Is Technological Change Biased Towards the Unskilled in Services? An Empirical Investigation*

ONLINE APPENDIX

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A Data

A.1 Labor supply and wage samples

I use data from the March Current Population Survey from 1964–2006 for all wage and labor quantities. Survey years pertain to the preceding year, so the sample is actually 1963–2005. I obtained the data from Unicon Research, by license to the Department of Economics at NYU. The CPS is a monthly survey of about 50,000 households conducted by the Bureau of the Census for the Bureau of Labor Statistics. The CPS includes data on employment, earnings, hours of work, and other demographic characteristics including age, gender and educational attainment. Also available are data on occupation and industry.

I follow the methodology of Katz and Murphy (1992) (henceforth KM) to construct wage and employment series. To make sure that my understanding of their documentation is correct, I replicated most of their tables and figures. I also replicate their estimate of the aggregate elasticity of substitution by fitting $\log(\omega_t) = c - (1/\sigma)\log(h_t) + \delta \cdot t$ (their equation 19), where ω is the relative wage of college graduates versus high school graduates, and h is their relative supply (college versus high school equivalents).

Cells

In every year I create 64 cells by gender, four education levels (less than 12 years of schooling, 12 years, 13–15 years and 16 or more years), and eight 5-year potential experience brackets (1–5, 6–10, ... 36–40). Potential experience is calculated as min{age-years of schooling-7, age-17}. For the purpose of replicating KM's tables and figures I use 40 single-year categories for experience, as

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they do. For the purpose of replicating KM's regression I use the eight 5-year potential experience brackets, as they do.

Series construction and sample restrictions

The CPS is used to create two samples, one for wages, the "wage sample", and one for labor supply, the "count sample". Both samples have an equal number of cells, so they can be merged. The rationale for constructing two separate samples is as follows. The count sample gauges supply in the broadest way. The construction of the wage sample reflects the need to create consistent time series of wages. For this purpose I focus on full time workers that are strongly attached to the labor market. These considerations are reflected in the sample restrictions detailed below.

The count sample includes all individuals in the labor force who worked at least one week in the preceding year. There are 3,335,991 observations in this sample in all years. Labor supply is defined as annual hours worked times the CPS sampling weights as a share of the total annual hours worked

$$hrs_{ct} = \frac{\sum_{n \in \langle c \rangle} \lambda_{nt} hrs_{nt}}{\sum_{n} \lambda_{nt} hrs_{nt}} \ , \tag{1}$$

where $t = 1963, 1964...2005$ is years, c denotes the cell and $n \in \langle c \rangle$ means that individual n is a member of that cell. hrs_{nt} is the number of hours worked by that individual and λ_{nt} are CPS sampling weights.

The wage sample includes all individuals that were in the labor force at least 39 weeks in the calendar year prior to the survey, worked full time for at least one week and were not self employed. The wage sample further excludes individuals whose reason for not working full year was being enrolled in school, retired or in the armed forces. There are 1,968,451 observations in this sample in all years.

The wage measure is weekly wages, which was calculated as annual wages divided by number of weeks worked. Wages are deflated using the implicit personal consumption expenditures deflator from the NIPAs (data from Bureau of Economic Analysis). The average wage for each cell is a weighted average of weekly wages, where the weights are annual hours worked times the CPS sampling weights

$$w_{ct} = \frac{\sum_{n \in \langle c \rangle} w_{nt} \lambda_{nt} hrs_{nt}}{\sum_{n} \lambda_{nt} hrs_{nt}} \ , \tag{2}$$

where $t = 1963, 1964...2005$ is years, c denotes the cell and $n \in \langle c \rangle$ means that individual n is a member of that cell. w_{nt} is the weekly wage of individual n and hrs_{nt} is the number of hours worked by that individual. λ_{nt} are CPS sampling weights.

A correction was used to account for different allocation procedures for wages in surveys 1968–1975, relative to the following surveys. See KM for details. Not using this correction has no effect on my results, but is relevant for replicating their's, so I maintain it.

Imputing hours and weeks before 1976

Starting with survey 1976, annual hours are the product of weeks worked last year and usual weekly hours. Before survey 1976 annual hours are the product of weeks worked and hours worked in the week before the survey. If no hours were reported, weekly hours were imputed by using the average hours worked after survey 1975, by full time\part time status and gender. Weeks worked last year are reported in six brackets until 1975. For those years weeks are imputed by using the average number of weeks in the following years, within those brackets, by gender.

Top coding

Until 1995, top coded wages are multiplied by 1.45. After 1995 an adjustment for top coding is not required, because a new method was used beginning in 1996. Individuals with values above the maximum reported wage are grouped by sex, race, and worker status (full time full year/other). A mean income value is calculated within these 12 groups and assigned to these individuals.

Industry and occupation re-classifications

Over the 1963–2005 sample there have been a few industry and occupation re-classifications, the most substantial of which was in CPS 2003. This results in a small jump in the share of the service sector employment, commensurate with a drop in the share of the goods sector. In order to mitigate these breaks, I adjust labor supply at the 1-digit level using crosswalks from Census Bureau (2003).

The crosswalks comprise a transition matrix M between the Census 2000 system of industrial classifications (used from CPS 2003) and the 1990 system (used until CPS 2002). Each $M(i_{2000}, i_{1990})$ element in the matrix reports the expected proportion of people in industry i_{2000} according to the Census 2000 system that would be allocated to industry i_{1990} according to the Census 1990 system. The original matrix actually gives the information in the opposite direction (i.e. from i_{1990} to i_{2000}). I apply Bayes' Rule to get the 2000-to-1990 transition in order to affect the minimal number of years.

A.2 Series used in estimation

The estimation procedure is fed the aggregate skill abundance, h. It tries to match the following data series: aggregate skill abundance h; skill intensity in services h_s; skill intensity in the goods sector h_g; the relative wage of college graduates versus high school graduates, ω; and the relative price of services, p. Here I describe in detail how they are constructed. As before, I follow the methodology of KM, except for the relative price of services.

As noted above, there are 64 cells in every year. I use a vector of 64 fixed weights (one for each cell) to aggregate wages (this is KM's N vector):

$$\overline{hrs}_c = \frac{\sum_t hrs_{ct}}{\sum_{ct} hrs_{ct}} \ ,$$

where hrs_{ct} is described above in (1). Using fixed weights to aggregate wages across groups has the benefit of keeping the composition of the labor force fixed, so that the results are not driven by changes in composition.

College and high school equivalents

The labor supply concept is annual hours worked. All labor supply series—h, h_s and h_g—are defined in terms of college and high school full time equivalents. First I collapse the merged count sample and wage sample into 4 cells by education level in every year

$$w_{et} = \frac{\sum_{c\in\langle e\rangle} w_{ct}\overline{hrs}_c}{\sum_{c\in\langle e\rangle} \overline{hrs}_c} \quad \text{and} \quad hrs_{et} = \sum_{c\in\langle e\rangle} hrs_{ct} \ ,$$

where $e = 11, 12, 14$ and 16 correspond to less than 12 years of schooling, 12 years, 13–15 years and 16 or more years, respectively. $c \in \langle e\rangle$ means that cell c has education level e. To obtain equivalence weights I fit the following regressions for 1963–2005

$$\begin{aligned} w_{11} &= \epsilon_{11}^{12} w_{12} + \epsilon_{11}^{16} w_{16} + \xi_{11} \\ w_{14} &= \epsilon_{14}^{12} w_{12} + \epsilon_{14}^{16} w_{16} + \xi_{14} \ , \end{aligned}$$

The regression embodies the assumption that the labor input of high school dropouts and individuals with some college education is a linear combination of the labor input of high school and college graduates. The estimates are $\epsilon_{11}^{12} = 1.11$, $\epsilon_{11}^{16} = -0.16$, $\epsilon_{14}^{12} = 0.93$ and $\epsilon_{14}^{16} = 0.14$.

Aggregate skill abundance

Using the same merged count sample and wage sample, I aggregate into high school and college equivalents as follows,

$$\begin{aligned} L_{hs} &= hrs_{12} + \epsilon_{11}^{12} hrs_{11} + \epsilon_{14}^{12} hrs_{14} \\ L_{col} &= hrs_{16} + \epsilon_{11}^{16} hrs_{11} + \epsilon_{14}^{16} hrs_{14} \ , \end{aligned}$$

and skill abundance is defined as $h = L_{col}/L_{hs}$.

