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

Note: This is a corrected version as of October 2016.

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 673 U.S. occupations from 2006-2014 to understand the effects of technological change on the demand for different skills. In a departure from prior methods, we use principal component analysis to identify latent dimensions of skill, rather than constructing a more limited set of measures a priori. These skill dimensions are orthogonal by construction, allowing the use of analytical methods that would not be feasible with prior skill constructs.

Consistent with theory, we find a reduction in occupational content of skills that compete with machines, an increase in skills that complement machines, and no significant change in skills where technology has not made major inroads over the period. The findings for some skills challenge conventional wisdom about the nature of technological capability improvements over the period studied, while increasing correlations among skills suggests the need for workers to develop proficiency in skills beyond their current areas of specialty.

The paper’s novel methodology will be useful for future research into skill-biased technical change. Meanwhile, the scale of changes we document in occupational skill content since 2006 portend even bigger changes for workers and employers in the 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 reduce intensive demand for some skills in occupations and that complementarity effects will amplify demand for other skills. The effect upon skills that are orthogonal is an empirical question.

We significantly broaden earlier research in three ways. First, we use a novel methodology to 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. For example, our procedure divided interpersonal skills (which prior literature has identified as important) into two distinct dimensions. On average, we are able to explain 74% of the variation in the importance of skill groups constructed in prior research as well as 64% to 66% of the variation in skill factors we derive from the O*NET data.

Second, in this paper, we focus on changes on the intensive margin of occupations rather than the extensive margin. That is, we analyze changes over time in the skill content of occupations, rather than changes in the number of people employed in various occupations. Prior work has largely 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 skills. Fewer studies examine changes on the intensive margin, or the ways in which technology is changing the composition of jobs themselves. Yet, while technological change affects demand for specific jobs, it also fundamentally alters the nature of jobs. For example, while extensive demand for secretaries has changed over recent decades, the nature of the secretarial job has also changed dramatically.

Third, we update prior research by investigating changes that have occurred in the period from 2006 to 2014. During this period, new automation and communication innovations, such as the fast rise of mobile devices, social media, and language processing technologies, have had effects that vary substantially from technologies of the past. Our findings provide evidence of technology both substituting for and complementing some skills in predicted ways, while also providing evidence that challenges conventional wisdom about the specific nature of technological capability improvements in organizations over the past decade.

1 For more details on these examples, and many others, see Brynjolfsson and McAfee (2014) and the many references therein.
In particular, skills that complement machinery, such as supervision and mathematical reasoning, have become more important in occupations. At the same time, occupational skill content of some basic interpersonal skills, once seen as immune to technological change, is now falling, possibly due to the introduction of self-service, voice recognition, and text-parsing technologies. Skills where machines have not made great in-roads thus far, such as initiative, exhibited no significant change over the study period. Our evidence also suggests that occupational content of physical skills, which were under technological threat from technology in past decades, experienced little change since 2006, suggesting that organizational improvements in technology related to touching and moving objects plateaued in the mid-2000s, although these skills may be threatened again in the near future.

Finally, the analysis provides evidence that complementarity across skills has changed. One striking example is that, as more jobs require facility with mathematics, it is no longer an independent skill dimension that differentiates between jobs. This suggests that workers must take a broader view toward skill development than they did in the past.

**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 cited 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)](image)

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 recent comovement 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.

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).

\[
\ln(Y) = \ln(A) + \beta_1 \ln(L_1) + \beta_2 \ln(L_2) + \beta_3 \ln(K) + \beta_4 \ln(L_1)\ln(K) + \beta_5 \ln(L_2)\ln(K) + \beta_6 \ln(L_2)\ln(K) \quad (1)
\]

where \(Y\) is output, and \(L_1\) and \(L_2\) are two types of labor, \(K\) is capital input, and \(A\) 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 \(\beta_4\) is positive due to complementarity and less valuable if \(\beta_3\) is negative due to substitutability. The same effect is present between \(\beta_5\) 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

---

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.
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.

