

The Evolution of Skill Use Within and Between Jobs*

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Abstract

We develop a tractable general equilibrium model that provides a framework for understanding within- and between-occupation changes in skill use over time. We apply the model to skill-use measures from the third, fourth and revised fourth editions of the *Dictionary of Occupational Titles* and data from the 1960, 1970 and 1980 Censuses and March Current Population Surveys. We find that relatively slow growth in abstract-skill and fast growth in finger dexterity productivity combined with an elasticity of substitution between abstract and routine-skill use of less than one explain skill-use shifts during this period, demonstrating the model's utility for analyzing such changes.

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1 Introduction

Consider the IBM Selectric, an electronic typewriter introduced in 1961 and that replaced the traditional strikebars with a golf-ball-like element and in later versions was ‘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. Previously, they covered it with a white fluid or retyped the page entirely.

This description only very imperfectly matches the canonical model of skill-biased technological change (Katz and Murphy 1992, Berman, Bound and Griliches 1994, Berman, Bound and Machin 1998, Juhn 1999), or SBTC, in which technological change makes skilled or more-educated workers more productive. The task model (Autor, Levy and Murnane 2003, Acemoglu and Autor 2011) views technological change as task replacing. However, while firms may have employed fewer secretaries, demand for typed documents probably rose, as the Selectric enabled each typist to produce each page in less time.

We integrate insights from both approaches. We model occupations as combining skills, akin to tasks in the tasks model, to produce intermediate goods. 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 the 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 to be generally plausible, demand for this occupation falls. We embed the occupation production function in a tractable general equilibrium model in which workers invest in skills, and jobs are heterogeneous with respect to how skills are used to produce output.

At the same time, we allow for shifts in product demand (possibly due to trade shocks) or labor demand (possibly due to robots or offshoring) that indirectly alter demand for workers with different skills. The model thus clarifies the distinction between technological changes to how skills are combined to produce outputs and changes to demand. The model provides us with a simple approach to measuring the relative increase in the technological productivity of different skills, at least up to a factor of proportionality, while taking account of product 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.

We demonstrate the model’s usefulness by applying its insights to changes in skill use within and between occupations from 1960 to 1983. We show that, during this period, men moved out of routine-intensive occupations, a shift that began somewhat later among women. This movement is familiar from Autor, Levy and Murnane (2003) and Autor and Dorn (2013), especially in the period following the one we study. The 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 also grew within occupations while routine-skill use fell. This pattern continued for men in the later period although less dramatically. We show how complementarity and substitutability of skills with respect to their own and other skills’ growth in productivity explain these patterns.

Our analysis uses a subset of the skills studied by Autor et al 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 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 important 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. 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. Cerina, Moro and Rendall (2020) find that polarization is primarily a female phenomenon, but the period they study is after ours, and they argue that polarization should not be ascribed to shifts in the importance of routine work.¹

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 not only our results but also the large literature in this area.

¹ALM 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.

2 A model of skill and job choice in general equilibrium

2.1 Skill acquisition and intermediate good production

Before employment, each worker chooses a vector of skills $S \in \mathbb{R}_+^N$, where each component S_i reflects ability at task i . Once workers have acquired skills, each chooses a job $J \in \mathcal{J}$, where $\mathcal{J}$ is the set of all jobs. If a worker with skills S is employed at job J , she produces a quantity $y((A_i S_i)_{i \leq n}, J)$ of ‘ 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 $A_i S_i$ is the ‘effective’ amount of input i .

Our intention is to 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 function², 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 $\sum_i S_i = 1$. 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.³

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

$$A_i y'_i(A_i S_i^*(J), J) = \lambda = y^*(J) \tag{3}$$

where the second equality follows straightforwardly from constant returns to scale.

² $y(\cdot, J)$ 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 .

³This 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.

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

$$\frac{\partial y^*(J)}{\partial A_i} = S_i^*(J) y'_i(A_i S_i^*(J), J) \quad (4)$$

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

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

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

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

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

which we can rearrange as

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

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). We extend it by assuming that instead of goods of intrinsic value, workers produce inputs in a CES final good production function

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

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

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

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

We can then pointwise differentiate the Lagrangian and obtain

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

which we can write as

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

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

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

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

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

or simply, using (5),

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

In other words, if and only if the elasticity of substitution among intermediate goods $\frac{1}{1-\varepsilon}$ 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, to summarize, when elasticities of substitution are less than one both within intermediate good production (on average) and across intermediate goods in final good production, an increase, for example, in A_R (a technological change that makes routine skills more productive) will

- Reduce routine use in all jobs (within).
- Shift workers to less-routine jobs (across).

