Estimating the Nature of Technological Change: Exploiting Shifts in Skill Use Within and Between Occupations*

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Abstract

Autor, Levy, and Murnane (2003) ask whether vulnerability to automation, measured by task content, can rationalize employment trends. We invert their approach, asking what technological changes rationalize skill content changes. We combine a tractable GE model with three editions of the Dictionary of Occupational Titles, the 1960, 1970, and 1980 Censuses, and March Current Population Surveys to estimate changes in the relative productivity of skills. We conclude that finger-dexterity productivity grew rapidly while abstract-skill productivity lagged, a form of 'skill bias'. Together with substitutability between abstract and routine inputs, these results explain changes in skill use within occupations.

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1 Introduction

Consider the IBM Selectric, an electronic typewriter introduced in 1961. It replaced the traditional strikebars with a golf-ball-like element and in later versions was even 'self-correcting'. The Selectric made typing much more productive. Secretaries and typists could produce many more and more attractive typewritten pages. Typists who caught a mistake quickly could correct it invisibly, where previously they retyped the page entirely.

One could say this change was biased towards specific tasks in the economy. In particular, it made typists far more productive than they were earlier. However, the interaction with task demand seems ambiguous. The Selectric did not replace typists or substitute for typing outputs, the approach used by the task model (Autor, Levy, and Murnane 2003, Acemoglu and Autor 2011, Acemoglu and Restrepo 2018). If anything, the demand for typed pages increased after the Selectric's introduction.

However, the Selectric did not make high-skilled labor more productive or more in demand, as in the canonical SBTC models (Katz and Murphy 1992, Berman, Bound, and Griliches 1994, Berman, Bound, and Machin 1998, Juhn 1999). Instead, it simply increased the speed at which everyone could type. Thus, the individuals whose productivity increased dramatically were largely middle-skilled workers in typing-intensive jobs. Further, this technological innovation might have changed the skills used in specific jobs, e.g., by expanding the set of occupations involving some typing.

Thus, the Selectric had two effects within occupations: a primitive effect, which made typing significantly more productive, and an adaptation effect, in which workers respond to the primitive effect by altering their use of typing skills. At first glance, one may expect that the second effect acts as a confounding factor, making it hard to recover the primitive technological change. However, we demonstrate that, in a fairly general model, a first-order approach allows pure employment changes to act as a "sufficient statistic" to identify relative skill productivity changes.

We integrate insights from both task-based and skill-biased approaches in a tractable general equilibrium framework. We model occupations as combining skills, akin to tasks in the tasks model, to produce intermediate goods. Occupations utilize workers' skills in heterogeneous ways, and we impose nearly no structure on their production technologies. Our model allows workers to choose first the skills they develop, and then their occupations. The market prices intermediate goods that aggregate to a single final good.

As in the SBTC model, we allow for skill-enhancing technological change. The Selectric made typing - or 'finger dexterity' - more productive. The number of typed pages produced must increase, but whether workers deepen their typing skills or not depends on the elasticity of substitution between skills in each specific occupation. Finger-dexterity use (typing) can decline in one occupation (secretaries) but increase in another (economics professors). Employment in typing-intensive occupations can increase or decrease. If the elasticity of demand for such an occupation's output is less than one, as we believe plausible, demand for that occupation falls.

We also allow for shifts in product demand (possibly due to trade shocks) or outside competition (possibly due to robots or 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.

The model provides us with a simple approach to measuring the relative increase in the technological productivity of different skills while taking account of demand shifts. In effect, we develop a transparent structural model for interpreting within and between-occupation changes in skill use that for local estimation relies only on ordinary least squares and weighted means, using readily observable variables.

Notice this is orthogonal to the exercises conducted by Autor, Levy, and Murnane and Goos, Manning, and Salomons (2014). They use the routine content of occupations as a measure of vulnerability to automation and offshoring (also measured directly in the latter paper). In our language, they assume the direction of 'skill-bias'[1] and leverage aggregate employment measures to infer the magnitude of technological change in each occupation. Our approach uncovers the direction of technological change, but not its magnitude.

To estimate the model, we use a subset of the skills studied by Autor, Levy, and Murnane 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 find that workers moved into abstract-intensive occupations in both periods, with the shift for women being slower in the earlier period but much faster in the later period. Our estimation exercise shows that relatively rapid growth of finger-dexterity productivity and slow growth of abstract-skill productivity explain between-occupation shifts, especially among women.

We also show that within-occupation shifts can dwarf those due to movement across occupations. In the earlier period, abstract-skill use among men grew within occupations while routine-skill use fell. This pattern slowed for men but accelerated for women in the later period. We show how complementarity and substitutability of skills with respect to

[1]In other words, they assume which jobs are *more* affected by automation in order to estimate the importance of the shift overall.

their own and other skills' growth in productivity explain these patterns.

We are not the first to look at within-occupation changes in skill use. 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. However, we develop a model to help us interpret the results.[2] Moreover, Atalay et al. are unable to examine gender differences. Autor and Price (2013) also study a very long period and decompose changes by gender but do not allow for within-occupation changes in skill use.