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 \( t-1 \).

\[
L_{n,t} = \beta_0 + \beta_1 L_{1,t-1} + \beta_2 L_{2,t-1} + \beta_3 L_{3,t-1} + \beta_4 L_{4,t-1} + \ldots + \varepsilon
\]  

(2)

If technological change exhibits no skill bias, then we would see \( \beta_0 \ldots \beta_n = 0 \), \( \beta_n = 1 \) and \( \beta_{n+1} \ldots \beta_N = 0 \). If technological change is skill biased then it will not affect all skills equally; some skills will be more amenable to technological substitution or complementarity 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:

**Physical.** 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 “physical” skills within jobs has decreased over time.

**Teamwork.** There has been a sustained trend toward self-service in many industries, ranging from now-traditional automated teller machines to familiar online help pages to emerging personalized recommendation engines. These technologies substitute for simple human-mediated interactions in much the same way that assembly line machines substitute for routine physical tasks. Meanwhile, voice recognition and text parsing technologies are increasing in capability, taking over tasks that were previously the sole domain of humans. 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).

Following reasoning in ALM and AA, automation’s new capability to substitute personal interactions with self-service may lead to similar changes in occupations where the execution of “routine” production tasks is currently considered “non-routine” due to working directly with people. We might expect a substitution of technology for labor in occupations that rely on this type of teamwork interaction, particularly in cases
that favor the machines’ inherent advantage of consistent performance over long periods without breaks and avoid the machines’ inherent disadvantage in being sociable (Walker, 2002).

**H2:** The importance of “teamwork” skills within jobs has decreased 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 management, more productive. Digital tools help graphic artists and product designers 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 wage 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. Technology may also 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 “information intensive” (for example, salesperson or machinist), tasks such as recognizing new patterns would become increasingly important. Similarly, as real time information becomes more readily available to workers, supervisory and managerial skills become more valuable for those who can convert that information into effective actions. These information flows are increasing the coordination, planning and resource responsibilities even in non-supervisory roles such as nurses.

**H3:** The importance of “pattern recognition” skills within jobs has increased over time.

**H4:** The importance of “supervision” skills within jobs has increased over time.

**Non-substitutable skills**

Although computers have made strong advances in many routine manual or interpersonal-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 situational awareness, such as navigating a complex environment without prior knowledge of the layout. While autonomous robots such as Atlas, Big Dog and autonomous cars have demonstrated impressive capabilities in navigating the real world, they still require very specific instructions and/or detailed prior mapping, and none is currently well-equipped to deal with a non-routine situation (such as a police officer directing traffic around an accident). While these capabilities are advancing rapidly, they are only beginning to make inroads into organizations.

Another non-substitutable skill is initiative. Automation exhibits persistence in conducting routine activities. However, computers have not yet made significant inroads in innovation, or bringing non-routine tasks to completion, both of which are important elements of initiative.

Theory suggests that occupations will shift toward those skills in which humans have a relative advantage over machines, but also suggests that the relative expense of employing these skills may limit their use in the economy. Since theory provides no dominant a priori direction for the net effect, we treat the change in occupational skill content of Awareness and Initiative as a purely empirical question.

**Equivocal skills**

The technology/skill relationship for Math skills is difficult to predict from theory. Computers are becoming capable of performing ever-more advanced mathematical calculations, suggesting a substitution

---

3 Questions about human-machine interaction are not new. 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)
relationship. However, mathematical skill involves much more than mechanical numeric manipulation. It also involves a measure of abstract thinking and creativity that machines have not yet mastered. To the extent that mathematical skill in jobs consists of abstract capabilities, then machines might complement mathematical skill by performing routine activities and freeing workers for more abstract activities. Because both substitution and complementary relations are possible for Math skills, we treat the effect as an empirical question.

**Skill interdependencies**

Finally, we can expect that skills will not be rebalanced across jobs at random, but rather that certain sets of skills will be observed to appear together in new ways. As new technological capabilities substitute and complement specific skills, managers will change job definitions to include new configurations of skills where humans have an advantage.

**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.

**Data and Methods**

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.

