The Nature of Technological Change 1960-2016*

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Abstract

We present a unified technological explanation of both the movement of workers across jobs using different skills and the changes in skill use within jobs. An envelope-theorem approach allows us to estimate relative skill-productivity growth from worker mobility using OLS while making minimal assumptions on each occupation's production function. Using six decades of data, we conclude that routine-cognitive- and finger-dexterity-skill productivity grew rapidly and abstract- and social-skill productivity grew slowly - a form of "skill bias." These effects, along with our estimated relationships between skill inputs, also explain changes in skill use within occupations.

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1 Introduction

Often technological change modifies how jobs are done rather than eliminating them outright. The IBM Selectric was an electronic typewriter. Its introduction in 1961 affected secretaries, whose primary tasks were typing, planning, and communicating. The Selectric replaced jam-prone typebars with a golf-ball-like element and, in later versions, was even "self-correcting." This made typing much more productive. Secretaries could now produce typewritten pages much faster; thus, fewer secretaries were needed to type the same number of pages. Hence, secretaries shifted *between* occupations toward less typing-intensive jobs. But just as importantly, secretaries reduced their time spent typing and instead did more planning and communicating, leading to *within*-occupation skill shifts.

We develop a transparent structural model that links changes in the productivity of individual skills to changes in skill use both within and between occupations. Relying only on readily observable variables and employing mere ordinary least squares and weighted means, our framework extracts skill-productivity changes from worker-mobility patterns between occupations with different skill use. We use these productivity changes to explain skill-use shifts within occupations, en passant deriving the complementarity and substitutability of skills with respect to their own and other skills' productivities - analogous to elasticities.

We study the US labor market since 1960. We reproduce the stylized fact that workers in this period moved away from routine- (both cognitive and manual) and manual-intensive occupations. In the first part of our study period (1959-83), workers move into nonroutine-cognitive-intensive occupations, both abstract and social-intensive. In contrast, in the second part (1995-2017), the shift occurs only toward social-intensive occupations, consistent with Deming [2017], who first highlighted the growing importance of social skills in an overlapping period. We also show that *within*-occupation, social-skill use grew while routine-skill (both cognitive and manual) use fell. For abstract-skill use we observe an increase in the first half of our period and a decrease in the second half. These within-occupation shifts frequently dwarf the between-occupation moves that dominate the literature. The pattern for manual-skill use is less consistent, but use fell in most periods.

Our formulation explains shifts across occupations by rapid productivity growth of routine skills and slow productivity growth of abstract and social skills. Our approach allows us to infer that complementarities with respect to other skills consistently explain a large proportion of skill use shifts for most skills and periods. The slow productivity growth of the social skills explains the increased within-occupation use of these cognitive skills throughout the period we study. Similarly, the fast growth of the two routine skills' productivity explains their reduced use within occupations. Perhaps surprisingly, the fast growth of routine-skill productivity partially offset the growth of abstract-skill use within occupation, and the slow growth of the cognitive skills' productivity offset some of the within-occupation decline in routine-cognitive skill use.

How does one compute skill-productivity changes? This would be straightforward if technological change did not affect how jobs are done. We could simply measure the number of pages a typical secretary typed before and after the Selectric. However, within-occupation shifts are a confounding factor. Secretaries became more productive typists but also altered their use of typing and other skills; perhaps they shifted to abstract skills to plan or social skills to communicate. In this case, we would underestimate the Selectric's effect on typing productivity.

We circumvent this problem by deriving a "first-order" approach that relates changes in employment to the levels of skill initially used in each occupation. Assuming that demand for different outputs is relatively inelastic, as we argue is likely, employment will fall in occupations that are intensive in their use of skills whose productivity is increasing more rapidly than average. We show how this allows us to estimate the relative productivity growth of different skills.

We combine these skill-productivity growth estimates with our estimates of skill complementarity/substitutability to uncover how skill acquisition responds to skill-productivity changes. We identify these cross-derivatives despite minimal assumptions on occupational production functions.

In our model, workers first choose skills and then occupations. Each occupation has its own production function, which maps a worker's skills to the output produced. Outputs are specific to each occupation. We allow for skill-enhancing technological change, a form of "skill bias," but leave open the character of the change. The Selectric's arrival boosts typing productivity, increasing the number of typed pages. However, whether workers respond by supplementing their typing skills depends on each occupation's elasticity of skill substitution. Typing might decline for secretaries but increase for economists (alas). Employment in typing-intensive jobs can rise or fall; if demand for their output is relatively inelastic, employment is likely to decrease.

We also allow for shifts in output demand (possibly due to trade shocks) or outside competition (possibly due to offshoring) that alter demand for workers with different skills. The model thus clarifies the distinction between technological changes to the productivity of individual skills and changes to demand for particular kinds of workers.

We use an analog of Roy's identity to show that the sensitivity of output to a skill's productivity is proportional to the amount of that skill workers possess, a readily observable quantity. Assuming output demand varies by industry, not occupation, allows us to separate the employment effects of technology and demand. We decompose occupational employment shifts into (elasticity-weighted) productivity-change-weighted skill-use terms and shifts in output demand.[1]

We then use our estimated changes in relative skill productivity to understand how workers' skills in each occupation evolve over time. This enables us to use changes in skill use *within* occupations to evaluate the results of our first exercise. We express within-occupation changes in skill use as products of skill-productivity changes and matrices representing the technological substitutability of skills within an occupation. Using Slutsky symmetry, we reduce the estimands to a manageable number.

To estimate the model, we use the skills studied by Autor et al. [2003] and measured in the *Dictionary of Occupational Titles*, using the third edition for skill use in 1960, the original fourth edition for 1971, and the revised fourth edition for 1983. We combine these measures with data from the Current Population Surveys and Censuses to measure between- and within-occupation changes in skill use from 1960 to 1983. We also create[2] and use skill measures from the 3.0, 12.0, and 22.2 versions of the O*NET. We combine those measures with data from the Current Population Surveys, American Community Surveys, and censuses to measure between- and within-occupation changes in skill use from 1995 to 2016. We focus on changes within each of the periods covered by the *DOT* and O*NET. For reasons discussed in the text, we are skeptical of changes occurring during the transition between the two sources.

Within data sets, our estimates of relative skill-productivity growth are broadly similar across periods. Unsurprisingly, the magnitudes differ between *DOT* and O*NET, given the difference in how skills are measured. Nevertheless, the broadly similar pattern of skill-productivity growth in the two data sets is reassuring. Both show routine-cognitive- and finger-dexterity-skill productivity growing much more rapidly than abstract- and social-skill productivity, with manual-skill productivity falling in between.

In brief, while confirming prior work that focuses on technological change that reduced the demand for routine-intensive work by increasing the productivity of those tasks, we establish an equally important role for the slow growth of abstract- and social-skill productivity and, to some extent of manual-skill productivity.

Still, there is a strong sense in which our approach is orthogonal to the exercises conducted by Autor et al. [2003] and Goos et al. [2014]. They use the routine intensity of occupations to measure the vulnerability to technological change and study its relation to employment

[1] We assume that the outputs of individual occupations are globally aggregated using a CES specification, though our results can readily be extended to nested CES setups.

[2] Except for finger-dexterity skills, for which the same variable is available in both the *DOT* and the O*NET

changes. Instead, our approach leverages employment changes to identify the relevant technological change. Autor et al. [2003] observe the correlation between computerization and the performance of routine tasks and show that this type of technological change can provide relevant insights into changes in employment in the United States. Goos et al. [2014] study the role of routine-biased technological change and offshoring in explaining changes in employment in 16 European countries, providing evidence of a much bigger role played by the former.

Our skill-based occupation-specific production model cannot be nested in a task-based model, the approach used by Autor et al. [2003], Acemoglu and Autor [2011], and Acemoglu and Restrepo [2018]. The Selectric did not replace typists or substitute for typing outputs. If anything, the demand for typed pages increased after the Selectric's introduction. Neither did the Selectric make high-skilled labor uniformly more productive or more in demand, as in the canonical SBTC models (Katz and Murphy [1992], Berman et al. [1994], Berman et al. [1998], Juhn [1999]). Instead, it simply increased the speed at which everyone could type - changing the productivity of only one skill secretaries used in production.

Kogan et al. [2021], too, adopt an approach orthogonal to ours. They create a measure of the similarity between the technology introduced by patents and the tasks performed in an occupation as a proxy for exposure to technological advances and use it to study its association with changes in employment and wages over a time span of almost two centuries. Bárány and Siegel [2020] estimate productivity change down to the sector/occupation level, assuming that each occupation uses only a single skill. In contrast, our occupations mix different skills in different amounts, and we account for sector-level demand. Acemoglu and Restrepo [2019] feature the emergence of entirely new occupations; our analysis is based only on the *relative* employment in existing occupations and is thus not influenced by such occurrences.