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 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

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

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

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

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

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

The model above distinguishes between changes that replace occupations by automating or offshoring them (a decline in h) as when data input is imported from abroad and those in which technology makes the skill 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 A increases, assuming that ε is negative and the intermediate-good elasticity of substitution is less than 1, the workers who do data input jobs end up being less skilled at data entry, and fewer workers are hired to do data input.

Interpreted within our model, Autor et al found that 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 and substitution between abstract and routine skills within 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.

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

$$\ln \frac{emp_{I,J,t}}{emp_{I,J,t-1}} = \frac{\varepsilon}{1 - \varepsilon} \sum_i \left(d \ln A_{it} \left(S_{i,J,t} - \bar{S}_{i,t} \right) \right) + \gamma_I + \mu_{J,t} \quad (19)$$

where $emp_{I,J}$ is 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 will capture changes due to occupation-specific factors such as robots or outsourcing. We

measure $S_{iJ,t}$ by the average of the measure in two proximate editions of the DOT. μ is a mean-zero error term.

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 $d \ln A$. We therefore rewrite the equation as

$$\ln \frac{emp_{J,t}}{emp_{J,t-1}} = \frac{\varepsilon}{1-\varepsilon} \Sigma_i \left((d \ln A_{it} - d \ln \bar{A}_t) (S_{iJ,t} - \bar{S}_{i,t}) \right) + \gamma_I + \mu_{J,t} \quad (20)$$

$$= \frac{\varepsilon}{1-\varepsilon} \Sigma_i \left((d \ln A_{it} - d \ln \bar{A}_t) S_{iJ,t} \right) + \gamma_I + \mu_{J,t} \quad (21)$$

$$: = \Sigma_i S_{iJ,t} \beta_i + \gamma_I + \mu_{J,t}. \quad (22)$$

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.

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. 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, the coefficients can be interpreted 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.

Equation (22) addresses only changes in the productivity of skills and not shifts in the demand for occupations. Our, admittedly imperfect, solution to capture changes in h is to augment the equation with 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) 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.

3 Data

Following Autor 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'). 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 the same variables of interest as the later *DOT* and its revision, allowing us to have consistent skill measures over time except 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. The 1965 *DOT* sometimes provides more than one value of an aptitude, temperament or ability for a single job title. In such cases, we use a simple average of the values reported.

Like Autor et al, 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,” and abstract by “General Education Development.” We drop interactive skills from the analysis, in part for simplicity and in part because our sense is that the explosion in the demand for social skills (Deming 2017) dates from a later period. 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 et al and Autor and Dorn in how we use these measures. Autor et al use the absolute value of each skill, while Autor and Dorn focus on routine intensity defined as ($RTI = \ln(R) - \ln(M) - \ln(A)$). 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 is:

$$\widetilde{skill}_i^J = \frac{skill_i^J - skill_i^{min}}{skill_i^{max} - skill_i^{min}} \quad (23)$$

where $skill_i^J$ 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 on the overall sum

$$S_i^J = \frac{\widetilde{skill}_i^J}{\sum_k \widetilde{skill}_k^J}$$

so that our four skill measures sum to 1.

Census occupations are more highly aggregated than the *DOT*’s job titles. Following Autor 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 et al, we use the DOT-augmented version of 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 cell. We therefore 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 et al and Autor and Prince (2013), we find that the use of routine-cognitive skills declined in the earlier period. The difference is that we use the *DOT 3rd edition* to measure skill use in the earlier period. 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), but 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 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 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:

$$Skill_{e,t} - Skill_{e-1,t-1} = \underbrace{(Skill_{e-1,t} - Skill_{e-1,t-1})}_{\Delta \text{ across}} + \underbrace{(Skill_{e,t} - Skill_{e-1,t})}_{\Delta \text{ within}} \quad (24)$$

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 what has typically been 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.

Thus, between 1960 and 1971 routine-skill use declined by .037. This decline was entirely (-.034) within occupation, with a trivial portion (-.003) due to occupation shifts. In contrast, in the case of women, the absence of any noticeable decline in routine-skill use in this period was *not* the result of within and between changes offsetting each other. Instead, we observe that each was essentially unchanged.

We begin by looking at across-occupation changes since these are akin to what the literature most frequently measures. We remind the reader than 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.⁴

⁴We use the standard deviation in the base year, 1960 or 1971, in all cases.

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 use declines by more than one-fifth of a standard deviation, offset by increases in abstract-skill and manual-skill use of .23 and .27 standard deviations.

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. With the exception of 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. Final, within-occupation changes account for more than 80% of their .4 standard deviation decrease in the use of finger dexterity.