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 focuses on the demand for specific jobs, whereas we focus on changes in the 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 and Generalized Work Activities to characterize jobs. The scales reflect highly trained labor experts' assessments of the importance of each skill to each occupation.4

Each year, data is updated for approximately 10%-15% of the occupations in O*NET. The current set of descriptors has been in use since 2006. In the intervening eight years 78.5% of the occupations had their data fully updated. Partial updates occur as well; all of the 673 occupations with full data in 2006 were at least partially updated as of 2014.

To compare our results with AA, we initially reconstructed their variables5 using data from 2006 and 2014. These variables are normalized to mean zero and standard deviation one.6

---

4 In a previous version of this paper we also used the Skills section of O*NET, but we later learned that its measurement methodology underwent significant changes during our 2006-2014 sample period. Up to 2009, skills were self-reported by incumbents, but updates from 2010 forward were rated by labor experts. The skills ratings under the two regimes show systematic differences, so we deemed them to be not comparable across the time period.

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

6 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,
In a departure from past research practice, we chose to identify orthogonal skill dimensions empirically, rather than use a priori categorizations. We did this not because it yields the “best” set of dimensions, but rather because it allows us to assess the effects of each dimension literally ceteris paribus. We performed principal component factor analysis on all Abilities and Generalized Work Activities characteristics in the O*NET dataset separately for 2006 and 2014. To maintain comparability with AA, we used importance measures rather than skill level measures for Abilities. We retained items that loaded on any factor with an absolute value of 0.7 or higher after varimax rotation, and dropped all other items. We then iterated the procedure until all remaining items loaded on one or more factors. Any items that cross-loaded at 0.5 or higher on another factor were dropped.

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, reducing potential issues from correlated explanatory 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, along with some of the items comprising each factor.

1. **Physical**: Handling and Moving Objects, Multilimb Coordination, Performing General Physical Activities, Stamina, and 9 other items
2. **Awareness**: Night Vision, Operating Vehicles, Peripheral Vision, Sound Localization, and 2 other items
3. **Supervision**: Coordinating Others’ Work, Developing and Building Teams, Training and Teaching Others, Coaching and Developing Others, and 2 other items
4. **Initiative**: Persistence, Initiative, Innovation, Analytical Thinking, and 2 other items
5. **Pattern Recognition**: Flexibility of Closure, Selective Attention, Speed of Closure, Hearing Sensitivity, and 2 other items
6. **Teamwork**: Cooperation, Concern for Others, Social Orientation, and 2 other items
7. **Math**: Mathematical Reasoning, and Number Facility

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

1. **Physical**: Handling and Moving Objects, Multilimb Coordination, Performing General Physical Activities, Reaction Time, Stamina, and 12 other items
2. **Supervision**: Coaching and Developing Others, Coordinating Others’ Work, Developing and Building Teams, Monitoring and Controlling Resources, and 3 other items
3. **Teamwork**: Assisting and Caring for Others, Cooperation, Self-Control, Social Orientation, and 2 other items
4. **Initiative**: Initiative, Innovation, Persistence, and 2 other items
5. **Pattern Recognition**: Flexibility of Closure, Selective Attention, Speed of Closure, and 1 other item

For 2014, the Awareness items remained intercorrelated with one another, but they also became too correlated with the Physical factor to remain distinct. Half of the items were removed for cross-loading, and the remainder were not distinct enough from Physical to define an independent factor. The Math factor’s two items actually became more correlated with each other in 2014, but they also became too

the complementarities between certain combinations of these factors are strong enough that they cannot be easily distinguished from one another in our analysis.

7 Note that this factor is closely related to what is labeled “Cognitive” in prior literature. We chose to label it “Math” to distinguish it from other types of cognitive tasks.
correlated with items in the Supervision, Initiative and Pattern recognition factors to remain a distinct factor. This could indicate that the usefulness of Math skills has diffused into many categories of jobs. The Physical factor for 2014 gained items related to rate control and reaction time, indicating that these abilities have become more likely to cluster within occupations alongside strength and dexterity. The Initiative factor included analytical thinking in 2006 but not 2014, potentially indicating that analytical thinking has become more broadly applicable across occupations.

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**

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 began by examining changes in AA constructs. We then investigated a new set of skill dimensions that have additional explanatory capability beyond prior methods.