We depart from the skill-weights approaches of Lazear [2009], Gathmann and Schönberg [2010], and Cavounidis and Lang [2020] by allowing the production function translating skills or tasks into output to be a general constant-returns-to-scale neoclassical production function. The earlier papers assume that output in each occupation is a linear function of skills, with occupation-varying weights. While Yamaguchi [2012] uses a somewhat more general specification for determining wages, it, too, makes wages in each occupation a linear function of the worker's skills. Moreover, Yamaguchi [2012] limits the analysis to cognitive and motor tasks. In addition, these papers focus on mobility across occupations and skill acquisition, either by investment or learning by doing, among individual employed workers. We abstract from the latter and focus on labor market equilibrium.

We are not the first to look at within-occupation changes in skill use. Spitz-Oener [2006] and Black and Spitz-Oener [2010], using German data, and Deming and Noray [2020], using Burning Glass data, track significant within-occupation shifts in skill use, but for a later period. Atalay et al. [2020], using keyword frequencies from three newspapers' job ads over an impressively long period, show that within-occupation changes account for most task variation over time. It is an open question as to how representative these ads are. The paper by Consoli et al. [2023] is closest to ours. It examines within-occupation changes in routine-task intensity (RTI) from 1980-2010. Much of their paper focuses on reconciling the *DOT* and O*NET measures so that they can examine changes between 1990 and 2000 (or more precisely, between the 1991 revision of the 4th edition of the *DOT* and the 2000 O*NET version 3.0). In our preliminary work, we, like them, found a large shift in within-occupation skill use when shifting between the two sources. We have, therefore, chosen to exclude this period from our analysis. Most significantly, we develop a model to help us interpret the results and apply it to a very long period. Like us, Freeman et al. [2020] detect within-occupation changes in O*NET skills but over a shorter period and using quite different measures. We confirm and explain the finding that most of the changes in the O*NET period took place within jobs. Autor and Price [2013] also study a very long period but do not allow for within-occupation changes in skill use.[3]

This paper can be read in two ways. Those interested solely in a better accounting of the changes from 1960 to 2016 can jump to the data section and then examine Tables 1 and 2 and the accompanying text in the results section. We think this analysis is a contribution in its own right. However, we are hopeful that readers will find that the model presents a simple, versatile framework allowing for different kinds of technological shocks and, therefore, assists in thinking about our results and the large literature in this area.

2 A model of skill and job choice in general equilibrium

2.1 Skill acquisition and intermediate good production

Before employment, each worker chooses a vector of skills $S \in \mathbb{R}^n_+$, where each component S_i reflects ability at task i. Once workers have acquired skills, each chooses a job $J \in \mathcal{J}$, where $\mathcal{J}$ is the set of all jobs. If a worker with skills S is employed at job J, she produces a quantity $y((A_i S_i)_{i \leq n}, J)$ of intermediate good J, where each $A_i > 0$ is common to all jobs and is a measure of the general productivity of skill i. Thus, each $A_i S_i$ is the "effective" amount of input i, and output y depends on the vector of effective inputs $(A_i S_i)_{i \leq n}$.

[3] Autor et al. [2003] examine the relationship between computer use and within-occupation change in task use between the 1977 and 1991 revisions of the *DOT* but do not discuss the magnitudes of these changes.

We place as little structure on $\mathcal{J}$ and y as possible. We assume only that $\mathcal{J}$ is a compact subset of a Euclidian space, that $y(\cdot, J)$ is a constant-returns standard neoclassical production function,[4] and that y is continuous.

For simplicity, we assume that workers have a fixed budget for skills, which we normalize to 1, so that for any individual $\Sigma_i S_i = 1$. This assumption captures the idea that a worker can study plumbing or philosophy, but if she chooses to spend more time on philosophy, she must spend less time learning plumbing. Allowing her to choose time spent learning could affect the comparative statics on total production through a labor/leisure/learning trade-off. However, it would only affect the effective number of labor units each worker provides. With a constant-returns-to-scale aggregate production function, it would not affect the objects of interest to us.

A worker who anticipates holding job J will therefore

$$\max_{S \geq 0} y((A_i S_i)_{i \leq n}, J) \tag{1}$$

$$\text{subject to} \sum_i S_i = 1. \tag{2}$$

The optimal $S^*(J)$ and $y^*(J) := y((A_i S_i^*(J))_{i \leq n}, J)$ are given by solving the Lagrangian. The Lagrangian's first-order condition at the optimum with respect to any S_i is

$$A_i y_i'((A_i S_i^*(J))_{i \leq n}, J) = \lambda = y^*(J) \tag{3}$$

where the second equality follows straightforwardly from constant returns to scale. We assume that workers always have skills that are optimal for the job they perform. Although this assumption is strong, we maintain that in the sort of timescales our empirics cover, workers will, at the least, endeavor to develop the right skills for the careers they select. Allowing for investment while employed, as in Cavounidis and Lang [2020], would make this a sensible assumption for workers not too far advanced in their work lives.

How do optimal output and skills change with A? From the envelope theorem,

$$\frac{\partial y^*(J)}{\partial A_i} = S_i^*(J) y_i'((A_i S_i^*(J))_{i \leq n}, J) \tag{4}$$

[4] $y(\cdot, J)$ is strictly increasing in each $A_i S_i$ on $\mathbb{R}^n_{++}$, is twice continuously differentiable, features a bordered Hessian with non-vanishing determinant on $\mathbb{R}^n_{++}$, is strictly quasi-concave, and $y((A_i S_i)_{i \leq n}, J) = 0$ iff $A_i S_i = 0$ for some i. This would imply that optimal skills are continuously differentiable in A and, more importantly, interior. If skills are quite occupation-specific, e.g., plumbing or surgery skills, this may be a bad assumption; however, the skills used in our empirical section are relatively general. We thus think that excluding corner solutions is unproblematic for our application.

so that substituting for y_i' using (3), we get

$$\frac{\partial \ln y^*(J)}{\partial \ln A_i} = S_i^*(J). \tag{5}$$

This is effectively an application of Roy's identity, with our skill constraint playing the role of the budget constraint in standard utility maximization.

To speak sensibly about the effect of changes in A on $S^*(J)$, we proceed by inspecting $y(\cdot, J)$'s i-j elasticity of substitution for any two inputs at the optimum

$$\sigma_{i,j}((A_i S_i^*(J))_{i\leq n}, J) = \frac{\partial ln \left(\frac{A_i S_i^*(J)}{A_j S_j^*(J)}\right)}{\partial ln \frac{A_i}{A_j}} = 1 + \frac{\partial \ln(S_i^*(J)/S_j^*(J))}{\partial \ln(A_i/A_j)} \tag{6}$$

which we can rearrange as

$$\frac{\partial \ln(S_i^*(J)/S_j^*(J))}{\partial \ln(A_i/A_j)} = \sigma_{i,j}((A_i S_i^*(J))_{i\leq n}, J) - 1. \tag{7}$$

Thus, if inputs i and j are gross substitutes (complements) in job J at the optimal skill bundle, a relative increase in the productivity of skill i will cause workers to acquire relatively more (less) of it. If all inputs are gross substitutes (complements) in job J at the optimal skill bundle, the constraint that $\sum_i S_i^*(J) = 1$ further implies that $\frac{\partial S_i^*(J)}{\partial A_i} > 0$ (< 0).

2.2 Final good production and worker allocation

So far, the model somewhat resembles the model in Cavounidis and Lang (2020) in the sense that workers are aligning their skill choices and occupation choices. We extend it by assuming that instead of goods of intrinsic value, workers produce inputs in a CES final good production function

$$Y(q) = \left[\int_{\mathcal{J}} h(J) q(J)^{\varepsilon}\right]^{\frac{1}{\varepsilon}}. \tag{8}$$

Here, $h(J)$ is the relative importance of input J for final production, and $q(J)$ is the total quantity of intermediate good J used as an input. We assume h is continuous. The economy has workers of total measure 1, and each worker acquires skills, subject to the constraint, and may choose any job in $\mathcal{J}$.

The model satisfies conditions under which the decentralized equilibrium is Pareto efficient. Therefore, we solve for the equilibrium by solving the planner's problem subject to the skill acquisition and worker measure constraints. Efficiency implies that workers producing good J will all be identical and acquire skills $S^*(J)$; therefore, $q(J) = y^*(J)f(J)$, where $f(J)$ is the density of workers assigned to producing intermediate good J.

Therefore, we can write the planner's problem as

$$\max_f \left[\int_{\mathcal{J}} h(J)\left[y^*(J)f(J)\right]^{\varepsilon}\right]^{\frac{1}{\varepsilon}} \tag{9}$$

$$\text{subject to} \quad \int_{\mathcal{J}} f(J) = 1. \tag{10}$$

We can then pointwise differentiate the Lagrangian and obtain

$$h(J)y^*(J)^{\varepsilon}f(J)^{\varepsilon-1} = h(J')y^*(J')^{\varepsilon}f(J')^{\varepsilon-1}, \tag{11}$$

which we can write as

$$f(J)h(J')^{\frac{1}{1-\varepsilon}}y^*(J')^{\frac{\varepsilon}{1-\varepsilon}} = f(J')h(J)^{\frac{1}{1-\varepsilon}}y^*(J)^{\frac{\varepsilon}{1-\varepsilon}} \tag{12}$$

so that we can now integrate out J' and using constraint (10) get

$$f(J) = \frac{h(J)^{\frac{1}{1-\varepsilon}}y^*(J)^{\frac{\varepsilon}{1-\varepsilon}}}{\int_{\mathcal{J}} h(J')^{\frac{1}{1-\varepsilon}}y^*(J')^{\frac{\varepsilon}{1-\varepsilon}}}. \tag{13}$$

2.3 Comparative statics

We consider the effect of technological progress that is broadly skill enhancing, as measured by A, and changes in the demand for intermediate goods, as measured by h. The distinction is imperfect. For example, the reduction in transportation costs, at least partly due to technological change, reduced demand for some locally produced intermediate goods that had hitherto been too expensive to import. Still, we think of changes in A as capturing broad-based technological progress, such as electronic calculators rather than adding machines for routine-cognitive skills and electric rather than manual drills for manual skills, and h as capturing the effects of trade and, more recently, robots.