Sector skill intensities

I start with creating a count sample and wage sample where in addition cells are also defined by sector. Thus, there are 128 cells in every year. The industries that fall under each sector are detailed in **Table 1**. I collapsed the merged count sample and wage sample into 8 cells by education level and sector in every year

$$w_{est} = \frac{\sum_{c\in\langle e,s\rangle} w_{ct}\overline{hrs}_c}{\sum_{c\in\langle e,s\rangle} \overline{hrs}_c} \quad \text{and} \quad hrs_{est} = \sum_{c\in\langle e,s\rangle} hrs_{ct} \ ,$$

where $e = 11, 12, 14$ and 16 correspond to less than 12 years of schooling, 12 years, 13–15 years and 16 or more years, respectively. $c \in \langle e, s\rangle$ means that cell c has education level e and is a member of sector $s \in \{goods, services\}$. $\overline{hrs}_c$ is calculated as above, except that cells are also defined by sectors. I use the same equivalence weights as before to aggregate into high school and college equivalents by sector. An alternative is to calculate aggregate and sector specific equivalence weights separately. Doing so has no qualitative effect on the results. Sector skill intensity is defined as $h_s = L_{col,s}/L_{hs,s}$.

Relative wage

I use the aggregate merged count sample and wage sample described above. The relative wage of college versus high school is defined as $\omega = w_{16}/w_{12}$. When computing sector-specific relative wage of college versus high school (ω^{goods} and $\omega^{service}$) I use the same methodology as in (2). The only difference is that I restrict the set of cells $\langle c \rangle$ to include one sector or the other.

Relative price of services

The Bureau of Economic Analysis (BEA) provides chain-type price indices for value added by 1-digit industries (starting in 1947). I allocate industries to sectors in a way that is consistent with the classification **Table 1**. For each sector in every period I calculate a weighted average of the chain-type prices of industries that fall in that sector, where the weights are value added

$$p_s = \frac{\sum_{i \in \langle s \rangle} p_i va_i}{\sum_{i \in \langle s \rangle} va_i} ,$$

where $i \in \langle s \rangle$ means that industry i is in sector $s \in \{goods, services\}$, p_i are BEA prices and va_i is value added. The relative price of services versus goods in 1963–2005 is the ratio $p = p_{services}/p_{goods}$. I normalize this price to one in 1963. The simulated price of services used in the method of moments estimation is also normalized to one in 1963 to reflect the arbitrary base year.

A.3 Construction of task indices

I start with the March CPS data 1964–2006 and use the same sample restrictions of the aggregate "count sample". The count sample includes all individuals in the labor force who worked at least one week in the preceding year. I characterize each individual in the sample by 3-digit industry, education level (4), 3-digit occupation and gender. I also keep the annual hours worked and CPS weight. Then I merge the task intensities from the Dictionary of Occupational Titles (DOT).

Consistent occupation classification

I re-classify the occupations throughout the sample into one consistent occupation classification, the 1990 Census system. This is done using Stata code obtained from Peter Meyer, which is based on Meyer and Osborne (2005). I slightly modified the code to capture a few additional occupations which were originally not reclassified. The consistent occupation classification performs well for the entire economy in the entire sample, in the sense that occupational employment share do not exhibit large "jumps". However, this classification does not perform well outside of the 1967–2001 sample at the sectoral level. In particular, the task indices that I calculate exhibit jumps at the beginning and end of that sample. There were major occupation re-classifications in the 1968 and 2003 CPS's. Therefore I restrict the analysis to 1967–2001.

Merging DOT task intensities

Five DOT task intensities by occupation (373) and gender (2) are used. The occupations are classified using the same consistent system of Meyer and Osborne (2005), with very minor modifications.

After merging, each individual in the sample has five task intensities: *DEX* (finger dexterity), *COORD* (eye hand foot coordination), *STAND* (set limits, tolerances and standards), *MATH* (math aptitude) and *PLAN* (direction, control and planning). **Table A1** provides more details and examples for the task intensities. Autor, Levy, and Murnane (2003) performed principle components analysis on five classes of task measures and these five come out as the principle components in their class. The task measures vary over the $[0, 10]$ interval. In **Table A2** I report summary statistics.

Originally, there were 3886 DOT occupations, which were assigned to 411 1970 Census occupations. This was done (in 1977) using the April 1971 CPS, for which experts from the National Academy of Sciences assigned DOT occupations. The task intensities for the 1970-Census occupations are weighted averages of the DOT occupation tasks that were assigned to them, using the CPS sampling weights. The averages were different for men and women, hence the separation by gender.

Task indices by industry-education-gender cells

After matching the task intensities into individuals' occupations I compute the average for each generic task by industry-education-gender (in each year)

$$TASK_{i,e,g} = \frac{\sum_{n \in \langle i,e,g \rangle} TASK_n \lambda_n hrs_n}{\sum_{n \in \langle i,e,g \rangle} \lambda_n hrs_n} \ ,$$

where $TASK \in \{DEX,\ COORD,\ STAND,\ MATH,\ PLAN\}$, n denotes a particular individual, i is industry, g is gender and $e \in \{11, 12, 14, 16\}$ denotes education. 11 means less than 12 years of schooling, 12 means 12 years, 14 means 13–15 years and 16 means 16 years or more. $n \in \langle i, e, g \rangle$ means that individual n is a member of the $\langle i, e, g \rangle$ cell. λ_n are CPS sampling weights and hrs are annual hours.

Converting to percentiles in the 1967 distribution

I construct the empirical distribution of each $TASK_{i,e,g}$ in 1967. Denote this distribution by $F(TASK_{i,e,g})$. There are 1066 cells in 1967, which constitute a grid. Store these numbers together in ascending order. Relabel the values and corresponding $F(TASK_{i,e,g})$ values by their position, i.e. $TASK_r$ and F_r, where $TASK_r < TASK_{r+1}$ and $F_r < F_{r+1}$, $r = 1, 2, ...1066$.

For each of the following years I assign an F value for each task value. This is done by finding where in the 1967 distribution that particular value lies. Formally,

$$F(TASK_{i,e,g}) = F_r \ \text{ if } TASK_r \leq TASK_{i,e,g} < TASK_{r+1} \ .$$

I do not interpolate between values because it is computationally taxing in Stata and because the grid for 1967 is very fine (there are 1066 points on the $[0, 1]$ interval). Not interpolating introduces a negligible downward bias in the indices for all years after 1967, but this does not affect how the index evolves after 1967. If a task value is above the maximum of 1967 it gets $F = 1$. If the highest F value in a particular year does not reach 1, then I rescale by dividing all the F values in that year by that highest F value in that year.

Task indices by sector and education

I use $F\left(TASK_{i,e,g}\right)$ to aggregate by sector and education level

$$TASK_{s,e} = \frac{\sum_{i\in\langle s\rangle,g} F\left(TASK_{i,e,g}\right)\lambda_{i,e,g} hrs_{i,e,g}}{\sum_{i\in\langle s\rangle,g}\lambda_{i,e,g} hrs_{i,e,g}} \ ,$$

where $i \in \langle s\rangle$ means that industry i is in sector $s \in \{goods, services\}$, and education, e, is defined above. I construct indices for high school and college equivalents using a similar procedure as for their labor supply, as described below.

Using the $F\left(TASK_{i,e,g}\right)$ rather than $TASK_{i,e,g}$ has two benefits. First, it makes the task indices comparable in magnitude. Second, it assigns smaller weight to extreme values of $TASK_{i,e,g}$ that are found in ranges of the support that are less dense in 1967. The results are qualitatively the same if I use simple weighted averages of $TASK_{i,e,g}$.

College and high school equivalents

In practice, I need to aggregate tasks into high school equivalents and college equivalents. Aggregating is done by using the same equivalence weights as reported above and a similar procedure. Consider

$$A_e L_e = \left(\sum_o \lambda_o^e a_o^e\right) L_e \ ,$$

where $e \in \{11, 12, 14\}$. Notice that this last expression resembles the one in the main text, except that here a_o^e is indexed by education level. This allows for two individuals with different education levels but the same occupation to have different occupational efficiency. For a particular sector,

$$\begin{aligned} A_{hs}L_{hs} &= \left(\sum_o \lambda_o^{12} a_o^{12}\right) L_{12} + \left(\sum_o \lambda_o^{11} a_o^{11}\right) L_{11} + \left(\sum_o \lambda_o^{14} a_o^{14}\right) L_{14} \\ &= \left(\sum_o \lambda_o^{12} a_o^{12}\right) L_{12} + \left(\sum_o \lambda_o^{11} a_o^{12}\epsilon_{11}^{12}\right) L_{11} + \left(\sum_o \lambda_o^{14} a_o^{12}\epsilon_{14}^{12}\right) L_{14} \\ &= \left(\sum_o \lambda_o^{12} a_o^{12}\right) L_{12} + \left(\sum_o \lambda_o^{11} a_o^{12}\right) \epsilon_{11}^{12} L_{11} + \left(\sum_o \lambda_o^{14} a_o^{12}\right) \epsilon_{14}^{12} L_{14} \ . \end{aligned}$$

The second line follows from the same assumption that led to the use of the equivalence coefficients.