**Changes in AA skill constructs over time**

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 the strongest predictor of that same construct in 2014. This is evident from the coefficients and significance levels on the diagonal.

<table>
<thead>
<tr>
<th>Table 1: Changes in Job Characteristics – Constructs from Acemoglu &amp; Autor (2010)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Model I(a)</strong></td>
</tr>
<tr>
<td>NR Cognitive Analytical ’06</td>
</tr>
<tr>
<td>NR Cognitive Interpersonal ’06</td>
</tr>
<tr>
<td>Routine Cognitive ’06</td>
</tr>
<tr>
<td>Routine Manual ’06</td>
</tr>
<tr>
<td>NR Manual Physical ’06</td>
</tr>
<tr>
<td>NR Manual Interpersonal ’06</td>
</tr>
<tr>
<td>(Intercept)</td>
</tr>
<tr>
<td>R²</td>
</tr>
</tbody>
</table>

**Note:** N = 673. * 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.

In addition, each construct also influences at least one other construct. Positive coefficients indicate that the two constructs have gained stronger covariance over time, potentially 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 Nonroutine Cognitive Interpersonal skills in 2006 has 0.222 standard deviations higher than average importance for Nonroutine Manual Interpersonal skills in 2014. However, Model I(a) shows that the same job would require slightly less Nonroutine Cognitive Analytical than before.

**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, those dependent variables are highly correlated. For the remainder of the analysis, we used principal component analysis to define a set of skill dimensions which are orthogonal by construction for each year. This analysis avoids potential issues with highly 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 call these Contemporaneous Factors. We also calculated hybrid factors for 2014 using the 2006-defined factor loadings on 2014 data. We call these Consistent Factors. The Contemporaneous and Consistent Factors allow 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 $L_{t-1}$’s from equation (2)). The dependent variable in each column is a Consistent Factor for 2014 calculated by applying 2006 factor weights to 2014 skill data. 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 most factors also influence others. Since the variables are 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. For example, Math was constructed to be orthogonal to Physical and Teamwork in 2006 but has become distinctly anticorrelated with each in 2014. Supervision has become more correlated with Initiative and Teamwork, but Initiative and Teamwork have become anticorrelated with each other.

Some of the effects in Table 2 have a well-defined direction. Jobs with higher Awareness requirements in 2006 have higher Physical requirements in 2014, while the reverse is true for jobs that had higher Initiative requirements in 2006. Jobs with higher Initiative requirements in 2006 have higher Math requirements in 2014, and jobs with higher Teamwork requirements in 2006 have lower Awareness requirements in 2014.

With the suggestive evidence in Table 1 and the stronger evidence in Table 2, we find that Hypothesis 5 is supported. The pattern of correlations among the skills that are important within jobs has changed over time.

**Changes in prevalence of skills across occupations**

Of particular interest are the intercept terms. Since all regressors are orthogonal, we can interpret the magnitude of the intercept in each column as a measure of the change in the requirement for the dependent variable for the average 2006 occupation over the 2006-2014 period. For four factors, a job with mean importance for all skills in 2006 would be significantly different from the mean in 2014. In particular, the average occupation in 2014 involves significantly fewer Teamwork-related skills, supporting Hypothesis 2. However, Hypothesis 1 related to Physical skills is not supported. On the other hand, occupations in 2014 demand more Supervision- and Pattern Recognition-related skills than the average occupation in 2006, supporting Hypotheses 3 and 4. The empirical question of non-substitutable Awareness- and Initiative-related skills shows that there was no statistically significant net change in requirements between 2006 and

---

8 In some cases, Seemingly Unrelated Regression (SUR) can extract information from the correlation between error terms to improve the interpretability of the coefficients. In our data, an SUR system using the same explanatory variables for each equation would produce the same results as independent OLS regressions.
Meanwhile, for the empirical question of Math-related skills, the positive and significant intercept term suggests that Math-related skills were complements to technology, rather than substitutes, over the 2006-2014 period.