This paper can be read in two ways. Those interested solely in a better accounting of the changes in the 1960s and 1970s 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 $y((A_iS_i)_{i\leq n}, J)$ of 'J-widgets', where each $A_i > 0$ is common to all jobs and is a measure of the general productivity of skill i. Thus, each A_iS_i is the 'effective' amount of input i.[3]

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.

[2] Autor et al. examine the relation 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.

[3] Thus output y depends on the vector of effective inputs $(A_iS_i)_{i\leq n}$.

[4] $y(\cdot, J)$ is strictly increasing in each A_iS_i on $\mathbb{R}^n_{++}$, is twice continuously differentiable, features a bordered Hessian with non-vanishing determinant on $\mathbb{R}^n_{++}$, is strictly quasiconcave, and $y((A_iS_i)_{i\leq n}, J) = 0$ iff $A_iS_i = 0$ for some i. This will 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 fairly general. We thus think that excluding corner solutions is unproblematic for our application.

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 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. We do not allow her to choose to spend more time on learning.[5]

A worker who anticipates holding job J will therefore

$$\begin{aligned} & \max_{S \geq 0} y((A_i S_i)_{i \leq n}, J) && (1) \\ \text{subject to} \sum_i S_i &= 1. && (2) \end{aligned}$$

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 worker not too far advanced in their work lives.

How do optimal output and skills change with A? From the Envelope Theorem,

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

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

[5] This is without loss of generality since we can always normalize the time she chooses to spend on learning to 1. This could affect comparative statics on total production through a labor/leisure/learning trade-off. That said, since this only adjusts the effective number of labor units each worker provides, with a constant returns to scale aggregate production function, it will not affect the objects of interest to us.

$y(\cdot, J)$'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 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

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

Here, $h(J)$ is the relative importance of input J for final production and $q(J)$ is the total quantity of 'J-widget' 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 widget 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 in part 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 towards jobs where it is used less than average. So, for example, if routine 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 skill more productive) will (a) reduce routine use in all jobs (within) and (b) shift workers to less routine-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 by analyzing the case where a skill used by all workers, but to different degrees, gains productivity less rapidly than other skills do.

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 have no effect on skill use within a job. A decrease in horseshoe demand 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

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

The model distinguishes between changes that replace (or reduce demand for) occupations by automating or offshoring them (a decline in h) as when data input is imported from abroad, and those in which technology makes relevant skills more productive 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. When the productivity A_i of a skill i important to data entry increases, if skill inputs are complements at data entry and intermediate good demand is inelastic, workers in data entry jobs end up with less of skill i, and fewer workers are hired to input data.

Interpreted within our model, Autor, Levy, and Murnane et al found that in a later period technological innovation increased the productivity of routine tasks. Since the demand for these tasks was inelastic, the amount of time individual workers spent on them declined as did total employment in routine-intensive tasks. Our interpretation of the period that we study will be that the productivity of abstract skill use did not increase as rapidly as the productivity of other skills, most notably finger dexterity. This caused a shift towards abstract-skill use because the elasticity of substitution between intermediate goods is less than one, thereby shifting employment to abstract-intensive occupations. Within occupations, declining relative abstract-skill productivity shifted skill use toward greater abstract and less routine-skill use. Strikingly, within occupations increased productivity of finger-dexterity, reduced the use of both abstract and finger-dexterity skills, and increased the use of routine skills.

We note that our model assumes *ex-ante* identical workers. In a richer model with *ex-ante* heterogeneous workers, demand changes might alter how jobs are done. Intuition suggests that workers "better at routine tasks" do jobs more routinely than other workers. In such a world, a reduction in demand for routine-intensive outputs *would* shift such workers to less-routine jobs who would then perform them *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 that captures demand changes 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 will capture changes due to occupation-specific factors such as robots. If we performed our analysis in a later period, we would want to include measures of robot adoption or potential for robot adoption. We measure $S_{i,J}$ by the average of the measure in two proximate editions of the DOT. μ is a mean-zero error term. We estimate (19) separately for each gender/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 $d\ln A.$, and we can rewrite the equation as

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

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

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

Equation (22) describes a regression of the (approximate) percentage change of employment in an occupation on the skills used in that occupation and industry dummies. The coefficients show the change in the productivity of each skill 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 the skills.

Although derived quite differently, our final equation is similar to the one in Goos, Manning, and Salomons. Their theoretical model includes wages in the equivalent of (22), which they proxy by industry-year and occupation dummies.[6] 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. The major difference in our specifications is that they include only routine-task intensity and not the other skills but also include offshorability, something of limited importance in our period.

Assuming an elasticity less than 1 seems natural. As Chad 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, Manning, and Salomons estimate that the elasticity of substitution across industry outputs is 0.42. Our case is even stronger; the outputs of secretaries, sales workers, plumbers, and truck drivers cannot easily substitute for each other. Note that this is different from the statement that someone who works as a secretary might be almost as productive if he worked in sales. In our model, this is quite plausible if the underlying skills required are close.

Note that we must drop a skill because the skills sum to 1. Therefore, we can interpret the coefficients as the rate of growth 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 relative

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

productivity of all the 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. Fortunately, in the period we study, these sources of employment loss are likely to be modest.

We estimate (22) by ordinary least squares. Consistent with Solon, Haideri and Wooldridge (2015) and Dickens (1990), we experimented with feasible weighted least squares and found no evidence of important heteroskedasticity with respect to occupation size.

