Skill Biased Technological Change in Services*

Ariell Reshef
University of Virginia

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Abstract

This paper demonstrates that our understanding of skill biased technological change (SBTC) can be improved by taking into account occupational mixes within broad education-sector groups. I fit a two-sector general equilibrium model to U.S. data in 1963-2005 and infer technological processes by directly exploiting the structure of the model. In skill intensive services factor augmenting technological change is slower for college graduates relative to less skilled workers. I find the opposite in the rest of the private sector. Both processes increase relative demand for college graduates due to differences in substitutability across sectors. Opposite technological processes are consistent with changes in occupational mixes: less skilled workers in services re-allocate into computer complementary occupations to a greater extent than college graduates in that sector. Occupational mixes in the rest of the private sector shift in the opposite direction. These results inform theoretical treatments of the underlying mechanisms of SBTC.

Keywords: wage inequality, technological change, computerization, occupations, tasks.

JEL classification: J23, J24, J31.

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Over the last 40 years the U.S. labor market has exhibited two important changes. The first is the substantial increase in the college premium despite growing supply of college graduates, documented in **Figure 1**. The leading explanation for this is that aggregate skill biased technological change (SBTC) shifts demand towards college graduates.[1] This theory is usually described and tested at aggregate education group levels. The second change is the increase in the employment share of the skill intensive service sector, documented in **Figure 2**.[2] Most explanations of the increase in the college premium have overlooked the second fact: the forces that drive the employment shift into skill intensive services may contribute to the increase in the college premium.[3] More importantly, they do not address the possibility of different technological processes in different sectors; *a priori*, there is no reason to think that they should be the same.

This paper demonstrates that our understanding of technological change can be improved by taking into account occupational mixes within broad education-sector groups. Changes in occupational mixes help interpret estimates of technological processes. The results of the analysis inform theoretical treatments of the underlying mechanisms of SBTC.

I estimate a two-sector general equilibrium model that is designed to answer two questions. Do the goods and service sectors exhibit different technological processes? And what is the role of the employment shift into the skill intensive service sector in explaining the increase in the college premium? After answering these questions I introduce evidence on changes in occupational mixes that offers an interpretation of the estimated technological processes.

I find that factor augmenting technological change for college graduates in services increases at a *slower* rate than for less educated workers. This *increases* relative demand for college graduates due to low substitutability in production of services; the elasticity of

[1] See Bound and Johnson (1992), Katz and Murphy (1992), Levy and Murnane (1992), Juhn, Murphy, and Pierce (1993), and Berman, Bound, and Griliches (1994). Krusell, Ohanian, Rios-Rull, and Violante (2000) investigate the role of capital-skill complementarity in explaining increased demand for college graduates. See Acemoglu (2002) and Hornstein, Krusell, and Violante (2005) for extensive surveys of this literature.

[2] The skill intensive service sector includes FIRE, business & repair services, personal services, Entertainment & recreation services, health services, educational services, and other professional & related services. The goods sector includes the rest of the private sector. See **Table 1**.

[3] This employment shift may be driven by changes in relative demand (i.e. preferences) or by supply factors, e.g. changes in relative Hicks-neutral productivity. This paper focuses on the latter. For a demand-based explanation for the rise of the service sector see Buera and Kaboski (2006).

substitution in services is estimated at 0.64, which is, critically, less than one.[4] Relative factor augmentation of college graduates in the goods sector increases faster than for less educated workers and there is high substitutability in production. In both sectors technological change increases relative demand for college graduates and drives up the college premium, but for apparently different reasons. In addition, I show that these results are consistent with inferring faster factor augmentation of college graduates at the aggregate level, despite finding the opposite in the growing service sector.