Now that all occupational efficiencies are in the same denomination, a_o^{12}, I drop the superscript. For a particular sector

$$A_{hs} = \left(\sum_o \lambda_o^{12} a_o\right) \frac{L_{12}}{L_{hs}} + \left(\sum_o \lambda_o^{11} a_o\right) \frac{\epsilon_{11}^{12} L_{11}}{L_{hs}} + \left(\sum_o \lambda_o^{14} a_o\right) \frac{\epsilon_{14}^{12} L_{14}}{L_{hs}} \ .$$

A_{hs} is the efficiency index of high school equivalents, which is the empirical counterpart to A and

L_{hs} is the empirical counterpart to L. Similarly,

$$B_{col} = \left(\sum_o \lambda_o^{16} b_o\right) \frac{H_{16}}{H_{col}} + \left(\sum_o \lambda_o^{11} b_o\right) \frac{\epsilon_{11}^{16} H_{11}}{H_{col}} + \left(\sum_o \lambda_o^{14} b_o\right) \frac{\epsilon_{14}^{16} H_{14}}{H_{col}} ,$$

where B_{col} is the efficiency index of college equivalents, which is the empirical counterpart to B, and H_{col} is the empirical counterpart to H.

The task indices are initially calculated by education $e \in \{11, 12, 14, 16\}$ and sector (see main text). I use the last expressions to calculate the indices for high school and college equivalents in both sectors

$$TASK_{hs} = TASK_{12} \frac{L_{12}}{L_{hs}} + TASK_{11} \frac{\epsilon_{11}^{12} L_{11}}{L_{hs}} + TASK_{14} \frac{\epsilon_{14}^{12} L_{14}}{L_{hs}}$$

and

$$TASK_{col} = TASK_{16} \frac{H_{16}}{H_{col}} + TASK_{11} \frac{\epsilon_{11}^{16} H_{11}}{H_{col}} + TASK_{14} \frac{\epsilon_{14}^{16} H_{14}}{H_{col}} .$$

Correction of equivalence weight for high school dropouts

Since $\epsilon_{11}^{16} = -0.16$, it causes a problem in calculating B_{col}: I get negative values for some tasks, which are intensive for high school dropouts and not intensive for college graduates. I fix this in the following way. The equivalence weights are used in order to translate the labor input of one class into that of another. Then for calculating the task indices let $\epsilon_{11}^{12} = 1.11 - 0.16 \cdot 1.75 = 0.84$ and $\epsilon_{11}^{16} = 0$. 1.75 is the average relative wage of college graduates versus high school graduates for the sample. To justify this procedure, manipulate the wage regression for high school dropouts

$$w_{11} = w_{12} \left(\epsilon_{11}^{12} + \epsilon_{11}^{16} \frac{w_{16}}{w_{12}} \right) + \xi_{11}$$

and replace w_{16}/w_{12} by its sample average, 1.75. This yields a similar result to fitting

$$w_{11} = w_{12} \widetilde{\epsilon}_{11}^{12} + \widetilde{\xi}_{11} ,$$

where $\widetilde{\epsilon}_{11}^{12}$ is approximately $\epsilon_{11}^{12} + \epsilon_{11}^{16} \left(\overline{w_{16}/w_{12}}\right)$. This way I avoid negative values, while maintaining the logic of relative efficiency.

A.4 IT capital share

I compute the share of information technology (IT) in the capital stock in each sector as follows. I use data from the BEA's fixed assets tables by industry, which provide both current-cost net capital stock of private nonresidential fixed assets, as well as chain-type quantity indices for these fixed assets. Denote k_t as current-cost net capital stock of some fixed asset, and denote q_t^{2000} as chain-type quantity index for that asset, where $q_{2000}^{2000} = 100$. I use the following formula to get constant price values for each fixed asset, $k_t^{2000} = q_t^{2000} \cdot k_{2000}/100$. Aggregation to goods and services sectors follows the classification used throughout the paper. The IT capital share is computed as the share of the k_t^{2000} series for "computers and peripheral equipment" plus "software", divided by the k_t^{2000}

series for the aggregate equipment fixed assets.

B Estimation

I estimate the parameters of the model by weighted nonlinear least squares, applying the method of simulated moments. Let

$$G^{*}(x,\theta) \equiv E(y|x,\theta) \ .$$

This is a high dimensional integral, which is evaluated by simulation. Approximating population moments by simulation increases the variance of estimators, but this increase vanishes as the number of simulations approaches infinity. See Stern (1997) for a clear explanation of the method of simulated moments and its implementation.

It follows that

$$y = G(x,u,\theta) = G^{*}(x,\theta) + e$$

where $E(e|x,\theta) = 0$ and e is a nonlinear function of u. I estimate θ by solving the following problem:

$$\text{choose } \theta \in \Theta \text{ to minimize } e'We = [y - G^{*}(x,\theta)]' W [y - G^{*}(x,\theta)] \ ,$$

where W is a positive definite symmetric weighting matrix and the set Θ restricts the elasticities to non negative numbers.

In order to deal with potential heteroscedasticity, I use $W=$diag(yy') (this transforms all errors into the same percent units). The time series in y are upward trending. Therefore errors may be larger when values in y are larger in the latter part of the sample; this might make the later observations more influential in the estimation. Translating the errors into percent terms solves this problem. However, results with $W = I$ are similar. In a generalized method of moments context, Altonji and Segal (1996) show that using the identity matrix has superior statistical properties (smaller bias and greater efficiency) to the optimal weighting matrix in small samples. Blundell, Pistaferri, and Preston (2006) use the diagonal of the optimal weighting matrix to account for heteroscedasticity.

In order to estimate θ, one must evaluate $G^{*}(x,\theta)$ by simulation (this is not feasible analytically), which requires knowing Ω or an estimate of Ω. Although it is possible to jointly estimate θ and Ω, it is computationally taxing. In order to proceed, consider

$$G^{0}(x,\theta) \equiv G(x,u,\theta)\,|_{u=0} \ .$$

Due to nonlinearities $G^{0}(x,\theta)$ is not equal to $G^{*}(x,\theta)$. Confronting $G_0(x,\theta)$ with actual data gives rise to

$$y = G^{0}(x,\theta) + v \ .$$

I use $G_0(x,\theta)$ to obtain initial values for the numerical searches for θ and for Ω. I proceed according to the following steps.

1. Obtain initial values for the search for θ by solving

$$\text{choose } \theta_0 \in \Theta \text{ to minimize } v'Wv = \left[y - G^0(x, \theta_0)\right]' W \left[y - G^0(x, \theta_0)\right] .$$

   $\widehat{\theta}_0$ is biased, but provides reasonable initial values for the search below.

2. Use $\widehat{v}$ from above to compute $\widehat{\Sigma}_v = \widehat{v}\widehat{v}'$, and solve

$$\text{choose } \Omega \text{ to minimize } d(\widehat{\Sigma}_v, \Sigma_e(\Omega)) ,$$

   where $\Sigma_e = E(ee')$ and $d(X, Y)$ is the sum of element-by-element squared differences between $\widehat{\Sigma}_v$ and $\Sigma_e(\Omega)$. Given $\widehat{\theta}_0$, I compute $\Sigma_e(\Omega)$ by simulating the model 500 times and averaging over those simulations for each guess of Ω. Each simulation r generates a $\widehat{\Sigma}_{e,r}$ matrix, $r = 1, 2, ...500$, and the average of those is used for $\Sigma_e(\Omega)$. The estimate of Ω here, $\widehat{\Omega}_0$, is used for approximating $G^*(x, \theta)$ in the next step. The price series is normalized, $p(1) = 1$, and the estimation procedure also forces this normalization. This creates a column and a row that are identically zero in $\widehat{\Sigma}_v = \widehat{v}\widehat{v}'$ and reduces the rank of $\widehat{\Sigma}_v$ by one. To avoid this, I drop the first observation in all variables, so that the dimensions of $\widehat{\Sigma}_v$ are $[4(T-1)] \times [4(T-1)]$.

3. Using the initial values $\widehat{\theta}_0$ and $\widehat{\Omega}_0$ from above, solve

$$\text{choose } \theta \in \Theta \text{ to minimize } e'We = [y - G^*(x, \theta)]' W [y - G^*(x, \theta)] ,$$

   where $\widehat{\Omega}_0$ is used to approximate $G^*(x, \theta)$ at every iteration in the search for θ. The approximation of $G^*(x, \theta)$ is done by simulating $G(x, u_r, \theta)$ 500 times, $r = 1, 2, ...500$, and computing the average.