3 Data

Following Autor, Levy, and Murnane et al, our skill-use measures 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. The 1965 DOT has not, to the best of our knowledge, 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, Levy, and Murnane et al As others have noted, the revised fourth edition is not a 'fifth' edition in that many occupations were not revisited between the fourth edition and the revised 1991 edition because the revision addressed only occupations that were thought to have changed the skills they used. Therefore, we probably underestimate the extent of within-occupation changes in skill use between 1971 and 1983.

The *DOT* identifies aptitudes, temperaments, and abilities used in a job, and measures them numerically. Observations are at the occupation-title level. Therefore, at a point in time, differences in skill use by sex reflect only differences in employment shares across occupation titles.

The 1965 DOT includes all of the skill-use (task) measures used in Autor, Levy, and Murnane. 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 in which we calculate General Education Development in the 1977 and 1991 *DOTs* as the average of the reasoning, mathematical, and language development measures. 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, Levy, and Murnane et al, we measure routine-cognitive skill using the variable "adaptability to situations requiring the precise attainment of set limit, tolerances, or standards," dexterity by "finger dexterity," manual skill by "eye-hand-foot coordination". For our measure of abstract skill we use "General Education Development." rather than only its mathematical component, to allow for consistency across all *DOTs*. We drop interactive skills from the analysis, in part for simplicity and in part because the explosion in the demand for social skills (Deming 2017) appears to date from a later period. In addition, given data limitations, adding a fifth skill would prevent us from measuring patterns of substitution among skills without additional very strong restrictions on parameters. For each census occupation, we use a weighted average (by employment share) of the skill use in the DOT occupations comprising that census occupation.

For consistency with our theoretical model, we depart from Autor, Levy, and Murnane et al and Autor and Dorn (2013) in how we use these measures. Autor, Levy, and Murnane et al use the absolute value of each skill, while Autor and Dorn focus on routine intensity defined as $(RTI = ln(R) - ln(M) - ln(A))$.[7] Instead, we first scale the absolute level of skill use by where it lies between the maximum and minimum of that skill's use in any occupation over our sample period. Thus, use of skill i in occupation J at time t is:

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

where $skill_{i,J,t}$ is the value obtained directly from the DOT measures aggregated at the occupation level, $skill_i^{min}$ and $skill_i^{max}$ are the minimum and maximum absolute values (at

[7]We, like everyone else in this literature, have to treat the ordinal measures in the DOT 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, 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.

the occupation level) for skill i in any version of the *DOT*. 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 four skill measures sum to 1.

Census occupations are more highly aggregated than the *DOT's* job titles. Following Autor, Levy, and Murnane et al's treatment of the 1977 *DOT* and the 1991 revision, we construct gender-specific skill measures for the 1965 *DOT* by aggregating the *DOT* titles to the census occupations separately for men and women. This accounts for the different distribution of workers by gender across job titles within each census occupation. Following Autor, Levy, and Murnane et al, we use the DOT-augmented version of the April 1971 Current Population Survey for this aggregation, since this is the only dataset with both DOT and census codes.

We use the consistent occupation system created by Dorn (2009) and the crosswalk files provided by Autor and Dorn, linking these occupations to previous census classifications. This gives us 212 occupations in the initial period, 265 in the intermediate period, and 329 in the later period. We create the occupation skill measures using occupation weights from all full-time workers not living in group quarters between age 18 and 64 in the IPUMS 1960 5% sample, in the IPUMS 1970 1% State sample, and the IPUMS 1980 5% sample.

Despite the tremendous insights measures of these skills have provided, about six and seven percent of workers work in jobs that purportedly make no use of manual and routine skill. We leave it to the reader to assess whether this is plausible.

Our data on the occupation distribution by sex come from the Census (IPUMS) and from March (Annual Social and Economic Supplement) Current Population Surveys (CPS) and are limited to workers age 25-64, but otherwise our sample restrictions are the same as for the calculation of the skill weights. Since these data are well known to economists, we do not describe them here. 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*. Before 1968, the CPS coded occupations in fewer than forty categories and did not use the Census classification. Therefore, we use the 1960 1% Census sample for our initial period. For the two later periods, we rely on the 1970 and 1980 Census samples when we believe greater accuracy in estimating the employment cells is critical. Thus, we use the censuses to aggregate from DOT 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 only on occupation and not industry and therefore relies on larger cells. Consequently, we use the current occupation in the 1970-72 and 1982-84 March CPS for this purpose.

4 Results

Table 1 shows the evolution of average skill use over our period. There are four panels, one for each skill. Within each panel, we show the mean and standard deviation of skill use for all workers, for men, and for women.

In contrast with Autor, Levy, and Murnane et al and Autor and Price, we find that the decline in routine skill use started in the earlier period. The difference is that we use the *DOT 3rd edition* to measure skill use in the earlier period, and therefore account for within-occupation shifts. This decrease is much less pronounced among women than among men, which is consistent with the relative direction of changes in Autor and Price. Consistent with earlier work, the use of abstract skills increased in the earlier period. Our results suggest that this change was solely among men. In contrast with earlier work, we find a decrease in finger dexterity (routine manual) and an increase in (nonroutine) manual, but with noticeable differences in the patterns between men and women.

