States. By identifying new skill dimensions such as *Initiative*, and highlighting the importance of others such as *Supervision* and *Interpersonal* that are underrepresented in prior quantitative literature, this research broadens the set of lenses through which researchers can examine the nature of skill-biased technical change.

We found that there was a statistically significant change in the prevalence of all seven skills over this eight year time period. In particular, the changes are consistent with our hypotheses regarding the potential for information technology to substitute for skills in some jobs, complement skills in other jobs, and (for the time being) have relatively little effect on a third set of skills.

Our results reveal that the recent changes in the skill content of occupations have been fundamental enough to change the underlying dimensions that distinguish one occupation from another. One clear example is facility with technology. In 2006, this skill was statistically visible as an orthogonal principal component called *Equipment*. However, by 2014, it evaporated into expectations that almost *every* occupation requires facility with technology.

We also found significant increases in the importance of *Interpersonal* skills, and decreases in the importance of *Perception* (e.g. voice recognition or vision) and *Supervision*. These patterns are consistent with the nature of the changes in technology. They have occasionally been documented in case studies and studies of particular technologies or occupations. However, they have not previously been identified on an economy-wide basis.

Because many digital technologies advance at an exponential rate, reflecting the nature of Moore's Law and its analogs for storage, communications and other information technologies, we expect even bigger advances in their capabilities in the next decade than we saw in the past decade. This suggests that the significant economic disruption — and the large changes in the demand for skills like perception, supervision, interpersonal facility, and equipment use — are likely to grow. The disruption is an opportunity for organizations, but may be a threat to many workers. Researchers, managers and policymakers need to understand these changes if they are to diagnose them correctly and ultimately prescribe effective solutions. Large-scale quantitative measurement and analysis, such as that provided in this paper, will be an important contribution to that kind of understanding.

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Appendix: Summary of Acemoglu and Autor (2012)

Acemoglu and Autor (2012), referred to as AA in the main text, argues that the *canonical model* of skill-biased technical change, “which includes two skill groups performing two distinct and imperfectly substitutable occupations (or producing two imperfectly substitutable goods)” comes up short in explaining current changes in the labor market, skill demand and the effect of technology. They argue that issues like polarization in employment and the earnings distribution cannot be explained through the canonical model.

They propose a new model that differentiates between a task and the skills used to perform that task. Production consists of many tasks, while workers are endowed with many skills. Workers choose to apply the appropriate skill to a specific task to produce a good or provide a service, based on labor market conditions and technology developments.

The authors develop a Ricardian task-based framework which consists of a continuum of tasks. They use the following model to represent production using Low-, Medium- and High-skill labor.

$$y(i) = A_L \alpha_L(i) L(i) + A_M \alpha_M(i) M(i) + A_H \alpha_H(i) H(i) + A_K \alpha_K(i) k(i)$$

where A terms represent factor-augmenting technology; $\alpha_L(i)$, $\alpha_M(i)$ and $\alpha_H(i)$ are productivities of Low-, Medium- and High-skill workers, respectively, in task i; and $L(i)$, $M(i)$ and $H(i)$ are the number of Low-, Medium- and High-skill workers, respectively, allocated to task i. The term K represents capital or technology (machines).

The model allows workers to move between different occupations (tasks). For example, as technology becomes more effective in performing tasks that were traditionally performed by Medium-skill workers, these workers will move to High or Low tasks, creating the polarization of employment and wages that was evident in the last decade. In particular, AA find it more plausible that medium-skill specialists would switch to low-skill tasks than high-skill tasks, creating pressure on workers that formerly performed low-skill tasks.

Acemoglu and Autor apply their model to wage and occupation data from the U.S. Census in the period 1959-2008 "as an example of an empirical approach rather than a test of the theory." They find that wages for workers specializing in routine (Middle skill) tasks have declined relative to those who specialize in abstract (High skill) or manual/service (Low skill) tasks.