### Table 2: Changes in Job Characteristics – Consistent Factors

<table>
<thead>
<tr>
<th></th>
<th>Model II(a)</th>
<th>Model II(b)</th>
<th>Model II(c)</th>
<th>Model II(d)</th>
<th>Model II(e)</th>
<th>Model II(f)</th>
<th>Model II(g)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Physical '14</td>
<td>Awareness '14</td>
<td>Supervision '14</td>
<td>Initiative '14</td>
<td>Pat. Rec. '14</td>
<td>Teamwork '14</td>
<td>Math '14</td>
</tr>
<tr>
<td>Physical '06</td>
<td>0.928***</td>
<td>0.028</td>
<td>-0.040</td>
<td>-0.022</td>
<td>0.006</td>
<td>-0.003</td>
<td>-0.089***</td>
</tr>
<tr>
<td>Awareness '06</td>
<td>0.034**</td>
<td>0.863***</td>
<td>-0.007</td>
<td>-0.008</td>
<td>0.013</td>
<td>-0.027</td>
<td>-0.061***</td>
</tr>
<tr>
<td>Supervision '06</td>
<td>-0.001</td>
<td>0.022</td>
<td>0.729***</td>
<td>0.079***</td>
<td>0.014</td>
<td>0.075***</td>
<td>0.038*</td>
</tr>
<tr>
<td>Initiative '06</td>
<td>-0.080***</td>
<td>0.008</td>
<td>0.055**</td>
<td>0.715***</td>
<td>0.013</td>
<td>-0.094***</td>
<td>0.067***</td>
</tr>
<tr>
<td>Pat. Rec. '06</td>
<td>-0.028*</td>
<td>0.036*</td>
<td>-0.006</td>
<td>0.041*</td>
<td>0.514***</td>
<td>0.014</td>
<td>0.011</td>
</tr>
<tr>
<td>Teamwork '06</td>
<td>-0.022</td>
<td>-0.061***</td>
<td>0.081***</td>
<td>-0.096***</td>
<td>-0.029</td>
<td>0.766***</td>
<td>-0.038*</td>
</tr>
<tr>
<td>Math '06</td>
<td>-0.092***</td>
<td>0.015</td>
<td>0.082***</td>
<td>-0.031</td>
<td>-0.017</td>
<td>-0.087***</td>
<td>0.732***</td>
</tr>
<tr>
<td>(Intercept)</td>
<td>0.014</td>
<td>-0.029</td>
<td>0.174***</td>
<td>0.012</td>
<td>0.124***</td>
<td>-0.073***</td>
<td>0.125***</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.864</td>
<td>0.774</td>
<td>0.574</td>
<td>0.597</td>
<td>0.483</td>
<td>0.683</td>
<td>0.652</td>
</tr>
</tbody>
</table>

**Note:** $N = 673$. * 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.

### Changes in what skills differentiate jobs from one another

Next, we investigate the difference in skill factors between 2006 and 2014. Recall that, in addition to empirically identifying skill dimensions in 2006, we also identified them independently for 2014. In this Contemporary Factor analysis, two of the 2006 factors faded into the others by 2014. This represents a shift in the complementarities between skills demanded across occupations over the eight year period.

In Table 3 we compare Contemporary Factors by using each occupation’s seven skill factors constructed using 2006 data to predict the same occupation’s five skill factors constructed 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 automation made inroads with some tasks, complementarities among the tasks remaining for humans have become more pronounced. For example, although the average 2014 job is more demanding of Math skills than the average 2006 job (see Table 2), Math skills themselves have ceased to be a distinct job characteristic in 2014. This Contemporary Factor analysis provides further support for Hypothesis 5.
### Table 3: Changes in Job Characteristics – Contemporary Factors