The estimates also show that there is faster Hicks neutral labor productivity growth in the goods sector. This, combined with strong complementarity between goods and services in consumption, entirely explains the employment shift towards services. If productivity growth had been equal in both sectors, the employment share of services would hardly change. The different rates of sectoral Hicks neutral labor productivity growth increase the relative college premium by 15%. Thus, the rise of the college premium is mostly driven by intra-sectoral forces.[5]

Technological change is usually indirectly inferred, not directly observed, and this paper is no exception.[6] But it is important to understand why the estimated technological processes are different. I support the estimated trends in technological change with evidence on changes in the occupational mix of the four groups of workers considered in the model: skilled and unskilled in each of two sectors. Using data on occupations allows a better understanding of technological change because occupations describe what people actually do much better than their level of education. Building on the work of Autor, Levy, and Murnane (2003), I consider non-routine tasks (e.g. communication, planning and analytical thinking) as computer complementary, whereas routine tasks (e.g. filing and assembly) as easily substituted by computers, because they can either be coded in software or auto-

[4] The intuition for this comes from the extreme case of zero substitutability, where production occurs in fixed proportions (Leontief). In that case, an increase in the efficiency in production of one factor (equivalently, a decrease in the unit factor requirement) will decrease its relative *physical* demand (while keeping relative demand in efficiency units unchanged).

[5] This is reminiscent of Berman, Bound, and Griliches (1994), who find that most of the skill upgrading in manufacturing is within 4-digit SIC industries, and is not mainly driven by industrial composition changes within manufacturing.

[6] One attempt to observe technological change directly is Xiang (2005), who uses new product definitions in U.S. manufacturing to identify technological progress directly. He then links new products to increased demand for skilled labor.

mated.[7] Computerization, automation and IT encompass the main technological changes in the last 40 years.[8] Given an increase in the use of computers, moving out of computer substitutable occupations and into computer complementary occupations raises individual worker efficiency.

The estimation results can be explained by compositional changes within broad categories of workers. In services less educated workers move out of occupations that are substitutable by computers into occupations that are complementary to computers. And they do this faster than college graduates. This may imply greater efficiency gains (not levels) for less educated workers in services relative to college graduates. In contrast, the occupational mixes in the goods sector shift moderately in the opposite direction in relative terms. If the effect of computerization on the efficiency of computer complementary occupations is not too high – i.e., if the compositional changes matter more than intra occupational effects – then these changes in occupational mixes fully explain the estimated technological trends.

In an important contribution, Lee and Wolpin (2006a) also study the technological determinants of the increase in the college premium in the context of a two-sector model. This paper differs from Lee and Wolpin (2006a) in two important ways. First, this paper contributes to the understanding and interpretation of estimated technological processes, whereas Lee and Wolpin (2006a) do not. Second, my methodology for estimating technological processes directly exploits all optimality conditions and general equilibrium restrictions of a closed economy. In contrast, Lee and Wolpin (2006a) do not close their goods markets and they postulate ad hoc wage and price processes. In addition, their definitions of sectors are different from mine.[9] However, by applying my estimation procedure to data that is organized according to their sectoral classifications, I obtain comparable results to theirs.[10] This is reassuring, because it implies that where my estimation results differ, it is due to

[7] See also Levy and Murnane (1996), Autor, Levy, and Murnane (2002), Bresnahan (1997) and Bresnahan, Brynjolfsson, and Hitt (1999).

[8] The IT share in the capital stock has increased from zero in 1960 to 4% in 2006 in the goods sector and to 12% in the skill intensive services (using 2000 constant prices). See also Autor, Katz, and Krueger (1998).

[9] They include retail and wholesale trade, and transportation in their definition of services (but not utilities). Another difference is that Lee and Wolpin (2006a) have three classifications of workers based on occupations, rather than two based on education.

[10] Like Lee and Wolpin (2006a), I also find that sectoral shifts in employment are not the main force behind the increase in the college premium. Rather, it is intra-sectoral technological processes that matter.

the sectoral classification, not due to differences in methodology.