In the later period, which corresponds most closely to the 1970-80 change in Autor, Levy, and Murnane et al and Autor and Price, we find a decline in the use of routine (cognitive) skills and an increase in abstract-skill use, as did the earlier papers, but that these changes are much more pronounced among women. Finally, overall the changes in manual and finger dexterity reverse the signs of the changes in the earlier period although again the pattern is somewhat different between men and women.

We treat the results for manual and finger dexterity with some caution. The correlation between the measures in the 3rd and 4th editions of the *DOT* are somewhat low, only .46 for finger dexterity and .49 for nonroutine manual compared with .68 for abstract and .63 for routine. While it is certainly possible that the 1960s saw dramatic change in the importance of the two manual skills in a way that changed their ranking of importance across occupations, it is also possible that, despite defining the skills similarly, the two editions measured them differently.

4.1 Within-occupation changes are important (sometimes)

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* edition, and t indicates the period considered. Thus, Δ within shows how much the use of each skill would have changed had the occupations in which, for example, males worked been the same in 1960 and 1971. In parallel, Δ across shows how much skill use would have changed had skill use in each occupation remained constant between 1960 and 1971 and only the occupations where workers were employed shifted. This latter measure corresponds to that typically presented in the literature, largely because of the limitations of the *DOT*. Black and Spitz-Oener (2007) which uses German data on a later period is an exception.

We begin by looking at across-occupation changes since these are akin to what the literature most frequently measures. We remind the reader that any differences from the prior literature may reflect our use of different editions of the *DOT* and/or our somewhat different use of the skill measures. In the early period, all across-occupation changes seem quite modest with the largest change for abstract-skill use. Still, this change amounts to only 0.06 standard deviations. In contrast, in the later period, across-occupation changes are much more important. The .022 increase in abstract-skill use corresponds to roughly one-eighth of a standard deviation and the corresponding declines in manual and routine-skill use to declines of .10 and .05 standard deviations.[8]

Perhaps the most important message of Table 2 is that between-occupation shifts miss a great deal of the action. In the earlier period, we observe, at most, very modest shifts in skill use across occupations, but there are large within-occupation changes; within occupation, routine-skill and finger-dexterity use decline by more than one-fifth of a standard deviation, offset by similar increases in abstract-skill and manual-skill use.

Thus, between 1960 and 1971 men experience a very substantial reduction in routine-skill use, with the overall decline (-.048) due almost entirely (-.044) to within-occupation changes. Importantly, the small decline in routine-skill use among women in this period was *not* the result of within and between changes offsetting each other. Instead, we observe that each was largely unchanged.

There are also notable differences between men and women in the skill shifts, which, in the early period, are much larger for men, particularly when we focus on within-occupation shifts. Except for a .2 standard deviation increase in manual-skill use within occupations, all of the shifts experienced by women are small. In contrast, during this period, men increased their abstract-skill use by almost .4 standard deviations, of which over 80% was within occupation. Similarly, their routine-skill use declined by about .3 standard deviations, almost all of which occurred within occupation. Their manual-skill use increased within occupation by about .3 standard deviations, more than offsetting a small between-occupation decrease. Finally,

[8]We use the standard deviation in the base year, 1960 or 1971, in all cases.

within-occupation changes account for more than 80% of their almost .5 standard deviation decrease in the use of finger dexterity.

The table tells a notably different story about the later period. When we do not separate the results by gender, changes in skill us remain large (between .1 and .2 standard deviations) but are smaller than in the early period by this metric. Most of the change in abstract and manual-skill use is between occupations. However, within-occupation shifts are the more important source of changes in routine and finger-dexterity use.

But, as in the earlier period, there are important differences in the changes we observe among men and women. The overall changes are consistently much larger for women than for men. Most importantly, women see an increase in abstract-skill use both within and between occupations (.15 and .19 standard deviations), roughly on par with the increase for men in the early period. This is largely offset by a reduction in routine-skill use of .27 standard deviations, almost entirely within-occupations. At the same time, women use more finger-dexterity within occupations, but move to occupations that make less use of it; while not ruled out by our model, this is somewhat surprising.

Our analysis would be misleading if within-occupation changes reflected shifts in the distribution of more disaggregated occupations within an occupation. The problem does not arise for the aggregation of *DOT* occupations to census occupations. We have only a single crosswalk for this aggregation so that the relative weight of legal and medical secretaries in the census occupation does not change over time. The problem arises if, for example, secretaries who work for litigators and those who work for bond lawyers use different skills, if one grows faster than the other, and if the shift in the relative importance of the more disaggregated occupations affects the skills the various *DOT* editions report for legal secretaries.

4.2 Relative skill-productivity growth matters (sometimes)

Recall that estimating (22) and imposing that the coefficients sum to 0 allows us to identify the relative growth of skill productivity.[9] Table 3 shows the results of this exercise.