<table>
<thead>
<tr>
<th></th>
<th>Model III(a)</th>
<th>Model III(b)</th>
<th>Model III(c)</th>
<th>Model III(d)</th>
<th>Model III(e)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Physical '14</td>
<td>Supervision '14</td>
<td>Teamwork '14</td>
<td>Initiative '14</td>
<td>Pat. Rec. '14</td>
</tr>
<tr>
<td>Physical '06</td>
<td>0.877***</td>
<td>0.016</td>
<td>-0.005</td>
<td>-0.001</td>
<td>-0.075***</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.027)</td>
<td>(0.020)</td>
<td>(0.026)</td>
<td>(0.027)</td>
</tr>
<tr>
<td>Awareness '06</td>
<td>0.285***</td>
<td>0.014</td>
<td>-0.099***</td>
<td>-0.069***</td>
<td>0.224***</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.027)</td>
<td>(0.020)</td>
<td>(0.026)</td>
<td>(0.027)</td>
</tr>
<tr>
<td>Supervision '06</td>
<td>0.031**</td>
<td>0.689***</td>
<td>0.117***</td>
<td>0.086***</td>
<td>-0.012</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.027)</td>
<td>(0.020)</td>
<td>(0.026)</td>
<td>(0.027)</td>
</tr>
<tr>
<td>Initiative '06</td>
<td>-0.075***</td>
<td>0.075***</td>
<td>-0.094***</td>
<td>0.772***</td>
<td>0.049*</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.027)</td>
<td>(0.020)</td>
<td>(0.026)</td>
<td>(0.027)</td>
</tr>
<tr>
<td>Pat. Rec. '06</td>
<td>0.018</td>
<td>-0.044</td>
<td>0.047**</td>
<td>0.010</td>
<td>0.657***</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.027)</td>
<td>(0.020)</td>
<td>(0.026)</td>
<td>(0.027)</td>
</tr>
<tr>
<td>Teamwork '06</td>
<td>-0.061***</td>
<td>0.057**</td>
<td>0.783***</td>
<td>-0.074***</td>
<td>-0.003</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.027)</td>
<td>(0.020)</td>
<td>(0.026)</td>
<td>(0.027)</td>
</tr>
<tr>
<td>Math '06</td>
<td>-0.134***</td>
<td>0.179***</td>
<td>-0.170***</td>
<td>-0.073***</td>
<td>0.189***</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.027)</td>
<td>(0.020)</td>
<td>(0.026)</td>
<td>(0.028)</td>
</tr>
<tr>
<td>(Intercept)</td>
<td>-0.022*</td>
<td>-0.058**</td>
<td>0.087***</td>
<td>-0.021</td>
<td>-0.074***</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.027)</td>
<td>(0.020)</td>
<td>(0.026)</td>
<td>(0.027)</td>
</tr>
<tr>
<td>R²</td>
<td>0.890</td>
<td>0.517</td>
<td>0.720</td>
<td>0.574</td>
<td>0.513</td>
</tr>
</tbody>
</table>

**Note:** $N = 673$. * 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 explores the nature of intensive changes in skill demand, i.e., 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 - changes in demand for occupations with particular skills - which would likely bias our results toward zero. As a result, our findings are probably conservative relative to the actual intensive-margin changes.

In the results section, we examined intercepts in Model II to assess the changes in occupational requirement for each skill. Figure 2 shows these effects using the changes in means between 2006 and 2014 for our consistent factor scores. On average, occupations in 2014 have significantly higher requirements for Supervision, Math, and Pattern Recognition than in 2006, as well as significantly lower requirements for Teamwork. This pattern is qualitatively similar to the intercept coefficients of Model II.

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.

Teamwork shows a negative intercept in Model II and a negative shift in Figure 2. On average, occupations require less of these skills in 2014 than they did in 2006. The data are consistent with the hypothesis that, for well-defined tasks, technologies have been developed over the 2006-2014 period to substitute, in part, for humans interacting with other humans. This may be surprising because computers have not shown much progress toward the tasks associated with “interpersonal jobs” like sales, childcare, or nursing. At least for now, computers are noticeably less able to show social orientation, interpersonal cooperation, adaptability, or concern for others in the way humans can.

However, it is important to remember that substitution is not replication (e.g., assembly line for artisanal craftsmanship, laser printing for calligraphy, motion detection for patrolling, etc.). In the case of interpersonal skills, self-service apps and websites can now substitute for many personal interactions at a cost advantage when the only nonroutine part of the task is interacting with the other person.9 The significantly negative intercept term of -0.073 (and negative shift of -0.072 in Figure 2) on Teamwork shows the degree to which the average occupation now requires less of this formerly human-only skill.

