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

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**Abstract**

We exploit employment trends to uncover changes in skills' productivities. Whereas Autor, Levy, and Murnane (2003) study the degree to which routine-intensity can rationalize employment trends, our reverse approach characterizes the kind of technological change that best explains shifts. We combine a tractable GE model with three DOT editions, the 1960, 1970, and 1980 Censuses, and the March CPS, to estimate changes in the relative productivities of skills. We find 'skill bias' - finger-dexterity productivity grew rapidly, while abstract-skill productivity lagged. With substitutability between abstract and routine inputs, these results also explain changing 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 quickly caught a mistake 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.

Neither did the Selectric 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 primarily middle-skilled workers in typing-intensive jobs. Further, this technological innovation might have also changed how much typing was done in other occupations.

Thus, the Selectric had two effects within occupations: a primitive effect, which made typing significantly more productive, and an adaptation effect, in which workers responded 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 relatively 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.[1] 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. Crucially, unlike most of the literature, we do not assume that either occupations, or the various skills they

[1]With a slight reinterpretation, our model applies equally well if one thinks that rather than measuring aptitudes, the DOT measures workers' task intensity, and workers face a time constraint rather than a skill budget constraint. The fact the discipline has varying views on what the DOT measures does not pose an impediment to our approach.

use, are hierarchical in any way.

As in the SBTC model, we allow for skill-enhancing technological change. However, this change does not affect occupations based on their average level of education, but rather by the extent the occupation uses affected skills.[2] 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 an occupation's output is less than one, as we believe plausible, demand for an occupation made relatively more productive 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 the 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 demand shifts into account. 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.

Note this is orthogonal to the exercises conducted by Autor, Levy, and Murnane and Goos, Manning, and Salomons (2014). They use routine intensity as a measure of vulnerability to technological change, and study the degree to which it drives employment changes. Our approach instead leverages employment changes to identify what is the relevant technological change. Autor, Levy, and Murnane observe the correlation between computerization and performance of routine tasks, and show that this type of technological change can provide relevant insights in understanding changes in employment in the United States. Goos, Manning, and Salomons 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.

Kogan, Papanikolau, Schmidt, and Seegmiller (2019), 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 of exposure to technological

[2] Thus, though we do not model wages directly, we conceive of jobs at the same income quantile being affected by a technological change very differently - nursing surely did not experience technological change in the same way as typing.

advancement and use it to study its association with changes in employment and wages over a time span of almost two centuries. BÃ¡rÃ¡ny and Siegel (2020) estimate productivity change down to the sector/occupation level, assuming that each occupation uses only a single skill, whereas our occupations mix different skills in different amounts, and we account for sector-level demand. Acemoglu and Restrepo (2019) features the emergence of entirely new occupations; our analysis is based only on the *relative* employment in existing occupations, and is thus uninfluenced by such occurrences.

We depart from the skill-weights approaches of Lazear (2009), Gathman and Schonberg (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 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.

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 (DOT), 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 Current Population Surveys (CPS) 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 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.[3] However, we develop a model to help us interpret the results. 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.

Cortes, Jaimovich, and Siu (2021) argue that the growing importance of social tasks in high-pay jobs has increased the sorting of women into those jobs. While we focus on an earlier period because we are less sanguine than they are about our ability to combine data from the DOT and O*Net, the primary difference is that they focus on an equilibrium outcome, the growing importance of social skills for certain jobs. In the context of our model, growing employment in these jobs suggests that during the period they study, the productivity of social skills grew more slowly than other skills. Moreover, the increased use of social skills in high-pay jobs despite the slow growth of their productivity suggests that they complement other skills.

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 $y((A_i S_i)_{i \le n}, J)$ 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 $i$.[4]

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

[3] Autor, Levy, and Murnane 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.

[4] Thus output $y$ depends on the vector of effective inputs $(A_i S_i)_{i \le n}$.

function,[5] 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. We do not allow her to choose to spend more time on learning.[6]

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,

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

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

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

[5] $y(\cdot, J)$ 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 quasiconcave, and $y((A_i S_i)_{i \leq n}, J) = 0$ iff $A_i S_i = 0$ 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 relatively general. We thus think that excluding corner solutions is unproblematic for our application.

[6] 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.