4. Using $\widehat{e}$ from above to compute $\widehat{\Sigma}_e = \widehat{e}\widehat{e}'$, solve

$$\text{choose } \Omega \text{ to minimize } d(\widehat{\Sigma}_e, \Sigma_e(\Omega)) ,$$

   where $d(\cdot)$ is the same distance function as before. Given $\widehat{\theta}$, I compute $\Sigma_e(\Omega)$ by simulating the model 500 times and averaging over those simulations for each guess of Ω. Each simulation r generates a $\widehat{\Sigma}_{e,r}$ matrix, $r = 1, 2, ...500$, and the average of those is used for $\Sigma_e(\Omega)$.

I use parametric bootstrapping to compute standard errors. This entails estimating $\widehat{\theta}_r$ by solving

$$\text{choose } \theta_r \in \Theta \text{ to minimize } e_r'We_r = [y - G(x, u_r, \theta)]' W [y - G(x, u_r, \theta)] ,$$

$r = 1, 2, ...500$ times, and computing the standard errors over all estimates, where each u_r is independently drawn from $F(\widehat{\Omega})$.

Standard errors for $\widehat{\theta}$ can also be approximated using the delta method, which relies on asymptotic variances. But the delta method may underestimate or overestimate standard errors in highly nonlinear models such as the present one.

C Discussion of modeling assumptions

A main assumption in the estimation strategy is the exogenous relative supply of skilled labor. In the face of a positive elasticity of relative supply of skilled labor, this may bias the estimates. One way to deal with this is to endogenize the supply of skill in a stylized way, along the lines of Findlay and Kierzkowski (1983) or Dinopolous and Segerstrom (1999). However, it is not clear how to identify the additional parameters that this will entail without credible instruments.

Given the incremental nature of investment in education (a flow), the elasticity of aggregate relative supply (a stock) to the relative wage is likely to be very small in any given period. The relative wage affects individuals' decision to go to college, typically when young, whereas the sample includes individuals with up to 40 years of potential experience. Therefore, the contemporaneous increase in supply in a given year will not have a large effect on the aggregate relative supply. Moreover, an increase in college enrollment in response to a higher relative wage will show up in supply only 4 years later. Thus, relative supply can be thought of as "almost exogenous" to contemporaneous demand shocks.

Another assumption is that the economy is closed. Ignoring this does not affect the estimation through relative prices, because relative prices are explicitly used in the estimation below. However, output effects of international trade may bias the estimates of changes in A_s/A_g. For example, if in the data the trade deficit becomes increasingly composed of goods, then this will bias any estimator of A_g upwards, since the model economy must satisfy all of the demand for goods domestically (estimators of A_s/A_g will be biased downwards). However, this is not the case. Although the trade deficit increases in this sample, the relative contributions of services and goods to the deficit do not exhibit trends. Using data from the BEA, I find that the trade deficit in goods as a proportion to the overall trade deficit in goods and services (usually greater than 1) does not exhibit a trend in the sample. Therefore, there is not bias in the estimator of A_s/A_g. In fact, the estimates of the changes in A_s/A_g imply changes in relative sectoral labor productivity that are in line with independent estimates from Jorgenson and Stiroh (2000). Thus, ignoring international trade does not seem to be a major concern. In fact, Freeman (2003) argues that trade has had a very small impact on the labor market. In addition, Feenstra and Hanson (1999) estimate that expenditures on IT are about twice as important as outsourcing in U.S. manufacturing.

Wages for the same type of worker are assumed to be the same in both sectors. If there is individual heterogeneity or mobility costs this may not hold. However, Lee and Wolpin (2006) argue that capital mobility, entry of new cohorts and entry from home production—including female labor force participation, which increases disproportionately in the services sector—are sufficient to prevent wages in services from increasing in the face of the growth of that sector. The data construction in this paper treats observations on women and men equally. See Goldin (2006) for a summary of the changes in female labor force participation and their determinants, while Goldin, Katz, and Kuziemko (2006) document the increase in women's share of college enrolment and attainment. It is worthwhile stressing that the wage series construction scheme neutralizes compositional changes within cells, *inter alia* gender composition.

Using the sectoral classifications of this paper I find that the high school weekly wage in the goods sector is on average 26% higher than that in services, and fluctuates around that number; see **Figure A3** and **Figure A6**. Since there is no trend, assuming equal wages is not a bad assumption, because the nature of the difference does not change over time. In contrast, the college weekly wage in the goods sector is on average 20% higher than that in services until 1985; after that college wages in services and goods catch up until they are almost equal. So the assumption of equal wages for college graduates is somewhat more tenuous. Consistent with this, the skill premium grows slightly faster in services than in the goods sector; see **Figure A7**. But their evolution over time is almost identical: the correlation between them is 0.97. Using sector-specific skill premia in non-structural estimation does not change the estimates materially, as shown in **Table 3**.

Ultimately, finding that the estimates of the technological processes are consistent with changes in the occupational mixes in Section 4 supports the credibility of the identifying assumptions that yield those estimates.

D Technical appendix

D.1 Calculating fixed Hicks neutral technology path

A_s/A_g captures relative Hicks neutral technological change only if β_g and β_s are fixed. In order to fix the relative Hicks neutral technological position, changes in β_g and β_s must be taken into account. To do this I proceed as follows. An alternative representation of the production technologies is

$$\begin{aligned} G &= Z_g \left[(1-\alpha_g) L_g^{\rho_g} + \alpha_g H_g^{\rho_g} \right]^{1/\rho_g} \\ S &= Z_s \left[(1-\alpha_s) L_s^{\rho_s} + \alpha_s H_s^{\rho_s} \right]^{1/\rho_s} \quad , \end{aligned}$$

where Z_i are Hicks neutral technology shifters and α_i are the distribution parameters in sector $i \in \{g, s\}$. Given a non zero value for ρ_i one can find Z_i and α_i that correspond to A_i and β_i:

$$\alpha_i = \frac{\beta_i^{\rho_i}}{1+\beta_i^{\rho_i}} \quad \text{and} \quad Z_i = A_i \left(1+\beta_i^{\rho_i}\right)^{1/\rho_i} \quad .$$

Given the estimates in **Table 2**, I calculate the inter-sector ratio of Hicks neutral sector productivities. I calculate the implied path for A_s/A_g which maintains the same initial inter-sector Hicks neutral productivity ratio, controlling for the estimated changes in β_g and β_s. Fix Z_s/Z_g in all periods to be equal to the initial value. Define this initial value as z_1

$$z_1 \equiv \frac{Z(1)_s}{Z(1)_g} = \frac{A(1)_s}{A(1)_g} \frac{\left(1+\beta(1)_s^{\rho_s}\right)^{1/\rho_s}}{\left(1+\beta(1)_g^{\rho_g}\right)^{1/\rho_g}} \quad .$$

From period 1 and on I use the estimated biases in technological change, β_i, to calculate a new implied path for A_s/A_g

$$\frac{A_s'(t)}{A_g'(t)} \equiv z_1 \frac{\left(1+\beta(t)_g^{\rho_g}\right)^{1/\rho_g}}{\left(1+\beta(t)_s^{\rho_s}\right)^{1/\rho_s}} ,$$

where z_1 is defined above and where $\beta_g(t)$ and $\beta_s(t)$ evolve according to the estimation results. $A_s'(t)/A_g'(t)$ maintains the same inter-sector Hicks neutral productivity ratio at $A(1)_s/A(1)_g$ at all subsequent periods.

D.2 An α-Z specification of the model

Output in the two sectors is given by

$$\begin{aligned} G &= Z_g\left[(1-\alpha_g)L_g^{\rho_g}+\alpha_g H_g^{\rho_g}\right]^{1/\rho_g} \\ S &= Z_s\left[(1-\alpha_s)L_s^{\rho_s}+\alpha_s H_s^{\rho_s}\right]^{1/\rho_s} ,\end{aligned}$$

where Z_i are Hicks neutral technology shifters and $\alpha_s \in (0,1)$ are the "distribution parameters" in sector $i \in \{g,s\}$. $\rho_i \leq 1$ and the elasticity of substitution (EoS) is given by $\sigma_i = 1/(1-\rho_i)$. σ_s need not equal σ_g. Unit cost functions are given by

$$c_g = \frac{1}{Z_g}\left[(1-\alpha_g)^{\sigma_g} w_L^{1-\sigma_g}+\alpha_g^{\sigma_g} w_H^{1-\sigma_g}\right]^{\frac{1}{1-\sigma_g}} \tag{3}$$

$$c_s = \frac{1}{Z_s}\left[(1-\alpha_s)^{\sigma_s} w_L^{1-\sigma_s}+\alpha_s^{\sigma_s} w_H^{1-\sigma_s}\right]^{\frac{1}{1-\sigma_s}} , \tag{4}$$

where w_L and w_H are the (nominal) wages of low skilled labor and high skilled labor, respectively. Labor mobility equalizes wages across sectors. By taking the derivative of the cost functions with respect to each wage, one obtains unit demand for each factor. Then, by taking the ratio of unit demands one gets relative demand of skilled labor, or skill intensity, for each sector

$$h_g = \omega^{-\sigma_g}\gamma_g^{\sigma_g} \quad \text{and} \quad h_s = \omega^{-\sigma_s}\gamma_s^{\sigma_s} , \tag{5}$$

where $\omega = w_H/w_L$ is the relative wage of skilled workers, $h_i = H_i/L_i$ is skill intensity and $\gamma_i = \alpha_i/(1-\alpha_i)$.