2.3.1 The effect of skill-augmenting technological change

What happens if skill i becomes more productive? Taking the derivative of (13) with respect to A_i gives

$$\frac{\partial f(J)}{\partial A_i} = \frac{\varepsilon}{1-\varepsilon}f(J)\left[\frac{\partial \ln y^*(J)}{\partial A_i} - \int_{\mathcal{J}} \frac{\partial \ln y^*(J')}{\partial A_i}f(J')\right] \tag{14}$$

or simply, using (5),

$$\frac{\partial \ln f(J)}{\partial \ln A_i} = \frac{\varepsilon}{1-\varepsilon}\left[S_i^*(J) - \int_{\mathcal{J}} S_i^*(J')f(J')\right]. \tag{15}$$

In other words, if and only if the elasticity of substitution among intermediate goods $1/(1-\varepsilon)$ is less than 1, will an increase in the productivity of skill i move workers away from jobs where it is used more than average, and toward jobs where it is used less than average. So, for example, if routine-cognitive skill is a complement to other skills in intermediate good production, and intermediate good demand is inelastic, an increase in A_R (a technological change that makes routine-cognitive skill more productive) will (a) reduce routine-cognitive use in all jobs (within) and (b) shift workers to less routine-cognitive-intensive jobs (across).

The idea that sectors experiencing slower productivity growth also experience faster employment growth is an old one (Baumol [1967]; see also Ngai and Pissarides [2007] and Acemoglu and Guerrieri [2008]). We build on that idea. In our case, jobs that make more use of skills whose productivity grows slowly will experience more employment growth.

2.3.2 The effect of changes in demand for intermediate goods

What about changes in h? In our setup, these will move workers around but not affect skill use within a job. A decrease in the demand for horseshoes merely alters how many people shoe horses, not how they shoe them.

To see the effect of changes in h on employment, we take the log of each side in (13) and totally differentiate to get

$$d\ln f(J) = \frac{1}{1-\varepsilon} d\ln h(J) + \frac{\varepsilon}{1-\varepsilon} d\ln y^*(J) - d\ln\left(\int_{\mathcal{J}} h(J')^{\frac{1}{1-\varepsilon}} y^*(J')^{\frac{\varepsilon}{1-\varepsilon}}\right). \tag{16}$$

For a change in h, the second term in (16) is 0 and the third term does not depend on J. A few manipulations yield

$$d\ln f(J) = \frac{1}{1-\varepsilon}\left[d\ln h(J) - \int_{\mathcal{J}} d\ln h(J') f(J')\right]. \tag{17}$$

Thus, the percentage employment growth in job J is proportional to the deviation of the percentage change in $h(J)$ from the employment-weighted average.

2.3.3 Putting it all together

Combining (15) and (17), we have

$$\begin{aligned} d\ln f(J) &= \frac{\varepsilon}{1-\varepsilon}\sum_i \left[S_i^*(J) - \int_{\mathcal{J}} S_i^*(J') f(J')\right] d\ln A_i \\ &\quad + \frac{1}{1-\varepsilon}\left[d\ln h(J) - \int_{\mathcal{J}} d\ln h(J') f(J')\right]. \end{aligned} \tag{18}$$

The model distinguishes between changes that replace (or reduce demand for) occupations by automating or offshoring them (a decline in h), such as when data input is imported from abroad, and those in which technology makes relevant skills more productive, such as when keypunch machines are replaced by input at computer terminals. When h declines, the number of workers employed in data entry in the home country falls, but any workers engaged in data input continue to input data using the same skill set. Suppose the productivity A_i of a skill i important to data entry increases. If skill inputs are complements of data entry and intermediate-good demand is inelastic, workers in data-entry jobs end up with less skill i, and fewer workers are hired to input data.

Interpreted within our model, Autor et al. [2003] found that, in the period they study, technological innovation increased the productivity of routine skills. Since the demand for these skills was inelastic, the amount of time individual workers spent on them declined as did total employment in routine-intensive occupations. Our interpretation of the longer period that we study will be that the productivity of abstract- and social-skill use did not increase as rapidly as that of routine-cognitive and finger-dexterity skill. This caused a shift toward abstract- and social-skill use because the elasticity of substitution between intermediate goods is less than 1, thereby shifting employment to abstract and social-skill-intensive occupations. Within occupations, declining relative abstract- and social-skill productivity shifted skill use within occupations toward these nonroutine-cognitive skills overall, while increasing relative routine-skill productivity (routine cognitive and finger dexterity) shifted skill use away from routine-cognitive skill.

We note that our model assumes *ex-ante* identical workers. In a richer model with *ex-ante* heterogeneous workers, changes in demand might alter how jobs are done. Intuition suggests that workers "better at routine-cognitive tasks" do jobs more routinely than other workers. In such a world, a reduction in demand for routine-cognitive-intensive outputs *would* shift such workers to less-routine jobs, and those workers would then perform those jobs *more* routinely than before, which is the reverse of what we observe.

2.4 Implications for empirical work

For empirical analysis, we rewrite (18) as

$$\Delta \ln(emp_{I,J}) = \frac{\varepsilon}{1-\varepsilon}\Sigma_i \left(d \ln A_i \left(S_{i,J} - \overline{S}_i\right)\right) + \gamma_I + \mu_{I,J} \tag{19}$$

where $\Delta \ln(emp_{I,J})$ is the change in the employment level in industry I in occupation J, the empirical counterpart of $f(J)$, and γ_I is the coefficient on an industry dummy that captures changes in demand due to shifts in industry demand. We note that this is an imperfect proxy for changes in h. It will capture changes in demand for an occupation resulting from, for example, import competition but not changes due to occupation-specific factors such as robots, although we note that robot penetration is typically measured at the industry or broad geographic level. We measure $S_{i,J}$ by its average in two proximate editions of the *DOT* or O*NET. μ is a mean-zero error term. We estimate (19) separately for each time-period pair.

Since each worker's skills sum to 1, skill use on a job sums to 1, as does mean skill use. Therefore, (19) still applies if we add a constant term to each $d\ln A_i$; we choose to subtract $\overline{d\ln A}$, the mean change. We thus rewrite (19) as

$$\Delta\ln(emp_{I,J}) = \frac{\varepsilon}{1-\varepsilon}\Sigma_i\left(\left(d\ln A_i - \overline{d\ln A}\right)\left(S_{i,J} - \overline{S}_i\right)\right) + \gamma_I + \mu_{I,J} \tag{20}$$

$$= \frac{\varepsilon}{1-\varepsilon}\Sigma_i\left(\left(d\ln A_i - \overline{d\ln A}\right)S_{i,J}\right) + \gamma_I + \mu_{I,J} \tag{21}$$

$$= \Sigma_i S_{i,J}\beta_i + \gamma_I + \mu_{I,J}. \tag{22}$$

Equation (22) describes a regression of the (approximate) percentage change of employment in an occupation/industry cell on the skills used in that occupation and industry dummies. The coefficients show the change in each skill's productivity relative to the average up to a factor of proportionality. This factor is negative if the elasticity of substitution between intermediate goods is less than 1, which we assume. Thus, a *negative* coefficient means that the productivity of that skill grew *faster* than the average of all the skills.

Although derived quite differently, our final equation is similar to the one in Goos et al. [2014]. Their theoretical model includes wages in the equivalent of (22), which they proxy by industry-year and occupation dummies.[5] Since we first-difference the data and estimate the model separately for each pair of years, we implicitly control for occupation and year while explicitly controlling for industry. They also use an alternative specification in which they explicitly control for wages but do not include it in the main text as there are concerns about endogeneity. While we agree with such concerns, we perform the same exercise and observe that the inclusion of wages does not alter the outcome of our analysis.[6] The major difference in our specifications is that they include only routine-task intensity and not the other skills but also include a measure of offshorability.

Assuming an elasticity less than 1 seems natural. As Jones [2011] notes in a somewhat different context, intermediate goods are unlikely to be substitutes. As he puts it, computers are close to essential for producing some goods. Consistent with this argument, Goos et al. [2014] estimate that the elasticity of substitution across industry outputs is 0.42. Our case is

[5] We ignore the country component since we study only one country.