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 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 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 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 old (Baumol 1967, see also Ngai and Pissarides 2007 and Acemoglu and Guerrieri 2008). We build on that idea In our case, jobs making 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 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 key-punch 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 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 found that, in a later period, 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 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 $\gamma_I$ 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 and product demand 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 its average in two proximate editions of the *DOT*. $\mu$ 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

$$\begin{aligned}
\Delta \ln(emp_{I,J}) &= \frac{\varepsilon}{1-\varepsilon}\Sigma_i \left(\left(d\ln A_i - d\ln \overline{A}\right)\left(S_{i,J} - \overline{S}_i\right)\right) + \gamma_I + \mu_{I,J} && (20)\\
&= \frac{\varepsilon}{1-\varepsilon}\Sigma_i \left(\left(d\ln A_i - d\ln \overline{A}\right) S_{i,J}\right) + \gamma_I + \mu_{I,J} && (21)\\
&: = \Sigma_i S_{i,J}\beta_i + \gamma_I + \mu_{I,J}. && (22)
\end{aligned}$$

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 the skills.

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, 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 entirely 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 productivity of all the skills.

We estimate (22) by ordinary least squares. Consistent with Solon, Haider, 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.

Although derived quite differently, our equation (22) 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. [7] 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.[8] 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.

# 3 Data

Following Autor, Levy, and Murnane, 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 used previously 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. 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 all but 41 of the 528 gender/occupations cells present in both 1971 and in 1983.[9]

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

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

[8] We do not model wages in our current framework. A case in favor of their inclusion could be made if we assumed the labor supply to an occupation to be less than infinitely elastic. However, this is unnecessary given that, empirically, including wages does not affect our results.

[9] We do not observe a change in the use of abstract skills for 94 cells, of routine skills for 112 cells, of manual skills for 118 cells, and of finger dexterity skills for 119 cells. It should be noted that these are changes for Census occupations, while skill use is reported for *DOT* occupations. Therefore, we observe a change for a Census occupation even if only one of the *DOT* occupations it comprises has been updated.

occupation titles.[10]

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 the individuals evaluating jobs 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, Levy, and Murnane, we measure routine-cognitive skill using the variable "adaptability to situations requiring the precise attainment of set limit, tolerances, or standards," routine-manual skill (hereafter, finger-dexterity skill) 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, partly for simplicity and partly 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 and Autor and Dorn (2013) in how we use these measures. Autor, Levy, and Murnane use the absolute value of each skill, while Autor and Dorn focus on routine intensity defined as $(RTI = ln(R) - ln(M) - ln(A))$.[11] Instead, we first scale the absolute level of skill use by

[10] While charges have been made on the gender bias in reporting on occupations dominated by one gender in the 3rd edition of the *DOT*, the main concern was expressed in relation to variables not used in our analysis: "data", "people", "things" (Cain and Treiman, 1981).

[11] 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

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 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'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, 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 economists know these data well, 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

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.

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. We rely on the 1970 and 1980 Census samples for the two later periods 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 on occupation, not industry, and therefore, uses 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 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, 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.

The later period corresponds most closely to the 1970-80 change in Autor, Levy, and Murnane and Autor and Price. Like these papers, we find a decline in routine (cognitive) skill use and increased abstract-skill use, but 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, $\Delta$ within shows how skill use would have changed had the occupations in which, for example, males worked been the same in 1960 and 1971. In parallel, $\Delta$ 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, primarily 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. All across-occupation changes seem quite modest in the early period, with the largest change for abstract-skill use. Still, this change amounts to only 0.06 standard deviations. In contrast, across-occupation changes are much more important in the later period. 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.[12]

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. Notably, the modest 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

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

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 decline of about .3 standard deviations, occurred almost entirely within occupation. Their manual-skill use increased within occupation by about .3 standard deviations, more than offsetting a small between-occupation decrease. Finally, 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 use 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.

Nevertheless, as in the earlier period, there are notable 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 aggregating *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. [13]

[13] The method used for the *DOT* data collection is another potential reason for concern, since job analysis is performed on an industry-by-industry basis, on a sample that does not reflect the population in the economy. Thus, some jobs might have a share of occupation titles in the data that differs from their share in the labor force (Spenner, 1990). At the aggregated level, this could lead to biased measures of skill use (and its changes) if there is heterogeneity across industries within an occupation. However, while this feature might still affect the measurement precision for occupation titles in underrepresented industries, the weighted aggregation to Census occupations performed using the April 1971 CPS should mitigate the problem.