This paper is related to other works that stress the sectoral composition of the economy in explaining the rise in the college premium. Haskel and Slaughter (2002) find that the concentration of demand shifts in skill intensive industries helps explaining the rise in the college (skill) premium. However, their empirical approach does not identify the technological processes behind these demand shifts, whereas my estimation procedure does. Beaudry and Green (2005) test the implications of a model of organizational change, where a modern sector (with new mode of organization) emerges alongside a traditional one. However, they estimate reduced form equations, which do not impose general equilibrium restrictions.[11]

The rest of the paper is organized as follows. In the next section I present the model. In section 2 I discuss the data and estimation, present the results, relate the results to previous aggregate results, and gauge the importance of the sectoral shift for the evolution of the college premium. Section 3 provides robustness checks for the estimation results. Section 4 presents evidence on changes in occupational mixes. Section 5 concludes.

1 A two-sector model

I in this sector I present a two sector general equilibrium model that provides a framework for inferring technological trends. The economy is populated by H skilled workers and L unskilled workers, and by an indefinite number of competitive firms that have access to constant returns to scale technologies. There are two such technologies, which define the two sectors in the economy. Workers are freely mobile across sectors and the economy is closed. Time is discrete. Since there is no investment, and therefore no inter-temporal dynamics, I drop time subscripts to ease the notation. The equilibrium evolves according to exogenous technological progress and according to changes in the relative supply of skilled versus unskilled labor.

Two technologies are available for producing goods (G) and services (S). These are

$$G = [(A_g L_g)^{\rho_g} + (B_g H_g)^{\rho_g}]^{1/\rho_g} \quad (1)$$

$$S = [(A_s L_s)^{\rho_s} + (B_s H_s)^{\rho_s}]^{1/\rho_s} \ , \quad (2)$$

[11] The theoretical implications that Beaudry and Green (2005) derive do rely on general equilibrium restrictions, but they do not carry these restrictions to the data.

where A_i and B_i are factor augmenting indices for low skilled labor (L) and high skilled labor (H), respectively, 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.

Cost minimization yields the following unit cost functions

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

$$c_s = \left[\left(\frac{w_L}{A_s}\right)^{1-\sigma_s} + \left(\frac{w_H}{B_s}\right)^{1-\sigma_s}\right]^{\frac{1}{1-\sigma s}} , \tag{4}$$

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, so w_L and w_H are not indexed by sector.[12]

By taking the partial derivative of the cost functions with respect to each wage, I obtain unit demands for each factor (Shephard's lemma). Then, by taking the ratio of unit demands I obtain relative demand of skilled labor, or skill intensity, for each sector

$$h_g = \omega^{-\sigma_g} \beta_g^{\sigma_g - 1} \tag{5}$$

$$h_s = \omega^{-\sigma_s} \beta_s^{\sigma_s - 1} , \tag{6}$$

where $\omega = w_H/w_L$ is the relative wage of skilled workers, $h_i = H_i/L_i$ is skill intensity and

$$\beta_i = B_i/A_i$$

is relative factor efficiency of skilled workers versus unskilled.

The partial effect (holding ω constant) of an increase in relative factor efficiency of skilled workers, β_i, on demanded skill intensity depends on the magnitude of the elasticity of substitution. If $\sigma_i > 1$, then $\partial h_i/\partial \beta_i > 0$, whereas if $\sigma_i < 1$, then $\partial h_i/\partial \beta_i < 0$. The intuition for the last result comes from the extreme case of zero substitutability, $\sigma_i = 0$ (fixed proportions, Leontief production function). In that case, if one factor becomes more efficient, then less of it is required per unit of output and relative demand for that factor

[12] Lee and Wolpin (2006b) show that mobility costs across occupations and sectors are consistent with wage equality due to the existence of a home sector, entry of new workers and capital mobility. Although capital is absent from this model, Lee and Wolpin's results imply that wage equality (on average) of workers across sectors is a reasonable assumption for the medium-long run perspective.

falls.

Notice that since σ_s need not equal σ_g there is no global ranking of skill intensity across sectors, giving rise for potential factor intensity reversals. However, in the data $h_s > h_g$ always holds, i.e. services are relatively more skill intensive. Imposing this does not change the theoretical analysis. In the empirical estimation the estimates will maintain this condition.