Competition and CRS production require that the zero profit conditions must be satisfied. Normalize the price of goods to one and rewrite (3)–(4) to get

$$\begin{aligned} c_g &= \frac{w_L}{Z_g(1-\alpha_g)^{\frac{\sigma_g}{\sigma_g-1}}}\left[1+\omega h_g\right]^{\frac{1}{1-\sigma_g}} = 1 \\ c_s &= \frac{w_L}{Z_s(1-\alpha_s)^{\frac{\sigma_s}{\sigma_s-1}}}\left[1+\omega h_s\right]^{\frac{1}{1-\sigma_s}} = p .\end{aligned}$$

Take the ratio and use (5) to get the relative price of services

$$p = \frac{Z_g}{Z_s} \frac{(1-\alpha_g)^{\frac{\sigma_g}{\sigma_g-1}}}{(1-\alpha_s)^{\frac{\sigma_s}{\sigma_s-1}}} \frac{[1+\omega h_s]^{\frac{1}{1-\sigma_s}}}{[1+\omega h_g]^{\frac{1}{1-\sigma_g}}} \; . \tag{6}$$

Unit factor demand is obtained by taking the derivative of the unit cost functions with respect to the wage. By using (5)

$$L_i^1 = \frac{1}{Z_i (1-\alpha_i)^{\frac{\sigma_i}{\sigma_i-1}}} [1+\omega h_i]^{\frac{\sigma_i}{1-\sigma_i}} \quad \text{and} \quad H_i^1 = \frac{1}{Z_i \alpha_i^{\frac{\sigma_i}{\sigma_i-1}}} \left[1+(\omega h_i)^{-1}\right]^{\frac{\sigma_i}{1-\sigma_i}} \; .$$

Labor market clearing is given by $L = SL_s^1 + GL_g^1$ and $H = SH_s^1 + GH_g^1$. Relative output is obtained by manipulating these expressions,

$$\frac{S}{G} = \frac{Z_s}{Z_g} \frac{(1-\alpha_s)^{\frac{\sigma_s}{\sigma_s-1}}}{(1-\alpha_g)^{\frac{\sigma_g}{\sigma_g-1}}} \left(\frac{h-h_g}{h_s-h}\right) \frac{(1+\omega h_g)^{\frac{\sigma_g}{1-\sigma_g}}}{(1+\omega h_s)^{\frac{\sigma_s}{1-\sigma_s}}} \; , \tag{7}$$

where $h = H/L$ is the relative skill abundance of the economy. Relative demand is given by $\frac{S}{G} = p^{-\varphi} \left(\frac{\mu}{1-\mu}\right)^{\varphi}$. Using this together with (7) and (5) the following equilibrium condition is obtained

$$\begin{aligned}
& \Phi\left(\omega, h, \gamma_g, \gamma_s, Z_s/Z_g\right) \\
= & \left[\frac{Z_s}{Z_g} \frac{(1-\alpha_s)^{\frac{\sigma_s}{\sigma_s-1}}}{(1-\alpha_g)^{\frac{\sigma_g}{\sigma_g-1}}}\right]^{(1-\varphi)} \left(\frac{h-h_g}{h_s-h}\right) \frac{(1+\omega h_s)^{(\varphi-\sigma_s)/(1-\sigma_s)}}{(1+\omega h_g)^{(\varphi-\sigma_g)/(1-\sigma_g)}} \\
= & \left[\frac{Z_s}{Z_g} \frac{(1-\alpha_s)^{\frac{\sigma_s}{\sigma_s-1}}}{(1-\alpha_g)^{\frac{\sigma_g}{\sigma_g-1}}}\right]^{(1-\varphi)} \left(\frac{h-\omega^{-\sigma_g}\gamma_g^{\sigma_g}}{\omega^{-\sigma_s}\gamma_s^{\sigma_s}-h}\right) \frac{\left(1+\omega^{1-\sigma_s}\gamma_s^{\sigma_s}\right)^{(\varphi-\sigma_s)/(1-\sigma_s)}}{\left(1+\omega^{1-\sigma_g}\gamma_g^{\sigma_g}\right)^{(\varphi-\sigma_g)/(1-\sigma_g)}} \\
= & \left(\frac{\mu}{1-\mu}\right)^{\varphi} \; .
\end{aligned} \tag{8}$$

The only differences between (8) and the implicit function Φ in the main text are in the expressions for sectoral productivity in brackets and the functions for skill intensities.

D.3 Relationship between α-Z and A-B specifications

Static equivalence

Consider a generic CES production function in the form that has been used above

$$
\begin{aligned}
Q &= \left[(AL)^{\rho} + (BH)^{\rho}\right]^{1/\rho} \\
&= \left(A^{\rho} + B^{\rho}\right)^{1/\rho}\left[\frac{A^{\rho}}{A^{\rho}+B^{\rho}}L^{\rho} + \frac{B^{\rho}}{A^{\rho}+B^{\rho}}H^{\rho}\right]^{1/\rho} \\
&= A\left(1+\beta^{\rho}\right)^{1/\rho}\left[\frac{1}{1+\beta^{\rho}}L^{\rho} + \frac{\beta^{\rho}}{1+\beta^{\rho}}H^{\rho}\right]^{1/\rho} ,
\end{aligned}
$$

where $\beta = B/A$. The alternative specification is

$$Q = Z\left[(1-\alpha)L^{\rho} + \alpha H^{\rho}\right]^{1/\rho} .$$

Given a *non-zero value* for ρ one can find A and β that correspond to Z and α:

$$\alpha = \frac{\beta^{\rho}}{1+\beta^{\rho}} \Leftrightarrow \beta = \left(\frac{\alpha}{1-\alpha}\right)^{1/\rho} = \gamma^{1/\rho} ,$$

and given β,

$$Z = A\left(1+\beta^{\rho}\right)^{1/\rho} \Leftrightarrow A = Z\left(1-\alpha\right)^{1/\rho} = Z\left(1+\gamma\right)^{-1/\rho} .$$

Dynamic difference

I drop time indices where there is no confusion. The specifications for the exogenous technology processes (without shocks) are $Z_s/Z_g = \exp\{z_0 + z_1 t\}$ and $\gamma_i = \exp\left\{\gamma_{0,i} + \gamma_{1,i}t\right\}$, versus $A_s/A_g = \exp\{a_0 + a_1 t\}$ and $\beta_i = \exp\left\{\beta_{0,i} + \beta_{1,i}t\right\}$, $i \in \{g, s\}$. There is an equivalent representation of β_i in terms of γ_i and vice versa. Since $\beta = \gamma^{1/\rho}$, $\beta_i = \left(\exp\left\{\gamma_{0,i} + \gamma_{1,i}t\right\}\right)^{1/\rho} = \exp\left\{\left(\gamma_{0,i}/\rho\right) + \left(\gamma_{1,i}/\rho\right)t\right\}$, which maintains the constant growth rate form of β_i, so that $\beta_{0,i} = \gamma_{0,i}/\rho$ and $\beta_{1,i} = \gamma_{1,i}/\rho$. However, Z_s/Z_g does not have a constant growth rate if A_s/A_g does, and vice versa. The reason is that given a constant growth rate for β_i and A_s/A_g, the growth rate of Z_s/Z_g would not be constant, since $Z_i = A_i\left(1+\beta_i^{\rho_i}\right)^{1/\rho_i}$. Alternatively, given constant growth rates for γ_i and Z_s/Z_g, the growth rate of A_s/A_g would not be constant since $A_i = Z_i\left(1+\gamma_i\right)^{-1/\rho_i}$.