Progress is now being made toward replicating other human interpersonal capabilities. 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). Virtual assistants, such as Siri and x.ai, are performing many of tasks that were formerly the domain of research assistants, librarians, and secretaries. As these and other technologies take hold, we might expect further erosion in the interpersonal content of the average occupation.

9 An important part of this shift is that people have become willing to meet the computer part way. Over time, people have become accustomed to phrasing requests so they are easier for a machine to understand (Branigan et al., 2010).
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. For example, tax advisors now have programs to assist with their calculations and queries, enabling them to do work faster and more accurately than before. Architects spend less of their time coordinating draftsmen and more time advising clients and creating designs.

We hypothesized that pattern recognition and supervision skills would display this effect. The analysis shows support for both hypotheses.

For Pattern Recognition skills, while computers compete directly with entry level tasks in many white-collar occupations (calculations for bookkeepers, “tweening” for animators, searches for legal aides, etc.), the technological cost reduction of those tasks amplifies the value of an occupation that uses them as inputs. For example, placing advertisements is now a largely technology-assisted job, with search engines’ tools doing many routine tasks while also providing performance information to help marketers make better choices about where to run ads. The need for this type of strategic thinking and exception handling has apparently spread from management roles into a much broader class of occupations. The intercept term of 0.124 on Pattern Recognition in Model II (and the positive shift of 0.124 in Figure 2) indicates an increase in demand for this category of skills among human workers.

A similar explanation can be proposed for complementarity with the Supervision factor. Rather than substituting for supervisory skills over the 2006-2014 period, computers appear to have complemented many of those skills. Computerized workflow tools improve process coordination among individuals, replacing routine activities performed formerly by supervisors. Electronic communication via email and conferencing reduces frictions in coordinating groups of individuals. Real time information on process status, customer satisfaction, and other organizational measures enhances managers’ ability to adjust processes and evaluate employee performance.

Theory was equivocal on the relationship between technological innovation and Math-related skills. The effect could have been one of substitution or complementarity. The significant positive intercept of Model II(g), and the strong positive shift in Figure 2 indicate that, at least for the 2006-2014 time period, the effect was one of racing with the machine rather than racing against it.

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, average occupational content of these skills has been largely unchanged. During the 2006-2014 period, occupations depending upon Initiative and Awareness skills have apparently had the least impact from technology, although it would incorrect to infer that there has been no impact at all.

Although Hypothesis 1 predicted that Physical would be in a substitution state, the analysis shows a near-zero change in the average Physical content of occupations between 2006 and 2014. We suspect that the null result for Physical is because much of the technology/labor substitution in this area had already taken place by 2006, and additional substitution needed to wait for further technological advances. New technologies toward the end our sample period, however, indicate that this technological pause may be coming to an end. For example, robots that pick fruit, pack boxes and carry supplies are now becoming cost-competitive with human labor, and DARPA’s recent grand challenge identified robots that can eventually replace humans in dangerous fire and rescue contexts.

Skills associated with Awareness of one’s physical surroundings, clustering primarily in vehicle operators and security professionals, may have been in a similar period of technological pause during the period we studied. Many technology/labor substitutions for Awareness, such as two-way communication (Baker & Hubbard, 2003) and remote sensors like fire alarms and CCTV cameras, may have been in place before 2006. Here, too, recent advances in autonomous vehicles and visual processing threaten to end the pause in technological substitution for Awareness skills.


**Initiative**, it seems, is the only human skill likely to remain unaffected by machines for the foreseeable future.

**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 resulted in a different set of dimensions in each period. Despite the relatively short 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 through examining intercepts, and its off-diagonal parameters indicate changes in complementarities between skills. Model III provides additional insight into changes in these complementarities. 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.

Five of the seven dimensions that differentiated occupations in 2006 are still relevant in 2014, although the constituent items have changed slightly. The items defining the other two factors, Awareness and Math, have become correlated enough with the remaining five factors that they ceased to be distinct dimensions that characterized jobs in 2014. Specifically, Awareness has become most strongly associated with Physical and Pattern Recognition skills, and anticorrelated with Teamwork. Math has become most strongly correlated with Supervision and Pattern Recognition skills and anticorrelated with Physical and Teamwork skills. Both are anticorrelated, though to a lesser degree, with Initiative.