Competition and constant returns to scale technologies require that the zero profit conditions must be satisfied (I consider only interior solutions). I normalize the price of goods to one and rewrite (3)-(4) to get unit cost functions

$$\begin{aligned} c_g &= \frac{w_L}{A_g}\left(1+\omega h_g\right)^{\frac{1}{1-\sigma_g}} = 1 \\ c_s &= \frac{w_L}{A_s}\left(1+\omega h_s\right)^{\frac{1}{1-\sigma_s}} = p \ . \end{aligned}$$

Taking the ratio of the above and using (5) and (6) gives

$$p = \frac{A_g}{A_s}\left(1+(\omega/\beta_s)^{1-\sigma_s}\right)^{\frac{1}{1-\sigma_s}}\left(1+\left(\omega/\beta_g\right)^{1-\sigma_g}\right)^{-\frac{1}{1-\sigma_g}} \ . \tag{7}$$

Unit factor requirements are obtained by Shephard's lemma. By using (5)-(6) the unit factor requirements can be written as follows

$$\begin{aligned} L_i^1 &= \frac{1}{A_i}\left(1+\omega h_i\right)^{\frac{\sigma_i}{1-\sigma_i}} \\ H_i^1 &= \frac{h_i}{A_i}\left(1+\omega h_i\right)^{\frac{\sigma_i}{1-\sigma_i}} \ . \end{aligned}$$

Full employment is given by multiplying the unit factor requirements by output for both sectors

$$\begin{aligned} L &= SL_s^1 + GL_g^1 = S\frac{1}{A_s}\left(1+\omega h_s\right)^{\frac{\sigma_s}{1-\sigma_s}} + G\frac{1}{A_g}\left(1+\omega h_g\right)^{\frac{\sigma_g}{1-\sigma_g}} \\ H &= SH_s^1 + GH_g^1 = S\frac{h_s}{A_s}\left(1+\omega h_s\right)^{\frac{\sigma_s}{1-\sigma_s}} + G\frac{h_g}{A_g}\left(1+\omega h_g\right)^{\frac{\sigma_g}{1-\sigma_g}} \ . \end{aligned}$$

By manipulating these last two equations I obtain the following expression for relative supply

$$\left[\frac{S}{G}\right]^s = \frac{A_s}{A_g}\left(\frac{h-h_g}{h_s-h}\right)\frac{\left(1+\omega h_g\right)^{\frac{\sigma_g}{1-\sigma_g}}}{\left(1+\omega h_s\right)^{\frac{\sigma_s}{1-\sigma_s}}} \ , \tag{8}$$

where $h = H/L$ is the skill abundance of the economy.

Workers of both types supply labor inelastically and their income is their wage. Their preferences over goods and services are represented by

$$U(S, G) = \left[\mu S^{\psi} + (1-\mu) G^{\psi}\right]^{1/\psi} ,$$

where $\psi \leq 1$. They choose $\{G, S\}$ to maximize U subject to their budget constraint $G + pS \leq w_j$, where $j \in \{H, L\}$. Due to homotheticity of U the economy can be treated as being populated with only one representative worker, who maximizes U subject to the economy wide budget constraint $G + pS \leq Lw_L + Hw_H$. The first order conditions of this problem give rise to the following relative demand function

$$\left[\frac{S}{G}\right]^{d} = p^{-\varphi}\left(\frac{\mu}{1-\mu}\right)^{\varphi} , \tag{9}$$

where $\varphi = 1/(1-\psi)$ is the elasticity of substitution in demand.

To solve the model I equate relative demand (9) to relative supply (8) and plug in the expression for the relative price (7); together with (5)-(6), I get