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Table A1: DOT Task Definitions and Examples

Variable	DOT task definition	Interpretation	Example tasks from *Handbook of Analyzing Jobs*
MATH (math aptitude)	General educational development, mathematics	Non-routine analytic	Lowest level: Adds and subtracts 2-digit numbers; performs operations with units such as cup, pint, and quart. Midlevel: Computes discount, interest, profit, and loss; inspects flat glass and compiles defect data based on samples to determine variances from and thermodynamic systems . . . to determine suitability of design for aircraft and missiles.
PLAN (direction, control, planning)	Adaptability to accepting responsibility for the direction, control, or planning of an activity	Non-routine interactive	Plans and designs private residences, office buildings, factories, and other structures; applies principles of accounting to install and maintain operation of general accounting system; conducts prosecution in court proceedings . . . gathers and analyzes evidence, reviews pertinent decisions . . . appears against accused in court of law; commands fishing vessel crew engaged in catching fish and other marine life.
STAND (set limits, tolerances, or standards)	Adaptability to situations requiring the precise attainment of set limits, tolerances, or standards	Routine cognitive	Operates a billing machine to transcribe from office records data; calculates degrees, minutes, and second of latitude and longitude, using standard navigation aids; measures dimensions of bottle, using gauges and micrometers to verify that setup of bottle-making conforms to manufacturing specifications; prepares and verifies voter lists from official registration records.
FINGDEX (finger dexterity)	Ability to move fingers, and manipulate small objects with fingers, rapidly or accurately	Routine manual	Mixes and bakes ingredients according to recipes; sews fasteners and decorative trimmings to articles; feeds tungsten filament wire coils into machine that mounts them to stems in electric light bulbs; operates tabulating machine that processes data from tabulating cards into printed records; packs agricultural produce such as bulbs, fruits, nuts, eggs, and vegetables for storage or shipment; attaches hands to faces of watches.
COORD (eye-hand-foot coordination)	Ability to move the hand and foot coordinately with each other in accordance with visual stimuli	Non-routine manual	Lowest level: Tends machine that crimps eyelets, grommets; next level: attends to beef cattle on stock ranch; drives bus to transport passengers; next level: pilots airplane to transport passengers; prunes and treats ornamental and shade trees; highest level: performs gymnastic feats of skill and balance.

Source: U. S. Department of Labor, Manpower Administration, *Handbook for Analyzing Jobs* (Washington, DC, 1972). Reproduced from Autor, Levy and Murnane (2003).

Table A2: DOT Tasks Summary Statistics

A. Sample Statistics

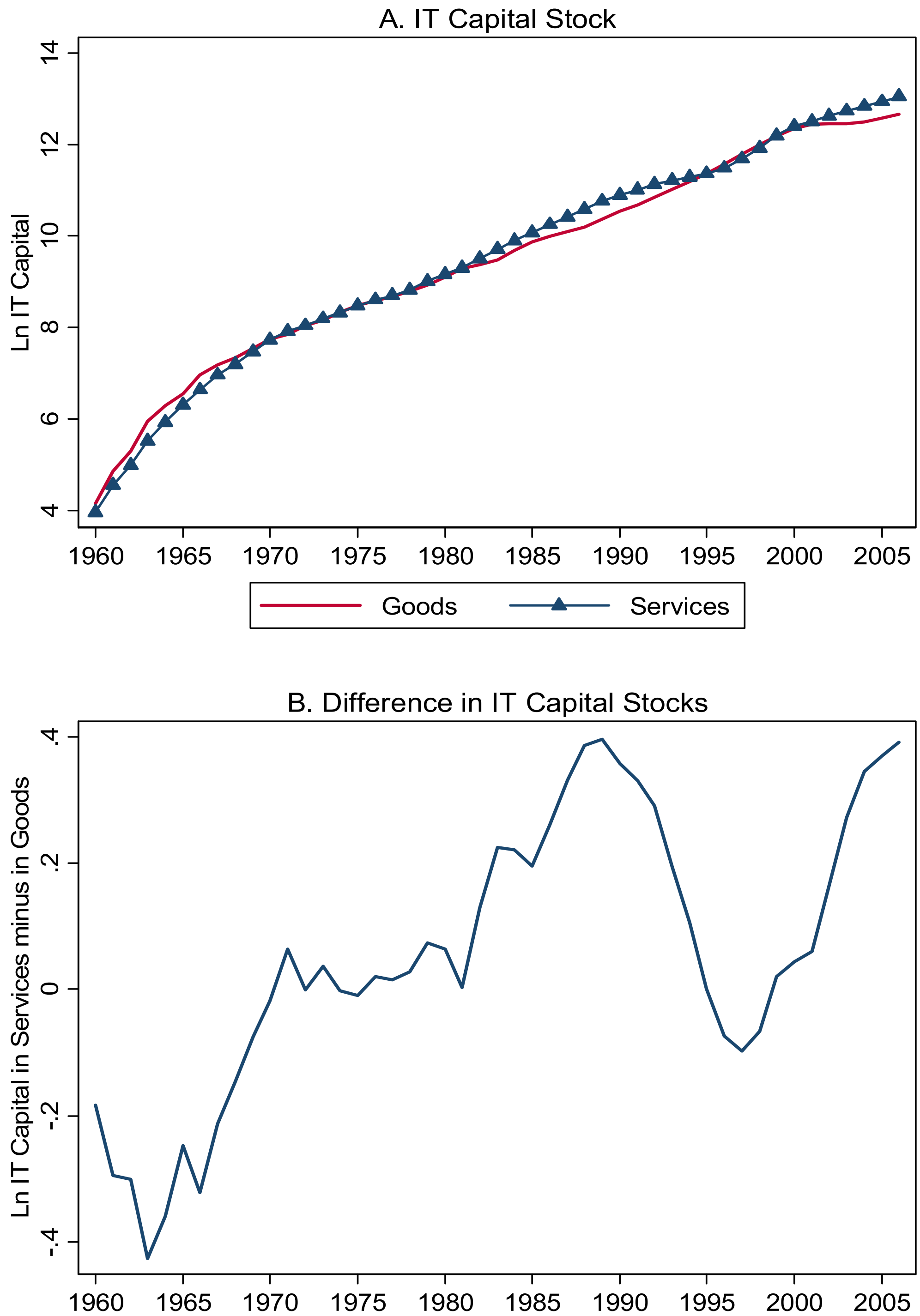
	Median	Mean	S.D.	Min	Max
FINGDEX	3.8	3.9	1.3	0	9
COORD	0.77	1.2	1.4	0	10
STAND	5.8	5.1	3.8	0	10
MATH	3.5	3.8	2.3	0	10
PLAN	0.5	2.3	3.2	0	10

B. Spearman rank correlations

	FINGDEX	COORD	STAND	MATH	PLAN
FINGDEX	1				
COORD	0.15*	1			
STAND	0.6*	0.12*	1		
MATH	0.02	-0.3*	-0.08	1	
PLAN	-0.3*	-0.18*	-0.39*	0.63*	1

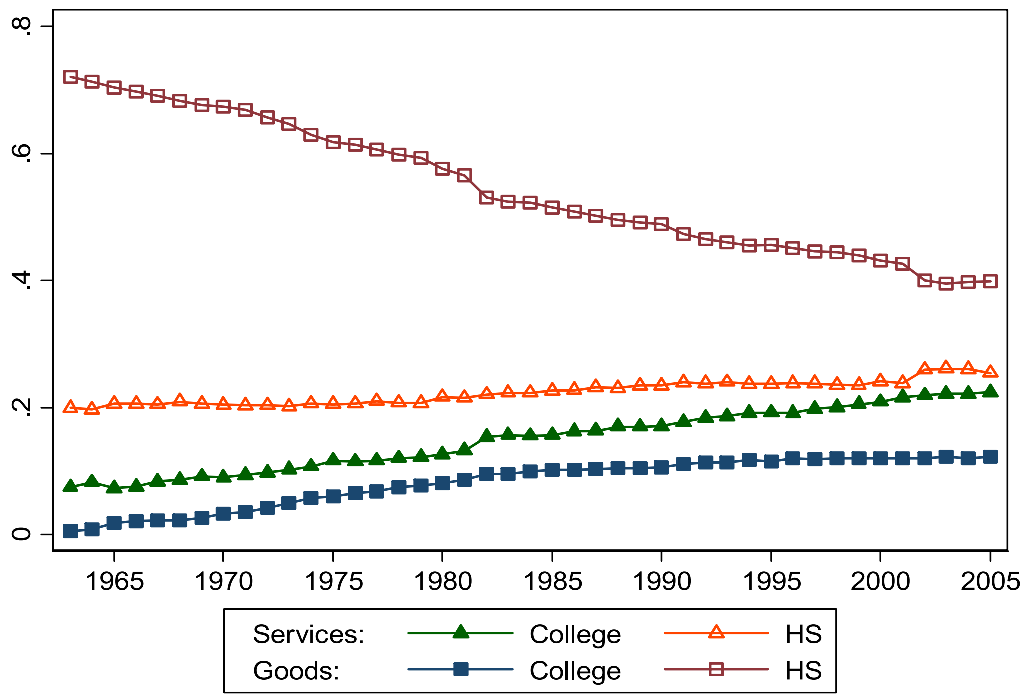
Notes: Statistics are calculated for 746 observations by occupation and gender. * denotes 5% statistical significance level.