[6] We do not model wages in our current framework. A case for their inclusion could be made if we assumed the labor supply to an occupation to be elastic but not infinitely elastic. However, this is unnecessary given that empirically, wages do not affect our results (Table 2A).

even stronger; the outputs of secretaries, sales workers, plumbers, and truck drivers cannot easily substitute for each other. Note that this differs from the statement that someone working as a secretary might be almost as productive if he worked in sales. This is entirely plausible in our model if the required underlying skills are close.

Note that we must drop a skill because the skills sum to 1. Therefore, we can interpret the coefficients as the growth rate of productivity of each skill relative to the excluded skill, again up to a multiplicative factor. Together with the requirement that the sum of the deviations from average productivity growth equals 0, this fully identifies the changes in relative productivity between skills.

Equation (22) addresses only changes in the productivity of skills and not shifts in the demand for occupations except through the inclusion of the two-digit industry dummies, in line with the effect of h in (17). Demand for occupations concentrated in industries facing import competition or declining demand will fall even absent technological change. Controlling for industry will capture employment losses due to import competition but not robots or outsourcing of specific occupations to other countries. We estimate (22) by ordinary least squares.

3 Data

Following Autor et al. [2003], our skill-use measures for the first part of our period come from the *Dictionary of Occupational Titles (DOT).* We use the third edition, issued in 1965 but compiled starting sometime after the release of the second edition in 1949, as our measure of skill use in an occupation in 1960, although it may be centered more on the late 1950s. To the best of our knowledge, the 1965 *DOT* has not been previously used for this type of analysis. We use the fourth edition, published in 1977 and based on data starting in 1965 for job use in 1970-72 ("1971"). Finally, we use the last revision of the fourth edition, based on revisions from 1977 to 1991 for skill use in 1982-84 ("1983"). The files for the 4th and revised 4th versions of the *DOT* come from Autor et al. [2003]. As others have noted, the revised fourth edition is not a "fifth" edition; many occupations were not revisited between the fourth edition and the revised 1991 edition because the revision addressed only occupations believed to have changed the skills they used. Therefore, we probably underestimate the extent of within-occupation changes in skill use between 1971 and 1983. However, we observe differences between the 4th and revised 4th editions for most of the occupations present in both 1971 and 1983.

For the second half of our time period, we follow Firpo et al. [2011] in relying on O*NET, the successor to the *DOT*, which was first issued in 1998. Since then, there have been multiple revisions of the O*NET. Each revision updates a subsample of occupations. We use version 3.0 issued in 2000 for skill use in 1994-96 (“1995”),[7] version 12.0, issued in 2007 for skill use in 2005-07 (“2006”) and the last before the Great Recession, and version 22.2, issued in February 2018 for skill use in 2015-17 (“2016”).

The *DOT* identifies aptitudes, temperaments, and abilities used in a job and measures them numerically. The O*NET identifies abilities, skills, work activities, and work contexts. In both data sets, observations are at the occupation-title level.

The 1965 *DOT* includes all of the skill-use (task) measures used in Autor et al. [2003]. With some small caveats discussed below, it recorded them on the same scales as the later edition, allowing us to have consistent skill measures. Of course, we cannot be sure that individuals interpreted the measures in the same way in the 1950s, 60s, and 70s, but we see no reason that this concern should be greater than for many measures used to compare time periods or geographies.

The one small change is that the earlier edition provides a single measure of “General Education Development,” while the later releases measure reasoning, mathematical, and language development separately. We experimented with using the average or the maximum of these three to generate a single measure comparable to the 1965 measure and checked whether this affected the correlation between the third- and fourth-edition measures. The correlations were similar. Looking across groups did not create a strong case for either. We present results using the average of the reasoning, mathematical, and language development measures for General Education Development in the 1977 and 1991 *DOT*s. In addition, the 1965 *DOT* sometimes provides more than one value of an aptitude, temperament, or ability for a single job title. In such cases, we use a simple average of the values reported.

Like Autor et al. [2003], we measure routine-cognitive skill using the variable “adaptability to situations requiring the precise attainment of set limits, tolerances, or standards”; finger-dexterity skill, which they call routine-manual skill by “finger dexterity”; manual skill by “eye-hand-foot coordination”; abstract-interactive skill, that we will call social skill, by “adaptability to accepting responsibility for the direction, control, and planning of an activity.” For our measure of abstract-cognitive skill, we use “General Education Development” rather than only its mathematical component to allow for consistency across all *DOTs*.

While the O*NET is the *DOT*'s successor, they have somewhat different variables and scales. We select variables present and measured consistently in all O*NET versions we use.[8] “Finger dexterity” is the only variable we used from the *DOT* that is also available

[7] We cannot use O*NET version 1.0 because its occupational classification cannot be aggregated to census occupations. We do not observe any differences in reported skill levels for those occupation titles common to 1998 and 2000. Hence, any changes in skills between the two versions probably reflect only different occupation classifications.

[8] As with the *DOT*, we cannot be sure that the measures were interpreted consistently over time but do

in the O*NET. We thus use it as our measure for finger-dexterity skill. In the absence of a perfect match between the two data sets, we measure manual skill by the average of "multilimb coordination" and "gross body coordination." We measure routine-cognitive skill by the average of "importance of being exact or accurate," "importance of repeating the same tasks," and "number facility." We measure social skill by the average of "guiding, directing, and motivating subordinates" and "developing objectives and strategies."

We measure the three components of General Education Development analogously to our measures from the *DOT* and average them. We use "mathematical reasoning" for the mathematical component; an average of "oral expression," "written expression," and "written comprehension" for the language component; and "critical thinking," "processing information," and "making decisions and solving problems" for the reasoning component.[9] For each census occupation, we use a weighted average (by employment share) of the skill used in the *DOT* or O*NET occupations comprising that census occupation.

For consistency with our theoretical model, we depart from Autor et al. [2003] and Autor and Dorn [2013] in how we use these measures. Autor et al. [2003] use the absolute value of each skill, while Autor and Dorn [2013] focus on routine intensity defined as ($RTI = ln(R) - ln(M) - ln(A)$).[10] Instead, we first scale the absolute level of each sub-component of skill use by where it lies between the maximum and minimum of that skill sub-component's use in any occupation over our three sample periods within each of the two data sets. Thus, use of the sub-component c in occupation J at time t is:

$$\widetilde{skill}_{c,J,t} = \frac{skill_{c,J,t} - skill_c^{min}}{skill_c^{max} - skill_c^{min}} \tag{23}$$

where $skill_{c,J,t}$ is the value obtained directly from the *DOT* or O*NET measures aggregated at the occupation level, and $skill_c^{min}$ and $skill_c^{max}$ are the minimum and maximum absolute values (at the occupation level) for skill sub-component c in any version of the *DOT* for *DOT* measures or O*NET for O*NET measures. We then average over the sub-components of skill i to obtain $\widetilde{skill}_{i,J,t}$, an intermediate measure of the use of skill i in job J in year t.

not see this as concerning.

[9]For more details on the chosen variables, see Table 3A.

[10]We, like everyone else in this literature, have to treat the ordinal measures in the *DOT* and the O*NET as measured on an interval scale. We do so with an unusual level of chagrin given that one of us has pointed out (Bond and Lang [2013], Bond and Lang [2019]) that findings can be sensitive to how an ordinal scale is converted to an interval scale. Unfortunately, the approaches in Bond and Lang are not available to us in this setting.

Finally, we compute the share of each skill in the overall sum

$$S_{i,J,t} = \frac{\widetilde{skill}_{i,J,t}}{\Sigma_k \widetilde{skill}_{k,J,t}} \tag{24}$$

so that our five skill measures sum to 1.

Census occupations are more highly aggregated than the *DOT's* and the O*NET's job titles. Following Autor et al. [2003], we use the *DOT*-augmented version of the April 1971 Current Population Survey for this aggregation in the first half of our period, since this is the only data set with both *DOT* and census codes. For the second part of our period, we use the Occupational Employment and Wage Statistics of the US Bureau of Labor Statistics,[11] which provide annual employment for each occupational title, as well as a crosswalk between occupational titles and census occupations.

We use the consistent occupation system created by Dorn [2009] and the crosswalk files provided by Autor and Dorn [2013], linking these occupations to previous census classifications. This gives us 192 occupations in the initial period, 259 in the second, 318 in the third, 316 in the fourth, 320 in the fifth, and 309 in the last period[12]. We create the occupation skill measures using occupation weights from all full-time workers not living in group quarters between ages 18 and 64 in the IPUMS 1960 5 percent sample, in the IPUMS 1970 1 percent State sample, the IPUMS 1980 5 percent sample, the IPUMS 2000 5 percent sample, and the 2005-2007 and 2015-17 ACS three-year samples.

Despite the tremendous insights that measures of these skills have provided, a non-negligible share of workers purportedly make no use of manual skills. In the first period, about 13 percent of workers do not use social skills, 9 percent do not use routine-cognitive skills, and 8 percent of workers do not use manual skills. Seven percent of workers do not use social skills in the second period. In the fourth and fifth periods, 5 and 9 percent of workers do not use manual skills. To address this latest issue and make sure that the decline in manual-skill use in our O*NET period was not driven by the share of workers who do not use it at all, we used an alternative definition for manual skill that included "Spend Time Using Your Hands to Handle, Control, or Feel Objects, Tools, or Controls," a measure that is not as closely related to the *DOT* original variable as the ones we selected but was used by Acemoglu and Autor [2011] and has only one occupation in 2006 reporting a value of 0 over the entire O*NET period. This change does not affect the patterns of the shifts in skill use (overall, within, and across occupations). Thus, we conclude that the sizable share of workers not using manual skills in the O*NET period is not a concern for our results.