Perhaps the most striking result is the rapid relative growth of the productivity of finger

[9] To reduce problems of measurement error, we restrict the sample to occupation/industry combinations comprising at least .0001% of employment in each year included in the pair and at least an average of .0002% over the two years. We impose this requirement separately for men and women so that an occupation might, for example, be included in the regression for men but not for women. The second requirement is designed to ensure 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 .01% 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. We winsorize the data fairly severely at the 20th and 80th percentiles. Winsorizing at the 10th and 90th percentiles gives results with a similar interpretation but that are generally larger in absolute value and much more imprecise. Finally, we average our skill-use measures from the two editions (or the revision) corresponding to the pair of years in our analysis.

dexterity among women as reflected in its negative coefficient. This is consistent with the importance of the IBM Selectric typewriter discussed in the introduction, the early versions of word processors that appeared towards the end of this period, and electronic calculators, which became widely available in the 1970s.

$$\begin{aligned} \frac{1}{1-\varepsilon} &= .42 \\ R^{-1} &= \frac{\varepsilon}{1-\varepsilon} \end{aligned}$$

, Solution is: $\{\varepsilon = -1.3810, R = -1.7241\}$, Solution is: $\{R = -0.58, \varepsilon = -1.3810\}$, Solution is: $\{\varepsilon = -3.0, R = -0.75\}$

Recall that 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, then $0 > \varepsilon/(1-\varepsilon) > -1$ and we can bound the difference relative to the average in the annualized rate of growth over the twelve years by the coefficient divided by twelve. The implied growth rate of the relative productivity of finger dexterity is large, at least about 8% per year among women in both periods, although the 95% confidence intervals include differences of less than 4% per year. As noted earlier, Goos, Manning, and Salomons estimate an elasticity of substitution across industry outputs of .42. This would entail multiplying the differences by 1.7. Since we believe there should be less substitutability across occupations, we find a somewhat lower multiplier more plausible, but the reader is not bound by our intuition.

The second striking result is the difference between our early and later periods. In the early period differences in the growth of skill productivity play little role in explaining employment changes. For men, we cannot reject that all skills grew at the same rate. While we can reject this hypothesis for women, the differences explain little of the between-occupation differences in employment growth. Using the Shapley-Owen decomposition, we find that the skill composition of occupations accounts for only about 16% of the explained sum of squares or about 2% of the total variance.

The later period is very different. The coefficients on skills are highly significant. Moreover, they account for a notable proportion of the explained sum of squares, 46% among women although less so (18%) among men. When we recognize that we have many more industry dummies than skills, it is apparent that we probably noticeably underestimate the relative importance of the skills measure.[10] For both men and women we cannot reject that

[10]Intuitively, while asymptotically a coefficient on a variable with no effect on the dependent variable has an expected value of 0, in finite samples it has a non-zero value with probability 1 and therefore contributes

routine and manual skill productivity grew at the same rate as the average of the skills. However, in both cases we see evidence of faster growth of the productivity of finger dexterity and slower growth of abstract skills.

4.3 Slow growth of abstract productivity and faster growth of other skills (mostly) explains the within shifts

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

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

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

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

In addition, we know from (5) that

$$\frac{\partial S_i(J)}{\partial \ln A_k} = \frac{\partial^2 \ln y^*(J)}{\partial \ln A_i \partial \ln A_k} = \frac{\partial S_k(J)}{\partial \ln A_i} \tag{29}$$

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 $d \ln A_n$:

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

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

to explaining the variance of the dependent variable.

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

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.

If we assume that these derivative terms do not change over time, after imposing symmetry as per (29), we have six equations and six unknowns for men and similarly for women. Unfortunately, one of the six equations is redundant. This is not a generic problem. If we had three skills rather than four, we would have three derivatives and four equations of which one would be redundant, giving us a unique solution. If we had three sets of changes and four skills, the problem would be overidentified.

For illustrative purposes, we impose that there is no substitutability between manual and abstract skill. With this restriction, in theory the derivatives are just identified. However, since the within-occupation changes are estimated with error and the equations are only a first-order approximation, the system has no solutions. We choose the parameter estimates that minimize the sum of the squared differences between the calculated within change and the predicted within change.

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.

Recall that in Table 3 we estimate $\varepsilon / (1 - \varepsilon) * d \ln A_i$. So, as ε is unknown, with a change of sign, the coefficients represent lower bounds on the absolute values of the skill-productivity changes. Using these coefficients therefore yields upper bounds on the derivatives. Consequently, we focus on the signs of the estimated derivatives rather than their precise magnitude and ignore the $\varepsilon / (1 - \varepsilon)$ 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 own intuition to divide the estimated derivative by something in the range 1.3 to 1.7.

Although the precise values of the estimated derivatives in Table 4 differ between men and women, their interpretation is broadly similar. All skills are, on average, A-substitutes for themselves, but the derivative is about an order of magnitude greater for routine skill than for finger dexterity or manual skill and noticeably larger for routine than for abstract skill. Routine and all other skills are A-complements, again averaged across occupations.

Table 5 leverages these results to show 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. Not surprisingly, given the imprecision of the skill-growth estimates for men in the earlier period, the model does much better for women than for men. For women, the largest gaps are for the shifts in the use of finger dexterity, which we over-predict in the earlier period and under-predict in the later period. For men, we greatly under-predict the growth of abstract-skill use in the early period and over-predict it in the later period.

The large shift from routine to abstract-skill use among men in the early period is accounted for by the slow growth of abstract-skill productivity and the somewhat above-average growth of routine-skill productivity, which the effect of the very rapid growth in the productivity of finger dexterity partially offsets.