Figure A1: IT Capital



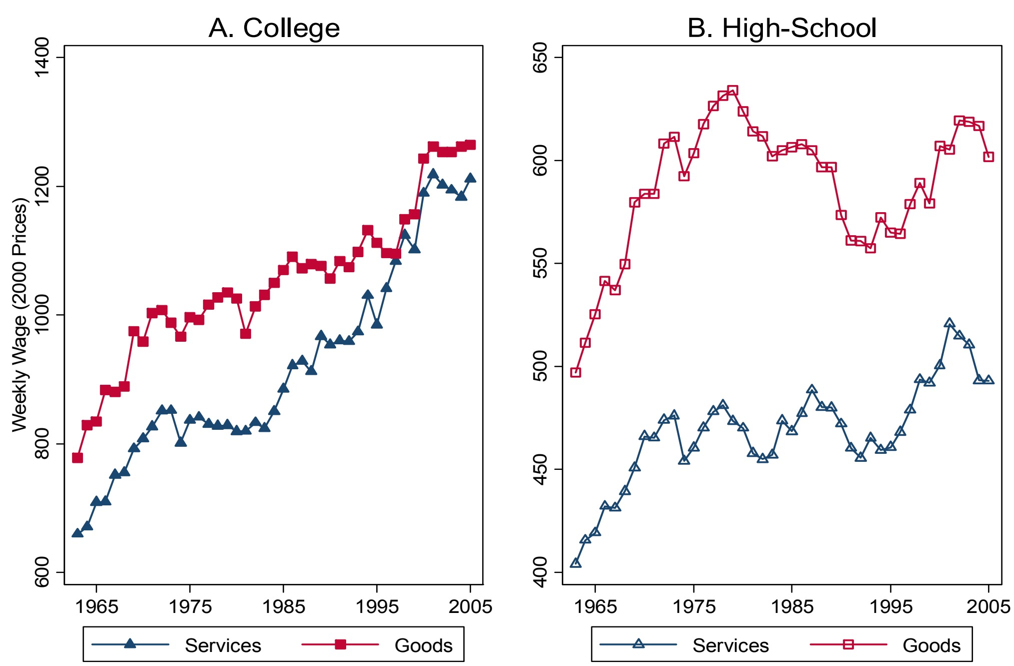
Notes: IT capital is computed using chain-type quantity indices and 2000 prices. Aggregation to goods and services sectors follows the classification used throughout the paper. Sectors are defined in Table 1. See appendix for complete details. Data source: BEA Fixed Assets Tables.

Figure A2: Employment Shares



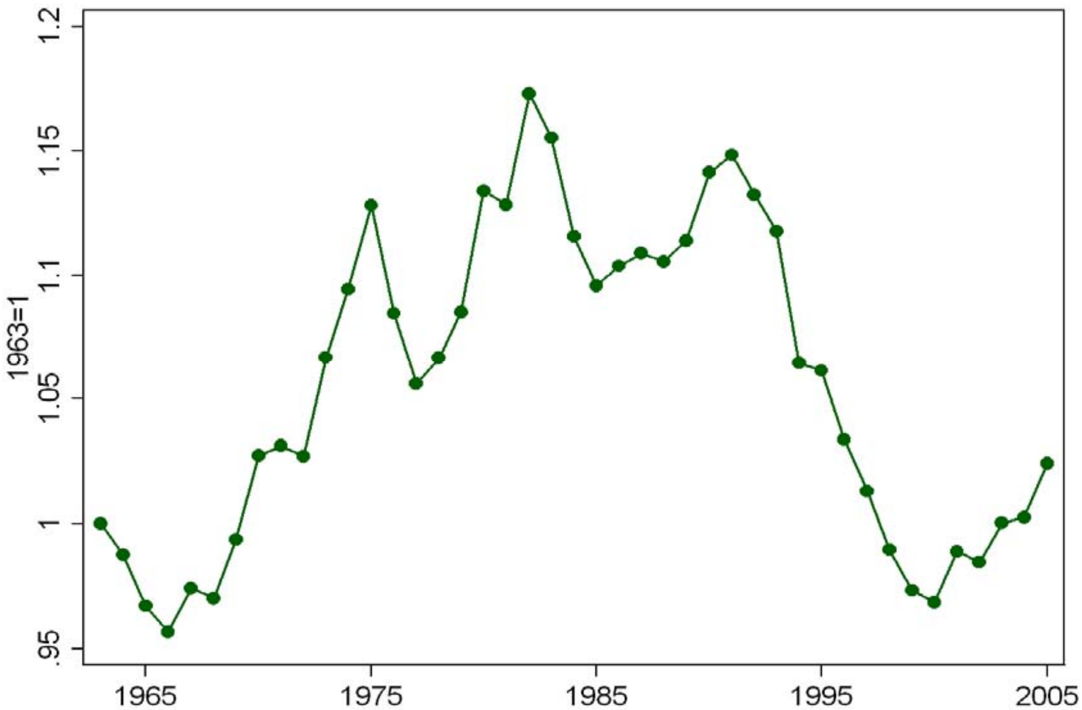
Notes: Employment shares are calculated for college and high school equivalents. The conversion to labor equivalents causes the sum of the four series to deviate slightly from the total employment in the private sector because the conversion weights do not sum exactly to one (see appendix). The series reported here are normalized to sum to one. Sectors are defined in Table 1. Source: March CPS 1964-2006.

Figure A3: Real Wages Across Sectors, within Education Groups



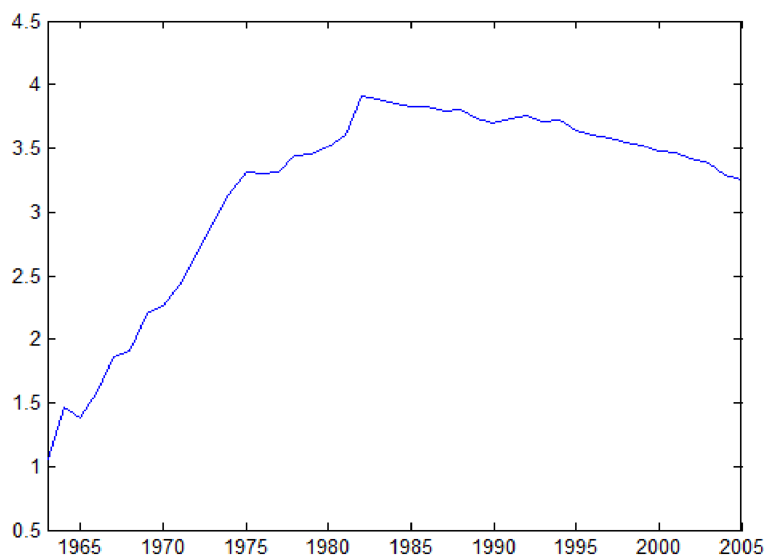
Notes: The figure reports the average weekly wage of each education group in the goods sector and in the services sector. The wages are calculated using the same methodology that is used throughout the paper, that controls for within-group compositional changes in gender and experience. Sectors are defined in Table 1. Source: March CPS 1964-2006.

Figure A4: Relative Output of Services versus Goods



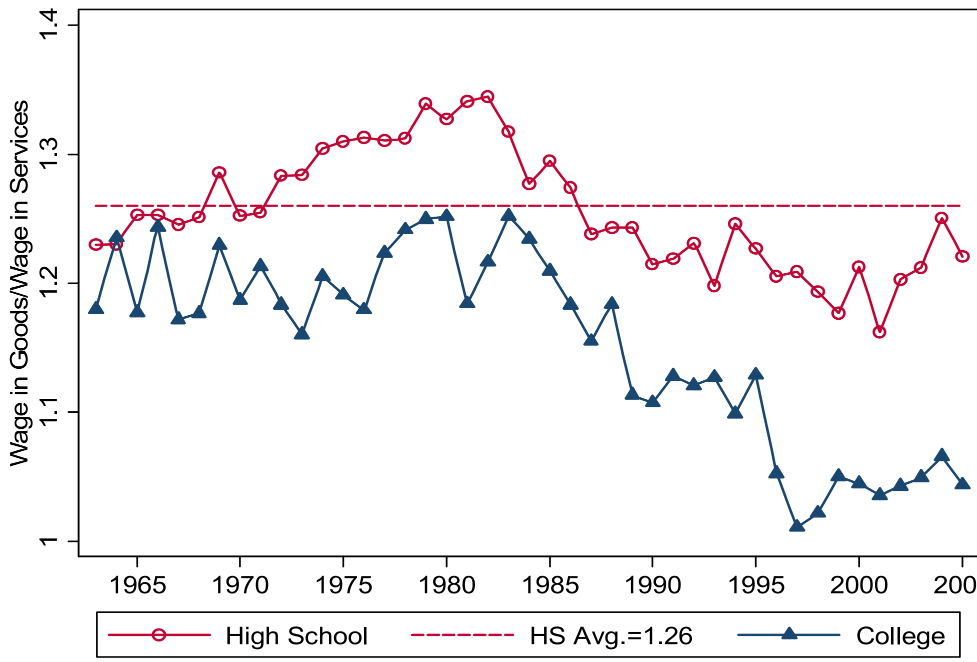
Notes: Relative output in skill-intensive services versus goods is calculated as the ratio of value-added in the service sector divided by value-added in the goods sector, further divided by the relative price of services, defined above in the text. The ratio is normalized to one in 1963. Sectors are defined in Table 1.