## 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.[14] Table 3 shows the results of this exercise.[15]

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

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. We cannot reject that all skills grew at the same rate for men. 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.

[14] To reduce 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 ensures that we do not create this 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. Since occupations are coded consistently across periods, we are not concerned that changes in occupation drive these changes. 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.

[15] See Table 1A in the Appendix for non-transformed coefficients

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.[16] For both men and women we cannot reject that 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.

As previously mentioned, we perform this exercise also including the % change in average wages. Table 2A in the appendix shows that this has no meaningful impact on our estimates.[17]

### 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

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

A short argument based on Slutsky symmetry and the regularity and constant returns

[16]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 to explaining the variance of the dependent variable.

[17]Although not reported, we also performed this analysis using the change in the average log wage, and reached the same conclusion, with point estimates for skills productivity that are even closer to those in Table 3. Table available upon request.

to scale assumptions on $y(\cdot, J)$ shows that[18]

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

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 $d\ln A_n$:

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

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

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

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.

Assuming that these derivative terms do not change over time, after imposing symmetry 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

[18]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 $y(\cdot,J)$, $(A_iS_i)_{i\leq n}$, can be thought of as 'effective' skills . Now, $A_iS_i$ is simply the Marshallian demand for effective skill $i$, where the price of effective skill $i$ is $1/A_i$. We denote by $A_iS_i^{Hicks}$ the Hicksian demand of effective skill $i$, and by $\omega$ the skill budget constraint. The Slutsky equation is $\frac{\partial(A_iS_i)}{\partial\frac{1}{A_k}}+\frac{\partial(A_iS_i)}{\partial\omega}A_kS_k=\frac{\partial(A_iS_i^{Hicks})}{\partial\frac{1}{A_k}}$. From Slutsky symmetry, $\frac{\partial(A_iS_i^{Hicks})}{\partial\frac{1}{A_k}}=\frac{\partial(A_kS_k^{Hicks})}{\partial\frac{1}{A_i}}$, and from constant returns to scale we have symmetric income effects $\frac{\partial(A_iS_i)}{\partial\omega}A_kS_k=A_iS_iA_kS_k=\frac{\partial(A_kS_k)}{\partial\omega}A_iS_k$. Thus, $\frac{\partial(A_iS_i)}{\partial\frac{1}{A_k}}=\frac{\partial(A_kS_k)}{\partial\frac{1}{A_i}}$, so that $-A_iA_k^2\frac{\partial S_i}{\partial A_k}=-A_kA_i^2\frac{\partial S_k}{\partial A_i}$ or simply $\frac{\partial S_i}{\partial\ln A_k}=\frac{\partial S_k}{\partial\ln A_i}$ as desired.

abstract skill.[19] With this restriction, in theory, the derivatives are just identified. However, the system has no solution since the within-occupation changes are estimated with error and the equations are only a first-order approximation. 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.[20]

Recall that in Table 3, we estimate $\varepsilon / (1 - \varepsilon) * d \ln A_i$. So, as $\varepsilon$ 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 $\varepsilon / (1 - \varepsilon)$ 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 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. However, 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 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 produc-

[19] In the appendix, we report the outcomes of this exercise with the alternate assumption that there is no substitutability between manual and routine skill. The results change only in the details. See Tables 3A and 4A.

[20] In contrast $A_i S_i$, the 'effective' amount of skill $i$ supplied by the worker, must increase with $A_i$.

tivity 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 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 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.

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**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, clustered at the occupation level. 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

| $\Delta\ lnA_i$ | Skill Used | | | |
|---|---|---|---|---|
| | Routine | Abstract | Manual | Finger Dexterity |
| | | **Women** | | |
| Routine | -0.263 | | | |
| Abstract | 0.151 | -0.095 | | |
| Manual | 0.021 | 0 | -0.015 | |
| Finger Dexterity | 0.910 | -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. The predictions can be compared with the within changes reported in Table 2 and repeated in the line labelled Data.