The table tells a notably different story about the later period. While all of the changes in skill use remain large and between .1 and .2 standard deviations, when we do not separate the results by gender, they are all smaller than in the early period by this metric. Most of the change in abstract and manual-skill use is between occupations. In fact, the within-occupation change in manual-skill use is negligible. However, within-occupation shifts are the more important source of changes in abstract 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. They range from .2 to over .3 among women compared with at most .14 standard deviations among men. The changes that we do observe also reflect across-occupation changes more for men than they do for women. Perhaps, the most striking aspect of the later period are the very large within-occupation shifts for women which amount to .32 (dexterity), .22 (routine), .15 (abstract), and .11 (manual) standard deviations. The sign reversal between the across and within shifts in the use of finger dexterity, while not ruled out by our model, 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.⁵ We augment the equation with two-digit industry dummies to capture product demand changes. Table 3 shows the results of this exercise.

Perhaps the most striking result is that 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 and the early versions of word processors that appeared towards the end of this period.

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, $0 > \varepsilon/(1 - \varepsilon) > -1$, 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.

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 15% 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

⁵To 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 ensures that we do not drop an occupation that saw a modest change in employment that caused it to cross the .01% 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.

relative importance of the skills measure.⁶ 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.

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:

$$dS_i^J = \sum_k \frac{dS_i^J}{d \ln A_k} d \ln A_k \quad (25)$$

and integrate over all jobs

$$\int_{J \in \mathcal{J}} dS_i(J) dJ = \sum_k \left(d \ln A_k \int_{J \in \mathcal{J}} \frac{dS_i(J)}{d \ln A_k} dJ \right). \quad (26)$$

We can replace the left-hand-side of (26) with the within estimates in Table 2 and $d \ln A_i$ with the estimates in Table 3. In addition, we know from (5)

$$\frac{dS_i(J)}{d \ln A_k} = \frac{\partial^2 \ln y^*(J)}{\partial \ln A_i \partial \ln A_k} = \frac{dS_k(J)}{d \ln A_i} \quad (27)$$

and since $\sum_k S_k = 1$, that

$$\sum_k \frac{dS_k^J}{d \ln A_i} = 0. \quad (28)$$

Therefore, after substituting and normalizing with respect to an arbitrary skill n , we have

$$within_i = \sum_{k \neq n} \frac{dS_i}{d \ln A_k} (d \ln A_k - d \ln A_n). \quad (29)$$

If we assume that the derivatives do not change over time, we have six equations for men and six unknowns after imposing symmetry, 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.

⁶Intuitively, 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.

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 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, $dS_i/d\ln A_k$, capture a concept analogous to p and q complementarity and substitutability. If the derivative is positive, the reduction in the cost of skill k increases the use of skill i . 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, with a change of sign, the coefficients represent lower bounds on the absolute values of the skill-productivity changes, and using these coefficients gives upper bounds on the derivatives. Consequently, we focus on the signs of the relations rather than their precise magnitude.

Although the precise values of the estimated derivatives 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 abstract than for routine skill. Routine and all other skills are A -complements, again averaged across occupations, while finger dexterity is an A -substitute for both abstract and manual.

Table 4 shows how the change in the productivity of each skill accounts for the overall within-occupation shift in skill use. It also compares the prediction 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 under-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 quarter 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](https://doi.org/10.1016/S0169-7218(11)02410-5).
- Atalay, Enghin, Phai Phongthientham, 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., Lawrence F. Katz, Melissa S. Kearney; “Trends in U.S. Wage Inequality: Revising the Revisionists,” *Review of Economics and Statistics*, 90(2) (May 2008): 300–323. doi: <https://doi.org/10.1162/rest.90.2.300>
- 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).
- 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)
- Cerina, Fabio, Moro, Alessio and Rendall, Michelle “A Note on Employment and Wage Polarization in the US,”(2021)
- 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).

Feenstra, Robert C. , Gordon H. Hanson, “The Impact of Outsourcing and High-Technology Capital on Wages: Estimates For the United States, 1979–1990,” *Quarterly Journal of Economics*, 114(3) (August 1999): 907–940, <https://doi.org/10.1162/003355399556179>

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>

Sarah Flood, Miriam King, Renae Rodgers, Steven Ruggles and J. Robert Warren. Integrated Public Use Microdata Series, Current Population Survey: Version 8.0 [dataset]. Minneapolis, MN: IPUMS, 2020. <https://doi.org/10.18128/D030.V8.0>