Figure A5: Aggregate Elasticity of Substitution



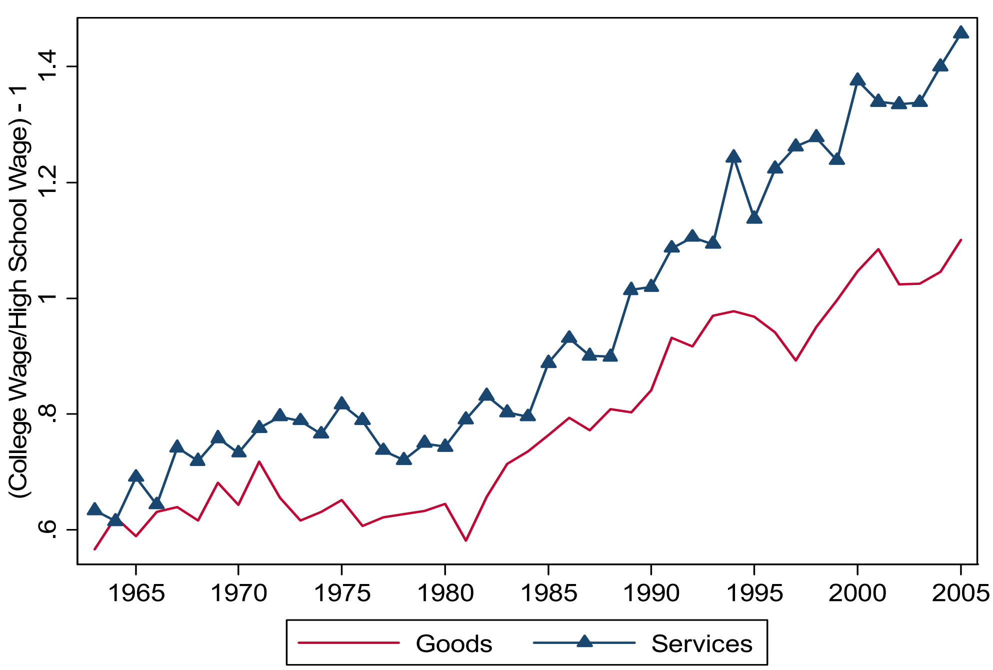
Notes: The aggregate elasticity of substitution is given by totally differentiating the equilibrium function Φ by the relative wage of skilled labor, ω, and skill abundance, h, and then applying the Implicit Function Theorem. The values reported here are calculated using the estimates of the model from Table 2.

Figure A6: Relative Wages Across Sectors, within Education Groups



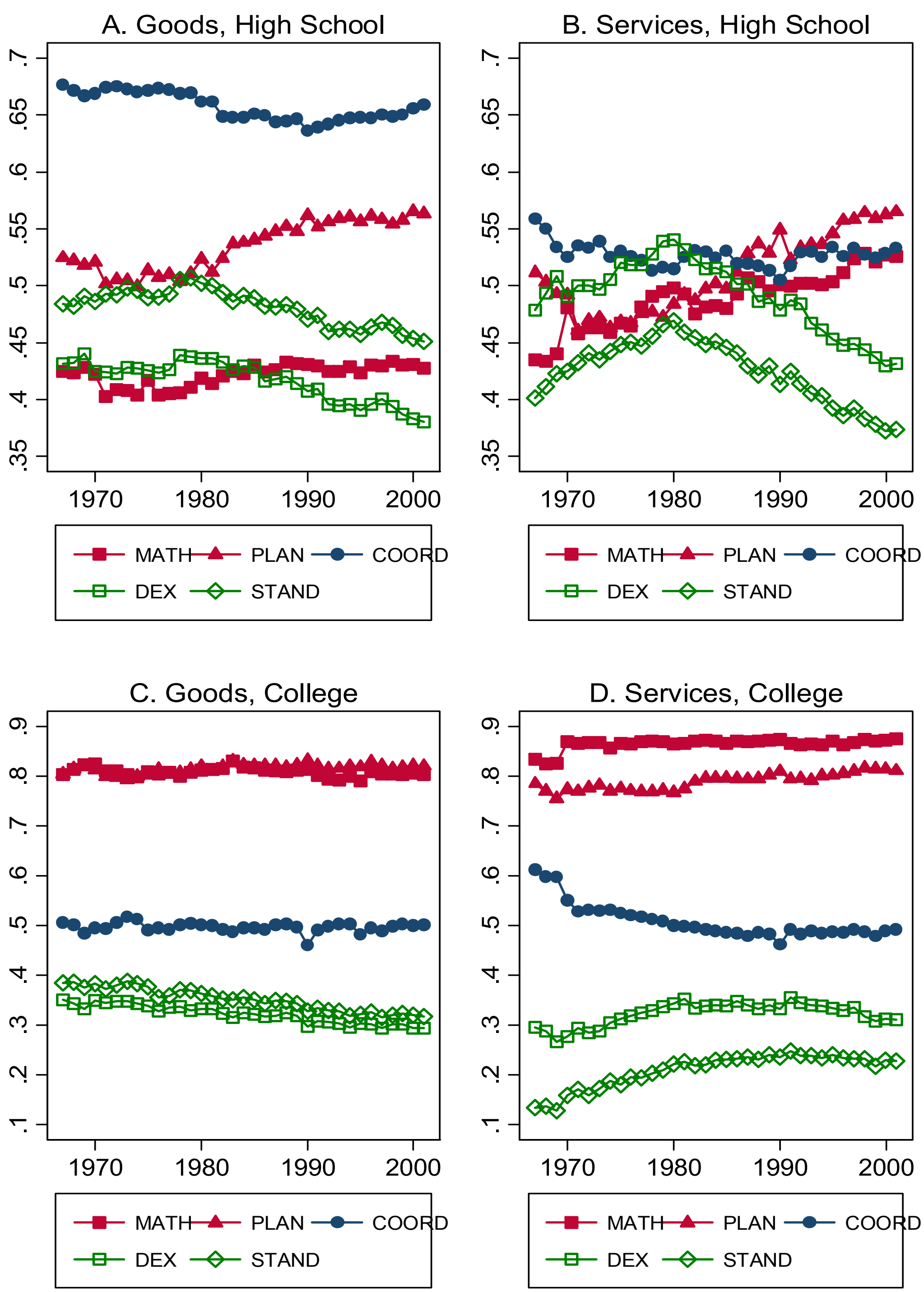
Notes: The figure reports the ratios of the average weekly wage of each education group in the goods sector to that in the services sector. The wages are calculated using the same methodology that is used throughout the paper, that controls for within-group compositional changes in gender and experience. Sectors are defined in Table 1. Source: March CPS 1964-2006.

Figure A7: College Premium in Goods and Services



Notes: The College Premium is equal to the ratio of the average weekly wage of college graduates to average weekly wage of high-school graduates, minus one. The figure reports the college premium in as it is calculated separately in each sector, using the same methodology that is used for the aggregate college premium (Figure 1). Sectors are defined in Table 1. The correlation between the two series is 0.97. Source: March CPS 1964-2006.

Figure A8: Task Intensities for High School and College Equivalents



Notes: Task indices are averages for high school equivalents and college equivalents in each sector . The units are percentiles in the 1967 distribution of each task. Task intensities are calculated from the Dictionary of Occupational Titles. *DEX* (finger-dexterity) captures routine manual tasks, *COORD* (eye-hand-foot coordination) captures non-routine manual tasks, *STAND* (set limits, tolerances and standards) captures routine cognitive tasks, *MATH* (math aptitude) and *PLAN* (direction, control and planning) capture non-routine cognitive tasks.