# ON-LINE APPENDIX TABLES

**Table 1A:** Skill Productivity Growth Relative to Average - non transformed coefficients

| | (1) women 60-70 | (2) women 70-80 | (3) men 60-70 | (4) men 70-80 |
|---|---|---|---|---|
| Routine | -0.415 | -0.896 | -0.360 | -0.462 |
| | (0.183) | (0.186) | (0.226) | (0.144) |
| Manual | 0.671 | -0.901 | -0.216 | -0.268 |
| | (0.421) | (0.484) | (0.366) | (0.196) |
| Finger dexterity | -1.238 | -1.894 | -0.549 | -0.940 |
| | (0.372) | (0.356) | (0.455) | (0.305) |

*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 (routine, manual, 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

| | (1) women 60-70 | (2) women 70-80 | (3) men 60-70 | (4) men 70-80 |
|---|---|---|---|---|
| Routine | -0.157 | 0.033 | -0.076 | -0.044 |
| | 0.151 | 0.163 | 0.156 | 0.103 |
| Abstract | 0.257 | 0.937 | 0.284 | 0.418 |
| | 0.160 | 0.186 | 0.188 | 0.123 |
| Manual | 0.903 | 0.002 | 0.073 | 0.149 |
| | 0.356 | 0.366 | 0.300 | 0.151 |
| Finger dexterity | -1.002 | -0.972 | -0.280 | -0.524 |
| | 0.289 | 0.260 | 0.313 | 0.207 |
| % Change mean wage 60 | 0.000 | | 0.012 | |
| | (0.000) | | (0.006) | |
| % Change mean wage 70 | | 0.000 | | 0.007 |
| | | (0.002) | | (0.003) |
| F(3, N3) | 21.97 | 10.16 | 22.42 | 14.63 |
| p | 0.000 | 0.000 | 0.000 | 0.000 |
| r2 | 0.17 | 0.16 | 0.15 | 0.12 |
| N | 3046 | 4588 | 4848 | 6997 |

*Notes*: Standard errors in parentheses, clustered at the occupation level. 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 3A:** Derivatives of Skill Use with Respect to Skill Productivity

| | Skill Used | | | |
|---|---|---|---|---|
| $\Delta$ $lnA_i$ | Routine | Abstract | Manual | Finger Dexterity |
| **Women** | | | | |
| Routine | -0.108 | | | |
| Abstract | 0.081 | -0.063 | | |
| Manual | 0 | 0.009 | -0.012 | |
| Finger Dexterity | 0.027 | 0.027 | -0.003 | -0.051 |
| **Men** | | | | |
| Routine | -0.522 | | | |
| Abstract | 0.277 | -0.127 | | |
| Manual | 0 | -0.045 | 0.054 | |
| Finger Dexterity | 0.245 | -0.105 | -0.009 | -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 routine and manual is set to 0. See the text for more detail.

**Table 4A:** Decomposition of Within-Occupation Changes in Skill Use

**Women 1960-1971**

Predicted Skill-Use Change

| Source of Change | Routine | Abstract | Manual | Finger Dexterity |
|---|---|---|---|---|
| Routine | -0.018 | 0.014 | 0 | 0.004 |
| Abstract | -0.020 | 0.016 | -0.002 | 0.006 |
| Manual | 0 | -0.008 | 0.011 | -0.003 |
| Finger Dexterity | 0.027 | -0.027 | 0.003 | -0.003 |
| Total Predicted | -0.011 | -0.005 | 0.012 | 0.004 |
| 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 | 0.003 | -0.002 | 0 | -0.001 |
| Abstract | -0.075 | 0.058 | -0.008 | 0.025 |
| Manual | 0 | 0.000 | 0.000 | 0.000 |
| Finger Dexterity | 0.026 | -0.026 | 0.003 | -0.003 |
| Total Predicted | -0.046 | 0.030 | -0.005 | 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 | -0.041 | 0.022 | 0 | 0.019 |
| Abstract | -0.078 | 0.036 | 0.013 | 0.029 |
| Manual | 0 | 0.003 | -0.004 | 0.001 |
| Finger Dexterity | 0.066 | -0.028 | -0.002 | -0.036 |
| Total Predicted | -0.053 | 0.033 | 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 | -0.023 | 0.013 | 0 | 0.010 |
| Abstract | -0.116 | 0.053 | 0.019 | 0.044 |
| Manual | 0 | 0.007 | -0.008 | 0.001 |
| Finger Dexterity | 0.128 | -0.055 | -0.008 | -0.065 |
| Total Predicted | -0.011 | 0.018 | 0.003 | -0.010 |
| 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. The predictions can be compared with the within changes reported in Table 2 and repeated in the line labelled Data.