[11] https://www.bls.gov/oes/tables.htm

[12] Like Autor and Dorn [2013], we exclude agricultural occupations.

Our data on the occupation distribution come from the census (IPUMS), March (Annual Social and Economic Supplement) Current Population Surveys (CPS), and the American Community Surveys (ACS) and are limited to workers ages 25-64, but otherwise, our sample restrictions are the same as for the calculation of the skill weights. Since economists know these data well, we do not describe them here. Except for the last two periods, for which we always use the 2005-07 ACS and 2015-2017 ACS three-year samples, our choice of which sources to use for different purposes reflects an admittedly arbitrary trade-off between sample size and proximity of the employment data to the timing of the *DOTs* or O*NET. Before 1968, the CPS coded occupations in fewer than 40 categories and did not use the census classification. Therefore, we use the 1960 1 percent census sample for our initial period. We rely on the 1970, 1980, and 1990 Census samples for the three later periods when we believe greater accuracy in estimating the employment cells is critical. Thus, we use the censuses or the ACS to aggregate from *DOT* and O*NET to census occupations and when using occupation/industry cells as observations in our regressions. Our decomposition of skill use into within- and between-occupation changes relies on occupation, not industry, and therefore, uses larger cells. Consequently, we use the current occupation in the 1970-72, 1982-84, and 1994-96 March CPS for this purpose.

4 Results

Table 1 shows how use of the five skills evolved from 1959 to 2016. Recall, however, that the measures in the first and last three periods are not comparable. Therefore, when discussing trends, we focus on changes within each sub-period. If the changes within each sub-period are directionally similar, it is plausible but not certain that the change applies to the entire period.

With this caveat in mind, we see a steady increase in the use of social skills. Social-skill use grew from .12 to .15 between 1959 and 1983 and from .15 to .23 between 1995 and 2016. As social-skill use increased, the use of routine-cognitive, finger-dexterity, and manual skills decreased. Note that this must be true for one or more skills in aggregate since skill use sums to 1. However, we observe declines in the use of these three skills over the full period. There are, however, some notable departures from trends. Manual-skill use increased in the 1960s, while the use of finger-dexterity skills marginally increased in the 1970s.

The use of abstract skills is the only one for which we observe different patterns in the two sub-periods analyzed. While their use increased between 1959 and 1983, it decreased from .24 to .22 between 1995 and 2016. These changes are not startling in light of the Deming [2017] finding that between 1980 and 2012, employment growth in abstract-intensive occupations only occurred in those characterized by high social-skill use.

Our results suggest that, within both sub-periods, overall abstract/social-skill use increased, and overall routine-skill use declined. Previous work has documented these trends, focusing only on the changes in three skills: nonroutine-cognitive skills, which are an average of abstract and social skills; routine skills, which are an average of routine-cognitive and finger-dexterity skill; and manual skills.

If we believed that the *DOT* and O*NET measures were comparable, we would, for instance, conclude that social-skill use fell between 1983 and 1995. We find differences between the measures to be a more plausible explanation for the decline. In the same period, we also observe major shifts in the use of finger-dexterity and manual skills, reinforcing the plausibility of this hypothesis. Between 1983 and 1995, we also observe that abstract-skill use decreased. Given the uncertainty generated by the combination of the two data sets, we abstain from determining whether the trend reversal for abstract-skill use started before 1995.

Differences in the standard deviations of skill use across occupations reinforce our concerns about treating the results from the *DOT* and O*NET as a single time series. Except for finger-dexterity and manual skills in 1959, the standard deviation of skill use is consistently higher in the *DOT*.

4.1 Within-occupation changes in skill use are important

Table 2 decomposes skill-use changes into within- and across-occupation changes using the following decomposition:

$$Skill_{e+1,t+1} - Skill_{e,t} = \underbrace{(Skill_{e+1,t+1} - Skill_{e+1,t})}_{\Delta \text{ across}} + \underbrace{(Skill_{e+1,t} - Skill_{e,t})}_{\Delta \text{ within}} \tag{25}$$

where e indicates the *DOT* or O*NET edition, and t indicates the period considered. Thus, Δ within shows how skill use would have changed had the occupations in which people worked been the same, for example, in 1959 and 1971. In parallel, Δ across shows how much skill use would have changed had skill use in each occupation remained constant between 1959 and 1971, and only the distribution of workers across occupations shifted. With the exceptions discussed in the introduction, this latter measure corresponds to that typically presented in the literature. Therefore, we begin with across-occupation changes. Differences from the prior literature may reflect our use of different editions of the *DOT* and O*NET and/or our somewhat different use of the skill measures.

The across-occupation patterns we observe are consistent with the prior literature. In each period, we observe movement toward abstract- and social-intensive occupations. This shift was particularly large in the 1970s. The change over the full period was more sizable for social than abstract skills. The movement away from routine-cognitive and finger-dexterity-intensive occupations was particularly notable during the *DOT* periods, while the movement away from manual-intensive occupations was greatest in the 1970s.

As with Table 1, we show changes between 1983 and 1995 for completeness, despite our concerns about their reliability. With this caveat in mind, we observe the general across-occupation shift from routine and manual skills to nonroutine-cognitive skills reported in Consoli et al. [2023].

Perhaps the most important message of Table 2 is that between-occupation shifts miss much of the action. Within-occupation changes are less consistent from period to period but are often large. Between 1959 and 1971, there were large within-occupation increases in abstract- and manual-skill use and large declines in the use of social- and routine-cognitive skills. Within occupation, social and finger-dexterity-skill use rose notably between 1971 and 1983. Over the first two periods, the within-occupation changes were considerable, significantly increasing the movement away from routine-cognitive skills and toward abstract skills, while partially offsetting the movement away from finger-dexterity and manual skills and toward social skills.

Changes between 1995 and 2016 are almost entirely within occupation. While the shift toward more social-intensive and less manual-intensive occupations continued in the period during which we rely on O*NET, the decline in routine-cognitive and finger-dexterity-intensive occupations and, to a lesser extent, abstract-skill use all but ended. The decreases we observe in abstract- and routine-skill use between 1995 and 2016 are driven entirely by changes within occupation.

If we look only across occupations, merging the *DOT* and O*NET gives plausible results. However, we must believe that the within-occupation shifts in social-, routine-cognitive-, and manual-skill use differed fundamentally between 1983 and 1995 compared with the 24 years before or 21 years after. We find this implausible, reinforcing our concerns about differences between the two data sources. Henceforth, we treat the periods relying on them as distinct and do not use changes between 1983 and 1995.

In sum, over our entire period, we observe a shift from routine-cognitive-, finger-dexterity-, and manual-skill use to social-skill use both between and within occupations, even though we observe some surprising changes within occupations in the *DOT* period. While increasing across occupations throughout the entire period, abstract-skill use within occupations increased between 1959 and 1983 and decreased between 1995 and 2016.

4.2 Relative skill-productivity growth matters

Recall that estimating (22) and imposing that the coefficients sum to 0 allows us to identify the relative growth of skill productivity.[13] Table 3 shows the results of this exercise (see Table 1A in the Appendix for untransformed coefficients). The coefficients in the table measure the relative growth rate of the productivity of the skills multiplied by $\varepsilon / (1-\varepsilon)$. Assuming that the elasticity of substitution is less than one, $0 > \varepsilon / (1-\varepsilon) > -1$, and we can bound the difference relative to the average in the annualized rate of growth over some period by the coefficient divided by the period's length.

The four coefficients are jointly significant in each period except the first. Recall that the mean change is normalized to 0, making one coefficient redundant so there are only four coefficients.

The table shows a clear pattern, even though most individual estimates are imprecise. The only strong statements we can make about individual coefficients are that 1) abstract-skill productivity grew slower and routine-cognitive productivity grew faster than the average in the most recent period, 2) finger-dexterity-skill productivity grew faster than average in the 1970s, and 3) there is weak evidence that social-skill productivity grew slower than average in the 1960s.

However, we can confidently conclude that over the entire *DOT* period, social skill productivity grew more slowly, while both routine- and finger-dexterity skill productivity increased more rapidly than average.[14] We can similarly conclude that during the O*NET period, abstract- and social-skill productivity grew more slowly, and routine-cognitive and finger-dexterity-skill productivity grew faster than average.