Similarly, among women in the later period, the large decline in routine-skill use and the offsetting increases in abstract-skill and finger-dexterity use are driven by the slow growth of abstract-skill productivity that is not fully offset by the rapid growth of the productivity of finger dexterity.

5 Summary and conclusion

We make two contributions. First, at a purely empirical level, we provide new evidence on changes in skill use in the 1960s and 1970s. We show that in the 1960s, such changes were important but were particularly important for men and were much more pronounced within than between occupations. In contrast, in the 1970s, skill use shifted both within and between occupations, and changes were particularly pronounced among women.

Second, we develop a simple model that reconciles or combines two approaches to technological change, the SBTC and task-based literatures, by modeling technological change as increasing the productivity of individual skills such as finger dexterity rather than, for example, college-educated workers. While our model also allows us to account for technological change that replaces occupations, we focus on detecting changes in skill productivity; we capture changing demand for occupations only through changes in industry demand.

We use the insights from the model to measure the pattern of skill-productivity growth needed to explain the employment shifts that we observe. For women in the 1960s, we find that differences in the productivity growth of skills account for very little of the employment changes that we observe. In contrast, in the 1970s they account for almost half of the explained difference among women and a fifth among men.

Our empirical results suggest that if a skill's productivity increases, use of that skill within an occupation generally decreases. Thus, skills generally are A-substitutes for themselves.

Abstract and routine skills are A-complements as are finger dexterity and routine skills. Among women in the later period, the very slow growth of abstract-skill productivity shifted skill use within occupations away from routine-skill use and towards abstract-skill use. The rapid growth of the productivity of finger dexterity, which shifted skill use towards routine and away from finger dexterity, only partially offset the decline in routine-skill use.

We hope and believe that we have demonstrated that our simple model provides a useful framework for understanding changes in skill use both between and within occupations. Obviously, readers must make that judgment for themselves.

References

Acemoglu, Daron and David Autor, "Skills, Tasks and Technologies: Implications for Employment and Earnings," in David Card and Orley Ashenfelter, eds., *Handbook of Labor Economics*, New York: Elsevier, Vol 4, Part B (2011): 1043-1171. https://doi.org/10.1016/S0169-7218(11)02410-5.

Acemoglu, Daron and Veronica Guerrieri, "Capital Deepening and Nonbalanced Economic Growth," *Journal of Political Economy*, 116:3 (2008): 467-498

Acemoglu, Daron and Pascual Restrepo. "The Race Between Man and Machine: Implications of Technology for Growth, Factor Shares and Employment," *American Economic Review*, 108(6) (2018):1488–1542.

Atalay, Enghin, Phai Phongthiengtham, Sebastian Sotelo, and Daniel Tannenbaum "The evolution of work in the United States,"*American Economic Journal: Applied Economics*, vol 12, no. 2 (2020): 1-34.

Autor, David H. and Dorn, David "The Growth of Low Skill Service Jobs and the Polarization of the U.S. Labor Market,"*American Economic Review*, 103(5) (2013): 1553-1597.

Autor, David H., Levy, Frank and Murnane, Richard J. "The skill content of recent technological change: An empirical exploration,"*The Quarterly journal of economics*, vol. 118, no. 4 (2003): 1279-1333.

Autor, David H. and Price, Brendan "The Changing Task Composition of the US Labor Market: An Update of Autor, Levy, and Murnane (2003),"*MIT Working Paper* (June 2013).

Baumol, William J. "Macroeconomics of Unbalanced Growth: The Anatomy of Urban Crisis." *American Economic Review,* 57, no. 3 (1967): 415-26.

Berman, Eli, John Bound, Zvi Griliches, "Changes in the Demand for Skilled Labor within U. S. Manufacturing: Evidence from the Annual Survey of Manufactures," *Quarterly Journal of Economics*, 109(2) (May 1994): 367–397. https://doi.org/10.2307/2118467

Berman, Eli, John Bound, Stephen Machin, "Implications of Skill-Biased Technological Change: International Evidence," *Quarterly Journal of Economics*, 113(4) (November 1998): 1245–1279, https://doi.org/10.1162/003355398555892

Black, Sandra E., and Alexandra Spitz-Oener "Explaining women's success: technological change and the skill content of women's work," *Review of Economics and Statistics* 92, no. 1 (2010): 187-194

Black, Sandra, and Alexandra Spitz-Oener "Explaining women's success: technological change and the skill content of women's work," NBER WP 13116 (2007).

Bond, Timothy N. and Kevin Lang. "The Evolution of the Black-White Test Score Gap in Grades K-3: The Fragility of Results." *Review of Economics and Statistics*, (December 2013): 1468-79.

Bond, Timothy N. and Kevin Lang. "The Sad Truth About Happiness Scales," *Journal of Political Economy*, 127:4 (August 2019):1629-1640.

Cavounidis, Costas and Lang, Kevin. "Ben-Porath meets Lazear: Microfoundations for Dynamic Skill Formation," *Journal of Political Economy*, 128:4 (April 2020): 1405-35.

Deming, David J. "The growing importance of social skills in the labor market," *Quarterly Journal of Economics*, vol. 132, no. 4 (November 2017): 1593-1640.