Steven Ruggles, 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		
	1959	1971	1983	1959	1971	1983
All						
Mean	0.313	0.276	0.242	0.299	0.342	0.377
Std. Dev.	(0.163)	(0.198)	(0.185)	(0.147)	(0.179)	(0.182)
Males						
Mean	0.318	0.271	0.248	0.294	0.353	0.379
Std. Dev.	(0.158)	(0.192)	(0.181)	(0.152)	(0.181)	(0.185)
Females						
Mean	0.298	0.288	0.233	0.314	0.317	0.375
Std. Dev.	(0.178)	(0.209)	(0.190)	(0.131)	(0.171)	(0.175)
	Manual skills			Finger dexterity skills		
	1959	1971	1983	1959	1971	1983
All						
Mean	0.084	0.097	0.083	0.304	0.285	0.298
Std. Dev.	(0.062)	(0.110)	(0.105)	(0.069)	(0.080)	(0.088)
Males						
Mean	0.093	0.109	0.103	0.295	0.267	0.270
Std. Dev.	(0.060)	(0.115)	(0.113)	(0.065)	(0.064)	(0.064)
Females						
Mean	0.059	0.070	0.049	0.329	0.325	0.343
Std. Dev.	(0.059)	(0.091)	(0.079)	(0.075)	(0.096)	(0.101)

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	0.043	0.035	0.013	-0.014	-0.019	0.013
Δ within	-0.034	-0.024	0.034	0.013	0.017	-0.003	-0.017	0.014
Δ across	-0.003	-0.010	0.009	0.022	-0.004	-0.011	-0.002	-0.001
Std. Dev.	(0.163)	(0.198)	(0.147)	(0.179)	(0.062)	(0.110)	(0.069)	(0.080)
Males	-0.047	-0.023	0.059	0.026	0.016	-0.006	-0.028	0.003
Δ within	-0.043	-0.014	0.048	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.	(0.158)	(0.192)	(0.152)	(0.181)	(0.060)	(0.115)	(0.065)	(0.064)
Females	-0.010	-0.055	0.003	0.058	0.011	-0.021	-0.004	0.019
Δ within	-0.009	-0.047	-0.004	0.026	0.012	-0.010	0.001	0.031
Δ across	-0.001	-0.008	0.007	0.032	-0.001	-0.011	-0.005	-0.012
Std. Dev.	(0.178)	(0.209)	(0.130)	(0.171)	(0.059)	(0.091)	(0.075)	(0.096)

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)	(2)	(3)	(4)
	women 60-70	women 70-80	men 60-70	men 70-80
Routine	-0.152 (0.146)	0.021 (0.171)	-0.073 (0.158)	-0.045 (0.103)
Abstract	0.264 (0.149)	0.909 (0.192)	0.294 (0.187)	0.417 (0.123)
Manual	0.817 (0.364)	0.090 (0.398)	0.080 (0.302)	0.150 (0.150)
Finger dexterity	-0.929 (0.294)	-1.019 (0.280)	-0.300 (0.321)	-0.523 (0.207)
r2	0.17	0.16	0.15	0.12
proportion due to skills	0.15	0.46	0.07	0.18
N	2980	4448	4853	7013
p(all skill coefs=0)	0.010	0.000	0.377	0.005
p(routine>manual=finger dext.)	0.014	0.006	0.779	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 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: Decomposition of Within-Occupation Changes in Skill Use

Men 1960-1971 Predicted Skill-Use Change				
Source of Change	Routine	Abstract	Manual	Finger Dexterity
Routine	-0.051	0.019	0.010	0.021
Abstract	-0.076	0.044		0.032
Manual	-0.011		0.008	0.003
Finger Dexterity	0.087	-0.033	-0.012	-0.042
Total Predicted	-0.052	0.031	0.007	0.014
Data	-0.043	0.048	0.019	-0.024

Men 1971-1983 Predicted Skill-Use Change				
Source of Change	Routine	Abstract	Manual	Finger Dexterity
Routine	-0.031	0.012	0.006	0.013
Abstract	-0.108	0.063		0.045
Manual	-0.022		0.016	0.006
Finger Dexterity	0.151	-0.057	-0.021	-0.073
Total Predicted	-0.010	0.018	0.001	-0.009
Data	-0.014	0.007	0.000	0.006

Women 1960-1971 Predicted Skill-Use Change				
Source of Change	Routine	Abstract	Manual	Finger Dexterity
Routine	-0.049	0.028	0.004	0.018
Abstract	-0.049	0.030		0.019
Manual	-0.020		0.014	0.006
Finger Dexterity	0.108	-0.066	-0.007	-0.035
Total Predicted	-0.011	-0.007	0.010	0.008
Data	-0.009	-0.004	0.012	0.001

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	-0.168	0.104		0.064
Manual	-0.002		0.002	0.001
Finger Dexterity	0.118	-0.072	-0.008	-0.038
Total Predicted	-0.046	0.028	-0.007	0.024
Data	-0.047	0.026	-0.010	0.031

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. Total predicted is the sum of the four values above. It can be compared with Data.