Finally, for each skill, we can test the null that the relative growth was average in both periods. We conclude that over this entire period, abstract- and social-skill productivity grew more slowly, and routine-cognitive- and finger-dexterity-skill productivity grew more rapidly than average. We do not find evidence that manual-skill productivity growth was different than average over our entire period or the *DOT* and O*NET periods individually.[15]

We provide further evidence of the importance of differences in skill-productivity growth

[13] To reduce measurement error, we restrict the sample to occupation/industry combinations comprising at least .0001 percent of employment in each year included in the pair and at least an average of .0002 percent over the two years. The second requirement ensures that we do not create bias by dropping observations near the threshold that saw a modest change in employment that caused it to cross the .0001 percent threshold but keep similarly small occupation/industry observations that happen not to cross the threshold. Nevertheless, many of the employment changes we observe remain implausible. Since occupations are coded consistently across periods, we are not concerned that changes in occupation drive these changes. We winsorize the data at the 5th and 95th percentiles. Finally, we average our skill-use measures from the two editions (or the revision) of the *DOT*, and the three editions of the O*NET corresponding to the pair of years in our analysis.

[14] These and similar results are based on an exponential bootstrap with weights assigned by cluster.

[15] We implicitly assume that changes in the 1980s would not undo these conclusions.

in the line labeled "proportion due to skills." This uses the Shapley-Owen decomposition to show the proportion of the R-squared allocated to skill. Strikingly, this proportion grows over the four periods. While accounting for only one-quarter of the explanatory power may appear modest, recall that the number of industries dwarfs the four skill variables included in the regression. We conclude that relative skill-productivity growth matters at least after 1970.

As noted previously, we also perform this exercise by adding the percentage change in average wages to the controls. Table 2A in the Appendix shows that this has no meaningful impact on our estimates.

4.3 Fast routine- and slow nonroutine-cognitive productivity growth changed how jobs are done

To understand what our model says about within-occupation skill shifts, we take a linear expansion of $S_i(J)$ with respect to relative changes in skill productivities:

$$dS_i(J) = \Sigma_k \frac{\partial S_i(J)}{\partial \ln A_k} d\ln A_k. \tag{26}$$

Now, we multiply by $f(J)$ and integrate over all jobs

$$\int_{\mathcal{J}} (dS_i(J) f(J)) = \Sigma_k \left(d\ln A_k \int_{\mathcal{J}} \frac{\partial S_i(J)}{\partial \ln A_k} f(J) \right). \tag{27}$$

Now, we use the fact that $\Sigma_k S_k = 1$ to get

$$\Sigma_k \frac{\partial S_k(J)}{\partial \ln A_i} = 0. \tag{28}$$

A short argument based on Slutsky symmetry and the regularity and constant-returns-to-scale assumptions on $y(\cdot, J)$ shows that[16]

$$\frac{\partial S_i(J)}{\partial \ln A_k} = \frac{\partial S_k(J)}{\partial \ln A_i} \tag{29}$$

[16] As we have assumed that $y(\cdot, J)$ is a neoclassical production function subject to a linear skill budget constraint, we can turn to standard demand theory. The arguments of $y(\cdot, J)$, $(A_i S_i)_{i\leq n}$, can be thought of as "effective" skills . Now, $A_i S_i$ is simply the Marshallian demand for effective skill i, where the price of effective skill i is $1/A_i$. We denote by $A_i S_i^{Hicks}$ the Hicksian demand of effective skill i, and by ω the skill budget constraint. The Slutsky equation is $\frac{\partial(A_i S_i)}{\partial \frac{1}{A_k}} + \frac{\partial(A_i S_i)}{\partial\omega} A_k S_k = \frac{\partial(A_i S_i^{Hicks})}{\partial \frac{1}{A_k}}$. From Slutsky symmetry, $\frac{\partial(A_i S_i^{Hicks})}{\partial \frac{1}{A_k}} = \frac{\partial(A_k S_k^{Hicks})}{\partial \frac{1}{A_i}}$, and from constant returns to scale we have symmetric income effects $\frac{\partial(A_i S_i)}{\partial\omega} A_k S_k = A_i S_i A_k S_k = \frac{\partial(A_k S_k)}{\partial\omega} A_i S_k$. Thus, $\frac{\partial(A_i S_i)}{\partial \frac{1}{A_k}} = \frac{\partial(A_k S_k)}{\partial \frac{1}{A_i}}$, so that $-A_i A_k^2 \frac{\partial S_i}{\partial A_k} = -A_k A_i^2 \frac{\partial S_k}{\partial A_i}$ or simply $\frac{\partial S_i}{\partial \ln A_k} = \frac{\partial S_k}{\partial \ln A_i}$ as desired.

so that we can rewrite (28) as

$$\Sigma_k \frac{\partial S_i(J)}{\partial \ln A_k} = 0. \tag{30}$$

Thus, we can normalize (27) with respect to an arbitrary $d \ln A_n$:

$$\int_{\mathcal{J}} \left(dS_i\left(J\right) f(J)\right) = \Sigma_{k \neq n} \left(d \ln A_k - d \ln A_n\right) \int_{\mathcal{J}} \frac{\partial S_i\left(J\right)}{\partial \ln A_k} f(J). \tag{31}$$

Denoting the integral on the right by $\partial \overline{S_i}/\partial \ln A_k$, and replacing the left-hand-side with the within estimates in Table 2 and the $d \ln A_k$ terms with the estimates in Table 3, we arrive at

$$\widehat{\text{within}_i} = \Sigma_{k \neq n} \left(\widehat{d \ln A_k} - \widehat{d \ln A_n}\right) \frac{\partial \overline{S_i}}{\partial \ln A_k}. \tag{32}$$

These $\partial \overline{S_i}/\partial \ln A_k$ terms represent the average changes in workers' skills brought on by isolated productivity changes, and we are most interested in extracting them. As Section 4.2 suggests, however, more than one A_k changed in each of our periods, making this exercise nontrivial.

Because of the measurement differences, we estimate these substitution effects separately for the *DOT* and O*NET periods. Assuming the derivatives do not change over time within data sets, in each case we have ten equations and ten unknowns after imposing symmetry per (29) and that the substitution effects sum to 0. We choose the parameter estimates that minimize the sum of the squared differences between the calculated within change and the predicted within change. Two of the equations within each set of ten are redundant. Rather than arbitrarily discarding two equations, we minimize the sum of the squared deviations.

The derivatives, $\partial \overline{S_i}/\partial \ln A_k$, capture a concept analogous to p and q complementarity and substitutability. If the derivative is positive, an increase in the productivity of skill k increases the amount of skill i acquired by workers. We refer to this case as A-complementarity. Note that, unlike p-complementarity, a skill may be A-complementary or A-substitutable with itself. In contrast, $A_i S_i$, the "effective" amount of skill i supplied by the worker must increase with A_i.

Recall that in Table 3, we estimate $\varepsilon/\left(1-\varepsilon\right) * d \ln A_i$. So, as ε is unknown, with a change of sign, the coefficients represent lower bounds on the absolute values of the skill-productivity changes. Therefore, using these coefficients yields upper bounds on the derivatives. Consequently, we focus on the signs of the estimated derivatives rather than their precise magnitude and ignore the $\varepsilon/\left(1-\varepsilon\right)$ term other than to assume that it is negative. Thus, in reading Table 4, which displays the results of this exercise, readers can rely on their intuition to divide the estimated derivative by something in the range of 1.3 to 1.7.

As a result of our exercise, the cross-derivatives of finger-dexterity and abstract skills, and finger-dexterity and social skills are set to 0 in both periods. This choice minimizes squared differences between derivatives in the *DOT* and their corresponding derivative in the O*NET period. As seen in Table 4, social, routine-cognitive, and manual skills are, on average, A-substitutes for themselves in both periods, while finger-dexterity skill is an A-complement for itself. The cross-derivative for abstract skill is one of the few that changes between the *DOT* and the O*NET, being respectively an A-complement and an A-substitute to itself in the *DOT* and the O*NET periods. Notably, abstract skill is an A-substitute with both social and routine-cognitive skills. Consequently, the slow productivity growth of abstract skills and social skills both contributed to the within-occupation growth in abstract-skill use, while the fast productivity growth of routine-cognitive skills contributed to the decline in routine-cognitive-skill use. At the same time, routine-cognitive-skill use increased due to the slow growth of abstract-skill productivity and to a lesser extent of social-skill productivity. Similarly, abstract-skill use decreased due to the rapid growth in routine-cognitive skill growth.

The results change very little between the *DOT* and the O*NET data. The only notable exceptions are represented by finger-dexterity skills, which are an A-complement in the *DOT* period and and A-substitute in the O*NET period with manual skills, and social skills, which are an A-substitute with routine-cognitive skills in the *DOT* period and the opposite (but with a negligible coefficient in terms of magnitude) in the O*NET period.

Still, we cannot discount the possibility that the changes reflect measurement differences. While we have done our best to match the measures of routine-cognitive skills, social skills, and manual skills, they are not identical and may affect the degree of A-complementarity or substitutability.

We remind readers that the parameters in Table 4 are averages. Increased productivity of finger dexterity could increase the use of abstract skill among secretaries and decrease its use among university faculty. Averaged across occupations, the cross-effect could be consistent with our estimate of no effect.

Table 5 leverages these results to provide more precise estimates of how the change in the productivity of each skill accounts for the overall within-occupation shift in skill use. It also compares the predictions of the model with the data. In general, the model predicts the direction and magnitude of changes very well. In fact, we closely match the changes in within-job skill use for all skills in all periods.