$$\begin{aligned}\Phi\left(\omega, h, \beta_g, \beta_s, A_s/A_g\right) &= \left(\frac{A_s}{A_g}\right)^{1-\varphi}\left(\frac{h-h_g}{h_s-h}\right)\frac{(1+\omega h_s)^{(\varphi-\sigma_s)/(1-\sigma_s)}}{(1+\omega h_g)^{(\varphi-\sigma_g)/(1-\sigma_g)}} \\ &= \left(\frac{A_s}{A_g}\right)^{1-\varphi}\left(\frac{h-\omega^{-\sigma_g}\beta_g^{\sigma_g-1}}{\omega^{-\sigma_s}\beta_s^{\sigma_s-1}-h}\right)\frac{\left(1+\omega^{1-\sigma_s}\beta_s^{\sigma_s-1}\right)^{(\varphi-\sigma_s)/(1-\sigma_s)}}{\left(1+\omega^{1-\sigma_g}\beta_g^{\sigma_g-1}\right)^{(\varphi-\sigma_g)/(1-\sigma_g)}} \\ &= \left(\frac{\mu}{1-\mu}\right)^{\varphi} . \end{aligned} \tag{10}$$

The function Φ is an implicit function in ω and all the exogenous parameters of the model. Solving for the unique ω completely determines the equilibrium in the economy. By totally differentiating (10) I obtain all the comparative statics for relative wages as a function of technology.[13] The function Φ plays a prominent role in the estimation below, as it determines all equilibrium outcomes. Changes in A_s/A_g affect the equilibrium unless $\varphi = 1$. Note that changes in A_s/A_g capture relative technological change in the Hicks neutral sense only when β_g and β_s are fixed.

[13] The derivative of ω with respect to either one of the β's depends on the elasticities of substitution and changes signs around a threshold ω^*. This threshold is given by the point at which sectoral factor intensities are reversed.

1.1 Discussion of model assumptions

One of the model assumptions is that the economy is closed. Ignoring international trade 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. Suppose that in reality the economy has a trade deficit that falls mostly on goods, which is increasing (which is the case for the U.S.). Then, *ceteris paribus*, domestic supply of goods should be lower than what the closed model implies ($[S/G]^s$ from equation (8) should be higher). Ignoring this will bias any estimator of A_g upwards, since the economy must satisfy all of the demand for goods domestically (estimators of A_s/A_g will be biased downwards). However, the actual 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.

Wages for the same type of worker are assumed to be the same in both sectors. In the face of individual heterogeneity or mobility costs this may not hold. However, Lee and Wolpin (2006b) show that average wages for broad types of workers are surprisingly similar in the goods and services sectors (this is what motivates their work). Lee and Wolpin (2006b) argue that capital mobility, entry of new cohorts and entry from home production (this includes 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. Using the sectoral classifications of this paper I find that the skill premium is slightly higher in services than in the goods sector. But their evolution over time is almost identical: the correlation between them is over 0.94. Thus, it seems that equal wages are not a bad assumption.

2 Data and estimation

I create a sample of labor supplies, wages and relative prices for 1963-2005. I use data from the March Current Population Survey from 1964-2006 for all wage and labor quantities (data years pertain to the year preceding the survey). For the relative price of services versus goods in 1963-2005 I use data from the Bureau of Economic Analysis. The definitions of the skill intensive services and goods sectors can be found in **Table 1**. The most skill intensive industries in the private sector are in the services sector; they are also the fastest growing industries. I aggregate them in the "skill intensive services sector", henceforth denoted the services sector for simplicity. The goods sector includes the rest of the private sector.

I follow the exact methodology of Katz and Murphy (1992) 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, as well as their estimate of the aggregate elasticity of substitution to a good degree of accuracy. The rationale for constraining myself to a predetermined sample construction methodology is that in this way I avoid making choices that might affect the results of the estimation later on. Moreover, it makes my aggregate results directly comparable to Katz and Murphy (1992). A complete and detailed description of the data can be found in the appendix. Here I report the main features of the series that are used for the estimation.