Deming, David J. and Noray, Kadeem "Earnings Dynamics, Changing Job Skills, and STEM Careers," *Quarterly Journal of Economics*, vol. 135, no. 4 (November 2020): 1965–2005.

Dickens, William T. "Error Components in Grouped Data: Is It Ever Worth Weighting?" *The Review of Economics and Statistics* vol. 72, no. 2 (1990): 328-33.

Dorn, David "Essays on Inequality, Spatial Interaction, and the Demand for Skills," *Dissertation University of St. Gallen* no. 3613 (September 2009).

Flood, Sarah, Miriam King, Renae Rodgers, Steven Ruggles and J. Robert Warren. Integrated Public Use Microdata Series, Current Population Survey: Version 8.0 [dataset].

Goos, Maarten, Alan Manning, and Anna Salomons, "Explaining Job Polarization: Routine-Biased Technological Change and Offshoring," *American Economic Review*, 104(8) (August 2014):2509-26.

Jones, Charles I. "Intermediate goods and weak links in the theory of economic development," *American Economic Journal: Macroeconomics*, vol. 3, no. 2 (April 2011): 1-28.

Juhn, Chinhui, "Wage Inequality and Demand for Skill: Evidence from Five Decades," *Industrial and Labor Relations Review*," 52(3) (April 1999): 424-43.

Katz, Lawrence, Kevin M. Murphy, "Changes in Relative Wages, 1963–1987: Supply and Demand Factors," *Quarterly Journal of Economics*, 107(1) (February 1992): 35–78, https://doi.org/10.2307/2118323

National Academy of Sciences. Committee on Occupational Classification and Analysis. Dictionary of Occupational Titles (DOT): Part I - Current Population Survey, April 1971, Augmented With DOT Characteristics and Dictionary of Occupational Titles (DOT): Part II - Fourth Edition Dictionary of DOT Scores for 1970 Census Categories. Inter-university Consortium for Political and Social Research [distributor], 2006-09-06. https://doi.org/10.3886/ICPSR07845.v2

Ngai, Rachel, and Christopher A. Pissarides. "Structural Change in a Multisector Model of Growth." *American Economic Review*, 97 (1) (2007): 429-443. Minneapolis, MN: IPUMS, 2020. https://doi.org/10.18128/D030.V8.0

Ruggles, Steven, Sarah Flood, Sophia Foster, Ronald Goeken, Jose Pacas, Megan Schouweiler and Matthew Sobek. IPUMS USA: Version 11.0 [dataset]. Minneapolis, MN: IPUMS, 2021. https://doi.org/10.18128/D010.V11.0

Gary Solon, Steven J. Haider and Jeffrey M. Wooldridge, “What Are We Weighting for?” J. Human Resources Spring 2015 vol. 50 no. 2 301-316

United States Department of Labor. Dictionary of Occupational Titles (DOT): Third edition, 1965. Volume 1 and 2. Washington, D.C.: US Government Printing Office

United States Department of Labor. United States Employment Service, and the North Carolina Occupational Analysis Field Center. Dictionary of Occupational Titles (DOT): Revised Fourth Edition, 1991. [distributor], 2006-01-12. https://doi.org/10.3886/ICPSR06100.v1

Table 1: Skills use levels by year

	Routine skills			Abstract skills		
	1960	**1971**	**1983**	**1960**	**1971**	**1983**
All						
Mean	0.314	0.276	0.242	0.298	0.342	0.378
Std. Dev.	(0.164)	(0.198)	(0.185)	(0.142)	(0.179)	(0.182)
Women						
Mean	0.299	0.288	0.233	0.312	0.317	0.375
Std. Dev.	(0.179)	(0.209)	(0.190)	(0.123)	(0.171)	(0.175)
Men						
Mean	0.319	0.271	0.248	0.293	0.353	0.379
Std. Dev.	(0.157)	(0.192)	(0.181)	(0.148)	(0.181)	(0.185)
	Manual skills			**Finger dexterity skills**		
	1960	**1971**	**1983**	**1960**	**1971**	**1983**
All						
Mean	0.084	0.097	0.083	0.305	0.285	0.298
Std. Dev.	(0.062)	(0.110)	(0.105)	(0.067)	(0.080)	(0.088)
Women						
Mean	0.058	0.070	0.049	0.331	0.325	0.343
Std. Dev.	(0.059)	(0.092)	(0.079)	(0.072)	(0.096)	(0.101)
Men						
Mean	0.093	0.109	0.103	0.296	0.267	0.270
Std. Dev.	(0.060)	(0.115)	(0.113)	(0.062)	(0.064)	(0.064)

Notes: Estimates use the occupation distributions from the 1960 Census, the March 1970-72, and 1982-84 Current Population Surveys. The skills used in each occupation are taken from the third, fourth, and revised fourth editions of the Dictionary of Occupational Titles. DOT occupations are aggregated to census occupations using the April 1971 Current Population Survey.