Recall that in Table 3, our skill measures increasingly explain changes in log employment as the period we examine becomes more recent. For the 1960s, they are jointly insignificant and explain little of the observed employment growth. Therefore, we treat the estimated sources of within changes cautiously.

In the last three periods, social-skill use increased markedly within occupation. Table 5 reveals that this shift was due primarily to the slow growth of abstract- and social-skill productivity. Over the same period, within occupation, there was a shift away from the use of routine-cognitive skills, largely explained by their rapid productivity growth, although the slow growth of abstract-skill productivity also contributed.

During the O*NET period, the rapid growth of routine-cognitive productivity reduced abstract-skill use, but the slow growth of abstract skills offset this, at least in the most recent period. In a similar manner, these two forces had largely offsetting effects on manual-skill use.

5 Summary and conclusion

We make two contributions. First, at a purely empirical level, we provide new evidence on changes in skill use between and within occupations over a very long period. Second, we develop a simple model of technological change that increases the productivity of individual skills. Our model allows us to identify the sources of technological change that generate movement across occupations and skill-use changes within occupations. It contrasts with the skill-biased technological change literature by focusing on skills rather than a one-dimensional skill, such as "college graduate." It also contrasts with the routine-biased technological change literature by focusing on how technology alters how jobs are done. Our model does account for technological change that replaces occupations but only through changes in industry demand.

The empirical application of the structural model is strikingly simple, requiring only OLS and algebra. Yet, it produces valuable insights. While the prior literature has focused on technological change as replacing routine tasks, we find that the slow growth of abstract- and social-skill productivity plays at least an equal role in explaining the shift within occupation to abstract- and social-skill use and in reducing the shift out of routine-cognitive-skill use.

The model and results highlight how substitutability and complementarity among skills within occupations interact with the relative growth rates of skill productivities to generate shifts in skill usage. While differential changes in skill productivity also generate movements across occupations, as emphasized in the RBTC literature, that literature has not focused on the link between the within and between changes. We believe that this paper is a significant step forward in addressing this gap. Obviously, readers must make that judgment for themselves.

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Table 1: Skills Use Levels by Year

	1959	1971	1983	1995	2006	2016
Abstract skills						
	0.231	0.264	0.280	0.241	0.224	0.220
	(0.082)	(0.121)	(0.115)	(0.072)	(0.050)	(0.047)
Social skills						
	0.121	0.122	0.154	0.149	0.204	0.225
	(0.139)	(0.167)	(0.176)	(0.109)	(0.060)	(0.065)
Routine cognitive skills						
	0.289	0.258	0.224	0.257	0.248	0.247
	(0.164)	(0.195)	(0.179)	(0.051)	(0.053)	(0.048)
Finger dexterity skills						
	0.289	0.272	0.274	0.194	0.185	0.183
	(0.075)	(0.098)	(0.098)	(0.083)	(0.045)	(0.037)
Manual skills						
	0.070	0.085	0.068	0.158	0.139	0.125
	(0.056)	(0.106)	(0.091)	(0.091)	(0.086)	(0.088)

Notes: Estimates use the occupation distributions from the 1960 census, the March 1970-72, 1982-84, and 1994-96 Current Population Surveys, the 2005-2007 3-Year ACS/PRCS, the 2015-2017 ACS. The skills used in each occupation are taken from the third, fourth, and revised fourth editions of the *Dictionary of Occupational Titles* and from the 3.0, 12.0, 22.2 versions of the O*NET. *DOT* occupations are aggregated to census occupations using the April 1971 Current Population Survey. O*NET occupations are aggregated using the Occupational Employment and Wage Statistics (OEWS). The data for 1959-1983 and 1995-2016 are not strictly comparable. Standard deviations across occupations are provided in parentheses.

Table 2: Within- and Across-Occupation Components

	1959-1971	1971-1983	1983-1995	1995-2006	2006-2016
Abstract skills					
Δ within	0.032	0.002	-0.044	-0.018	-0.005
Δ across	0.001	0.014	0.005	0.001	0.002
Social skills					
Δ within	-0.018	0.013	-0.014	0.052	0.017
Δ across	0.018	0.019	0.009	0.003	0.003
Routine cognitive skills					
Δ within	-0.022	-0.019	0.035	-0.009	0.000
Δ across	-0.009	-0.015	-0.002	0.000	-0.001
Finger dexterity skills					
Δ within	-0.008	0.012	-0.073	-0.009	-0.000
Δ across	-0.009	-0.009	-0.007	-0.001	-0.001
Manual skills					
Δ within	0.016	-0.008	0.096	-0.017	-0.011
Δ across	-0.001	-0.010	-0.006	-0.003	-0.003

Notes: This table decomposes the change in the use of each of five skills into the change that would have been observed if the occupation distribution had been the same at the end of the period as at the beginning of the period (Δ within) and what would have been observed if the skill use were always the skill use at the end of the period but the occupation distribution had changed. Estimates use the occupation distributions from the 1960 census, the March 1970-72, 1982-84, and 1994-96 Current Population Surveys, the 2005-2007 3-Year American Community Survey/PRCS, and the 2015-2017 American Community Survey. The skills used in each occupation come from the decennial censuses and the American Community Survey samples for the last two periods. *DOT* occupations are aggregated to census occupations using the April 1971 Current Population Survey. O*NET occupations are aggregated using the Occupational Employment and Wage Statistics (OEWS).

Table 3: Skill-Productivity Growth Relative to Average

	1960-1970	1970-1980	1990-2006	2006-2016
Abstract	-0.344	0.424	0.216	1.615
	(0.477)	(0.316)	(1.071)	(0.498)
Social	0.749	0.340	1.251	-0.062
	(0.408)	(0.273)	(0.767)	(0.325)
Routine cognitive	-0.163	-0.037	-0.972	-1.123
	(0.220)	(0.194)	(0.733)	(0.334)
Finger dexterity	-0.307	-0.841	-0.173	-0.564
	(0.481)	(0.370)	(0.746)	(0.363)
Manual	0.066	0.113	-0.322	0.134
	(0.490)	(0.323)	(0.545)	(0.204)
R-squared	0.16	0.14	0.17	0.15
N	4784	7137	8926	8977
Proportion due to skills	0.13	0.17	0.20	0.25
p(all skill coefs=0)	0.264	0.034	0.001	0.000
p(abstract=social=rout.cog.=fing.dext.)	0.168	0.016	0.003	0.000

Notes: Standard errors clustered at the occupation level are in parentheses. Estimates are transformed from regression of change in log employment in an occupation/industry cell on average skill (Abstract, Social, Routine cognitive, Finger dexterity) use in that cell over the period (equation (22) in the text) and imposing that the mean deviation from mean skill growth for all five skills is 0. Proportion due to skills is the proportion of the R-squared attributable to the five skills in the regression using the Shapley-Owen decomposition.

Table 4: Derivatives of Skill Use with Respect to Skill Productivity

	1960-1983				
	Skill Used				
$\Delta\ lnA_i$	Abstract	Social	Routine cognitive	Finger dexterity	Manual
Abstract	0.010				
Social	-0.060	-0.025			
Routine cognitive	-0.068	-0.052	-0.052		
Finger dexterity	0.000	0.000	-0.047	0.018	
Manual	0.118	0.137	0.219	0.029	-0.502
	1995-2016				
	Skill Used				
$\Delta\ lnA_i$	Abstract	Social	Routine cognitive	Finger dexterity	Manual
Abstract	-0.081				
Social	-0.008	-0.029			
Routine cognitive	-0.099	0.002	-0.105		
Finger dexterity	0.000	0.000	-0.013	0.025	
Manual	0.188	0.036	0.215	-0.012	-0.427

Notes: Each cell shows the derivative of the average use of the column skill with respect to a change in the relative productivity of the row skill. Estimates are up to a factor of proportionality of $\frac{-\varepsilon}{1-\varepsilon}$ (which is strictly between 0 and 1). The estimates are derived from combining changes in skill use across time with estimates of relative productivity growth from Table 3. See equation (32) in the text for the precise formulation. See the text for more detail.