Brynjolfsson and Milgrom (2013) state that increased correlation can be evidence of complementarities (their “correlation test”). For example, managing resources and analyzing statistics were considered distinct job roles but recently the surge in evidence-based decision-making has surfaced significant value in people who are competent in both. It is now more common to expect managers to analyze data and (what are now called) data scientists to champion solutions. The simultaneous anticorrelations with Teamwork paint a picture of both skills migrating from team-based to individual roles, with Awareness complementing blue collar and Math complementing white collar occupations.

The malleability of dimensions over the past eight years indicates that specialization in certain skills may be detrimental for human workers in the long term. In the past, hyper-specialization on math could have been a differentiating role. However, such specialization may be less useful for all but the most-expert workers, as Math skills have become more broadly applicable across occupations. This does not mean that all hyper-specialization loses value, but that, on average, the market may be placing an increasing value on people with multiple complementary skills.

Table 3 also reveals additional evidence that workers may need more flexibility in the future. For any given skill one can think of, some computer scientist somewhere may already be trying to develop an algorithm to do it. Workers – especially those with many years left in their careers – should be agile in developing new skills or finding occupations with new complementarities.

**Conclusion**

Perhaps the most important challenge facing advanced economies today is the economic dislocation reflected in stagnating 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, the locus of technological advance has expanded beyond automation to also include cognition. In the past, laborers and factory workers were threatened, but now lawyers and journalists are. And yet, these new technologies could augment human skills in addition to substituting for them. The effects of technology are highly diverse, affecting at least five distinct dimensions of skills. Moreover, the effects vary over time, which can explain the notable changes in occupational skill composition that 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 analyze, 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, rather than relying on a small number of skill measures identified ex ante, we let the data reveal seven orthogonal skill categories — including some novel dimensions -- that characterize more than 600 occupations in the United States.

Our approach — empirically deriving skill dimensions that are orthogonal by construction, and then comparing changes in those dimensions over time — is useful. However it is not without limitations. In particular, identification of the skill dimensions depends on accuracy in the detailed skill measurements in the O*Net database. Furthermore, our assessment of change in occupational skill requirements assumes that the government has maintained consistent measurement methods over the time span. In addition, our analysis examines change in skill demand only on the intensive margin, not the extensive margin. For example, while we find that the average job, as measured by the O*net database, requires less teamwork skill in 2014 than in 2006, this does not mean that the economy at large is demanding fewer jobs with teamwork skills. Further analysis of extensive demand is a topic for future research.

By identifying new skill dimensions such as Initiative, and highlighting the importance of others such as Supervision and Teamwork 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 four of seven skills within jobs 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 also 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 mathematics. In 2006, this skill was statistically visible as an orthogonal principal component. However, by 2014, it appears to have diffused into expectations that many white-collar occupations require some facility with mathematics and interpreting numerical data. Awareness suffered a similar fate, disappearing into other dimensions rather than remaining a distinguishing feature of occupations.

We also found significant increases over the 2006-2014 period in the importance of Pattern Recognition, Supervision, and Math skills within occupations, and decreases in the importance of Teamwork. These are in line with our theoretical expectations and with some case studies of changes in particular technologies or occupations over the period studied. However, the analysis also produced information we did not expect. For example, we found counterintuitive evidence that the level of substitution of technology for human physical skills plateaued during the period studied, although recent technological advances may spur a new wave of substitution in the near future.

Because many digital technologies advance rapidly, 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. This suggests that labor market disruption — and concomitant positive or negative changes in the demand for skills like awareness, supervision, teamwork, and initiative — may increase in the future. The disruption is an opportunity for organizations, but may be a threat to many workers. Researchers, managers and policymakers must understand the dynamics behind these changes if they are to prescribe effective solutions. Novel conceptualizations and large-scale quantitative analysis, such as those provided in this paper, will be important contributions to that kind of understanding.
Acknowledgements

The authors would like to thank Susan Young and the anonymous reviewers for helpful comments that greatly improved this paper. The Masdar Institute & MIT Collaborative Program and the MIT Initiative on the Digital Economy provided generous funding for this research.

References