Table 2: Within- and across-occupation components

	Routine skills		Abstract skills		Manual skills		Fingdex skills	
	60-71	**71-83**	**60-71**	**71-83**	**60-71**	**71-83**	**60-71**	**71-83**
All	-0.037	-0.034	0.044	0.035	0.013	-0.014	-0.020	0.013
Δ within	-0.035	-0.024	0.035	0.013	0.018	-0.003	-0.018	0.014
Δ across	-0.003	-0.010	0.009	0.022	-0.004	-0.011	-0.002	-0.001
Std. Dev.	(0.164)	(0.198)	(0.142)	(0.179)	(0.062)	(0.110)	(0.067)	(0.080)
Women	-0.011	-0.056	0.005	0.058	0.013	-0.021	-0.007	0.019
Δ within	-0.009	-0.047	-0.003	0.026	0.014	-0.010	-0.002	0.031
Δ across	-0.001	-0.008	0.007	0.032	-0.001	-0.011	-0.005	-0.012
Std. Dev.	(0.179)	(0.209)	(0.123)	(0.171)	(0.059)	(0.092)	(0.072)	(0.096)
Men	-0.048	-0.023	0.061	0.026	0.016	-0.006	-0.029	0.003
Δ within	-0.044	-0.014	0.049	0.007	0.019	0.000	-0.024	0.006
Δ across	-0.004	-0.009	0.012	0.019	-0.003	-0.006	-0.004	-0.004
Std. Dev.	(0.157)	(0.192)	(0.148)	(0.181)	(0.060)	(0.115)	(0.062)	(0.064)

Notes: This table decomposes the change in the use of each of four 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. Fingdex refers to finger dexterity. Estimates use the occupation distributions from the 1960 Census, the March 1970-72, and 1982-84 Current Population Surveys. The skills used in each occupation come from the decennial censuses. DOT occupations are aggregated to census occupations using the April 1971 Current Population Survey. Standard deviation in the base years in parenthesis.

Table 3: Skill Productivity Growth Relative to Average

	(1) women 60-70	(2) women 70-80	(3) men 60-70	(4) men 70-80
Routine	-0.169	0.027	-0.078	-0.045
	(0.149)	(0.162)	(0.157)	(0.103)
Abstract	0.246	0.923	0.281	0.417
	(0.157)	(0.185)	(0.189)	(0.123)
Manual	0.916	0.022	0.065	0.150
	(0.349)	(0.361)	(0.301)	(0.150)
Fingdex	-0.993	-0.971	-0.268	-0.523
	(0.284)	(0.259)	(0.314)	(0.207)
r2	0.16	0.16	0.15	0.12
proportion due to skills	0.16	0.47	0.07	0.18
N	3089	4628	4853	7013
p(all skill coefs=0)	0.006	0.000	0.428	0.005
p(routine=manual=finger dext.)	0.004	0.005	0.824	0.101

Notes: Standard errors in parentheses. Estimates are transformed from regression of change in log employment in an occupation/industry cell on average skill (routine, manual, 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 four skills is 0. Proportion due to skills is the proportion of the R-squared attributable to the three skills in the regression using the Shapley-Owen decomposition.

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

	Skill Used			
$\Delta\ lnA_i$	Routine	Abstract	Finger Dexterity	Manual
Women				
Routine	-0.263			
Abstract	0.151	-0.095		
Manual	0.021	0	-0.015	
Finger Dexterity	0.91	-0.056	-0.006	-0.039
Men				
Routine	-0.576			
Abstract	0.246	-0.143		
Manual	0.081	0	-0.066	
Finger Dexterity	0.249	-0.103	-0.015	-0.131

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. The cross-derivative between abstract and manual is set to 0. See the text for more detail.

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

Women 1960-1971
Predicted Skill-Use Change

Source of Change	Routine	Abstract	Manual	Finger Dexterity
Routine	-0.044	0.026	0.004	0.015
Abstract	-0.037	0.023	0	0.014
Manual	-0.019	0	0.014	0.006
Finger Dexterity	0.090	-0.056	-0.006	-0.029
Total Predicted	-0.010	-0.007	0.011	0.006
Data	-0.009	-0.003	0.014	-0.002

Women 1971-1983
Predicted Skill-Use Change

Source of Change	Routine	Abstract	Manual	Finger Dexterity
Routine	0.007	-0.004	-0.001	-0.002
Abstract	-0.139	0.088	0	0.052
Manual	0.000	0	0.000	0.000
Finger Dexterity	0.088	-0.054	-0.006	-0.028
Total Predicted	-0.044	0.029	-0.006	0.021
Data	-0.047	0.026	-0.010	0.031

Men 1960-1971
Predicted Skill-Use Change

Source of Change	Routine	Abstract	Manual	Finger Dexterity
Routine	-0.045	0.019	0.006	0.019
Abstract	-0.069	0.040	0	0.029
Manual	-0.005	0	0.004	0.001
Finger Dexterity	0.067	-0.028	-0.004	-0.035
Total Predicted	-0.053	0.032	0.007	0.014
Data	-0.044	0.049	0.019	-0.024

Men 1971-1983
Predicted Skill-Use Change

Source of Change	Routine	Abstract	Manual	Finger Dexterity
Routine	-0.026	0.011	0.004	0.011
Abstract	-0.103	0.060	0	0.043
Manual	-0.012	0	0.010	0.002
Finger Dexterity	0.130	-0.054	-0.008	-0.069
Total Predicted	-0.010	0.017	0.006	-0.012
Data	-0.014	0.007	0.000	0.006

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 four values above. It can be compared with Data.