Table 5: Decomposition of Within-Occupation Changes in Skill Use

Predicted Skill-Use Change			**1959-1971**		
Source of Change	Abstract	Social	Routine cognitive	Finger dexterity	Manual
Abstract	0.004	-0.021	-0.023	0.000	0.041
Social	0.045	0.019	0.039	0.000	-0.103
Routine Cognitive	-0.011	-0.008	-0.008	-0.008	0.036
Finger Dexterity	0.000	0.000	-0.014	0.006	0.009
Manual	-0.008	-0.009	-0.014	-0.002	0.033
Total Predicted	0.030	-0.019	-0.022	-0.004	0.015
Data	0.032	-0.018	-0.022	-0.008	0.016
Predicted Skill-Use Change			**1971-1983**		
Source of Change	Abstract	Social	Routine cognitive	Finger dexterity	Manual
Abstract	-0.004	0.026	0.029	0.000	-0.050
Social	0.021	0.009	0.018	0.000	-0.047
Routine Cognitive	-0.003	-0.002	-0.002	-0.002	0.008
Finger Dexterity	0.000	0.000	-0.040	0.015	0.024
Manual	-0.013	-0.016	-0.025	-0.003	0.057
Total Predicted	0.000	0.017	-0.020	0.010	-0.008
Data	0.002	0.013	-0.019	0.012	-0.008
Predicted Skill-Use Change			**1995-2006**		
Source of Change	Abstract	Social	Routine cognitive	Finger dexterity	Manual
Abstract	0.017	0.002	0.021	0.000	-0.041
Social	0.011	0.036	-0.002	0.000	-0.045
Routine Cognitive	-0.096	0.002	-0.102	-0.013	0.209
Finger Dexterity	0.000	0.000	-0.002	0.004	-0.002
Manual	0.061	0.012	0.069	-0.004	-0.138
Total Predicted	-0.008	0.051	-0.016	-0.012	-0.016
Data	-0.018	0.052	-0.009	-0.009	-0.017
Predicted Skill-Use Change			**2006-2016**		
Source of Change	Abstract	Social	Routine cognitive	Finger dexterity	Manual
Abstract	0.130	0.014	0.160	0.000	-0.304
Social	-0.001	-0.002	0.000	0.000	0.002
Routine Cognitive	-0.111	0.002	-0.118	-0.015	0.242
Finger Dexterity	0.000	0.000	-0.007	0.014	-0.007
Manual	-0.025	-0.005	-0.029	0.002	0.057
Total Predicted	-0.006	0.009	0.006	0.001	-0.009
Data	-0.005	0.017	0.000	0.000	-0.011

Notes: Each entry is the predicted change in the within-occupation use of the column skill due to changes in the productivity of the row skill according to equation (32) in the text and using the values from Tables 3 and 4. Total predicted is the sum of the five values above. The predictions can be compared with the within changes reported in Table 2 and repeated in the line labelled Data.

Appendix

Table 1A: Skill-Productivity Growth Relative to Average - Nontransformed Coefficients

	1960-1970	1970-1980	1990-2006	2006-2016
Abstract	-0.411	0.311	0.538	1.481
	(0.601)	(0.458)	(1.112)	(0.484)
Social	0.683	0.227	1.573	-0.196
	(0.740)	(0.489)	(1.036)	(0.431)
Routine Cognitive	-0.229	-0.151	-0.650	-1.257
	(0.636)	(0.432)	(0.883)	(0.361)
Finger Dexterity	-0.373	-0.954	0.149	-0.697
	(0.895)	(0.582)	(1.233)	(0.545)
R-squared	0.16	0.14	0.17	0.15
N	4784	7137	8926	8977
	0.13	0.17	0.20	0.25
p(all skill coefs=0)	0.264	0.034	0.001	0.000
p(abstract=social=rout.cog.=fing.dext.)	0.168	0.016	0.003	0.000

Notes: Standard errors in parentheses, clustered at the occupation level. Estimates from regression of change in log employment in an occupation/industry cell on average skill (Abstract, Social, Routine cognitive, Finger dexterity) use in that cell over the period (equation (22) in the text) before the transformation shown in Table 3.

Table 2A: Skill-Productivity Growth Relative to Average - Including Wages

	1960-1970	1970-1980	1990-2006	2006-2016
Abstract	-0.336	0.427	0.214	1.609
	(0.478)	(0.315)	(1.075)	(0.499)
Social	0.745	0.352	1.249	-0.058
	(0.409)	(0.274)	(0.767)	(0.325)
Routine cognitive	-0.170	-0.034	-0.970	-1.122
	(0.220)	(0.194)	(0.736)	(0.334)
Finger dexterity	-0.314	-0.843	-0.174	-0.564
	(0.482)	(0.370)	(0.748)	(0.362)
Manual	0.075	0.099	-0.320	0.135
	(0.492)	(0.324)	(0.551)	(0.204)
% Change mean wage 60	-0.043			
	(0.038)			
% Change mean wage 70		0.034		
		(0.012)		
% Change mean wage 90			0.005	
			(0.045)	
% Change mean wage 06				0.039
				(0.015)
R-squared	0.16	0.14	0.17	0.15
N	4784	7110	8926	8977
Proportion due to skills	0.13	0.17	0.20	0.25
p(all skill coefs=0)	0.263	0.031	0.001	0.000
p(abstract=social=rout.cog.=fing.dext.)	0.166	0.015	0.003	0.000

Notes: Standard errors in parentheses, clustered at the occupation level. Nominal wages are converted to 1999 dollars with CPI99 provided by IPUMS - USA. Estimates are transformed from regression of change in log employment in an occupation/industry cell on average skill (Abstract, Social, Routine-cognitive, Finger-dexterity) use in that cell over the period (equation (22) in the text) and imposing that the mean deviation from mean skill growth for all five skills is 0. Proportion due to skills is the proportion of the R-squared attributable to the five skills in the regression using the Shapley-Owen decomposition.

Table 3A: Variables Used for Skill Measures

Skills	**DOT**		**O*NET**	
	Variable	**Description**	**Variable**	**Description**
Abstract skills	General Educational Development: Reasoning Development	Apply principles of logical or scientific thinking to a wide range of intellectual and practical problems. Deal with nonverbal symbolism (formulas, scientific equations, graphs, musical notes, etc.) in its most difficult phases. Deal with a variety of abstract and concrete variables. Apprehend the most abstruse classes of concepts.	Critical Thinking	Using logic and reasoning to identify the strengths and weaknesses of alternative solutions, conclusions, or approaches to problems.
			Processing Information	Compiling, coding, categorizing, calculating, tabulating, auditing, or verifying information or data.
			Making Decisions and Solving Problems	Analyzing information and evaluating results to choose the best solution and solve problems.

Skills	**DOT**		**O*NET**	
	Variable	**Description**	**Variable**	**Description**
	General Educational Development: Mathematical Development	Advanced calculus: Work with limits, continuity, real number systems, mean value theorems, and implicit functions theorems. Modern Algebra: Apply fundamental concepts of theories of groups, rings, and fields. Work with differential equations, linear algebra, infinite series, advanced operations methods, and functions of real and complex variables. Statistics: Work with mathematical statistics, mathematical probability and applications, experimental design, statistical inference, and econometrics.	Mathematical Reasoning	The ability to choose the right mathematical methods or formulas to solve a problem.

Skills	DOT		O*NET	
	Variable	**Description**	**Variable**	**Description**
	General Educational Development: Language Development	Reading: Read literature, book and play reviews, scientific and technical journals, abstracts, financial reports, and legal documents.	Written Comprehension	The ability to read and understand information and ideas presented in writing.
		Writing: Write novels, plays, editorials, journals, speeches, manuals, critiques, poetry, and songs.	Written Expression	The ability to communicate information and ideas in writing so others will understand.
		Speaking: Conversant in the theory, principles, and methods of effective and persuasive speaking, voice and diction, phonetics, and discussion and debate.	Oral Expression	The ability to communicate information and ideas in speaking so others will understand.
Social Skills	Adaptability to accepting responsibility for the direction, control, or planning of an activity (DCP)	Consider jobs for this factor when the worker is in a position to negotiate, organize, direct, supervise, formulate practices, or make final decisions. Do not consider when the planning is for one's own activities.	Guiding, Directing, and Motivating Subordinates *	Providing guidance and direction to subordinates, including setting performance standards and monitoring performance.
			Developing Objectives and Strategies	Establishing long-range objectives and specifying the strategies and actions to achieve them.

Skills	DOT		O*NET	
	Variable	**Description**	**Variable**	**Description**
Routine Cognitive Skills	Adaptability to situations requiring the precise attainment of set limits, tolerances, or standards. (STS)	Consider jobs for this factor when the worker must be precise, thorough, exacting, or meticulous in regard to material worked; or in activities such as numerical determinations, record preparation, or inspecting.	Importance of Being Exact or Accurate *	How important is being very exact or highly accurate in performing this job?
			Importance of Repeating Same Tasks *	How important is repeating the same physical activities (e.g., key entry) or mental activities (e.g., checking entries in a ledger) over and over, without stopping, to performing this job?
			Number Facility	The ability to add, subtract, multiply, or divide quickly and correctly.
Finger Dexterity Skills	Finger Dexterity	Ability to move fingers, and manipulate small objects with fingers, rapidly or accurately.	Finger Dexterity	The ability to make precisely coordinated movements of the fingers of one or both hands to grasp, manipulate, or assemble very small objects.

Skills	**DOT**		**O*NET**	
	Variable	**Description**	**Variable**	**Description**
Manual Skills	Eye-Hand-Foot Coordination	Ability to move the hand and foot coordinately with each other in accordance with visual stimuli. (Not measured by GATB)	Multilimb Coordination	The ability to coordinate two or more limbs (for example, two arms, two legs, or one leg and one arm) while sitting, standing, or lying down. It does not involve performing the activities while the whole body is in motion.
			Gross Body Coordination	The ability to coordinate the movement of your arms, legs, and torso together when the whole body is in motion.

* indicates O*NET variables used also by Acemoglu and Autor [2011].
O*NET variables description from the 22.2 version.