Labor supply

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 equivalents. Labor supply of individuals who are not college graduates or high school graduates exactly (less than 12 years of schooling and 13-15 years) is allocated to college and high school according to a weighting scheme. The weights are obtained from wage regressions which embody the assumption that the productivity of high school dropouts and individuals with some college education are linear combinations of the productivity of high school and college graduates. Aggregate skill abundance, h, is the ratio of total college equivalents to high school equivalents in the sample. Sector skill intensities, h_s and h_g, are calculated in a similar way. I use the same equivalence weights for all labor supply series to keep the accounting consistent.[14]

Relative wages

The wage concept is average weekly wages. The relative wage is defined as $\omega = w_{COL}/w_{HS}$, where w_{COL} and w_{HS} are the economy wide average wages of college and high school graduates, respectively. Wages are deflated using the personal consumption expenditures

[14] An alternative is to calculate aggregate and sector-specific equivalence weights separately. Doing this does not effect the results qualitatively.

deflator, which is obtained from the Bureau of Economic Analysis.

Relative prices

The Bureau of Economic Analysis (BEA) provides chain-type price indices for value added by 1-digit industries. The industries correspond to the industrial classification of the CPS in 1963-2001 (top panel of **Table 1**). For both sectors 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. Denote these as p_i, $i \in \{g, s\}$. The relative price of services versus goods is the ratio $p = p_s/p_g$. I normalize this price to one in 1963, which reflects the arbitrary starting year. The relative price of services to goods, p, is increasing throughout almost the entire sample, as can be seen in **Figure 3**.

2.1 Model specification

As equation (10) makes clear, four exogenous processes – h, β_g, β_s and A_s/A_g – determine ω and, therefore, determine all the endogenous outcomes at any point in time. The exogenous processes are given by

$$h(t) = h\_data(t) \cdot \exp\{u_t^h\} \tag{11}$$

$$\beta_i(t) = \frac{B_i}{A_i}(t) = \exp\left\{\beta_{0,i} + \beta_{1,i}t + u_t^i\right\} \ , \ i \in \{g, s\} \tag{12}$$

$$\frac{A_s}{A_g}(t) = \exp\{a_0 + a_1 t + u_t^a\} \ . \tag{13}$$

h_data is skill abundance as it is calculated in the data. u_t^i are AR(1) processes

$$u_t^i = \rho^i u_{t-1}^i + \varepsilon_t^i \ ,$$

where ε_t^i are i.i.d. normal with zero mean and standard deviation v_i, $i \in \{h, g, s, z\}$. I abstract from demand shifts and set $\mu = 1/2$.[15]

The choice of constant growth rates is not innocuous. It reflects the usual assumption in the theoretical literature of constant growth rates, e.g. Acemoglu (1998), and in empirical implementations, e.g. Katz and Murphy (1992). Goldin and Katz (2008) argue that the bias in technological change has grown at a constant rate over the 20th century. They also argue that there is little evidence for an acceleration post 1980. Nevertheless, I experiment with

[15] Proportional changes in $\mu/(1-\mu)$ and A_s/A_g affect ω in a similar way.

piecewise log linear trends with breaks around 1980, as well as log quadratic trends. Using these alternative specifications does not materially affect the results, since their estimates are almost log linear.

Denote the endogenous outcomes by $y_t = [\omega(t)\ h_s(t)\ p(t)\ h_g(t)]'$ and denote the four shocks by $u_t = [u_t^h\ u_t^g\ u_t^s\ u_t^a]'$. The model can be written as

$$y_t = G_t(x_t, u_t, \theta) \ ,$$

where $x_t = h\_data(t)$. θ summarizes all the parameters of the model: elasticities and trend parameters. The time index in G makes it explicitly dependent on time, as implied by (11)-(13). Stacking all exogenous and endogenous variables, as well as shocks, allows writing the model as

$$y = G(x, u, \theta) \ .$$

I summarize all the parameters that govern the stochastic processes by Ω, i.e. $u \sim F(\Omega)$.

2.2 Motivation for different elasticities

The model allows different magnitudes of σ_s for σ_g. But is there any reason to expect them to be very different? If skill intensive services require stronger coordination between inputs, then this will show up as a lower elasticity of substitution. For example, without bank tellers that facilitate deposits, bank executives cannot make investments. Hygiene standards may require a tight relationship between the numbers of doctors and cleaning staff. In contrast, in manufacturing, once an engineer designs a product and a production process is implemented, the engineer is no longer needed for daily operations and the demand for unskilled labor may respond more to relative wages than in services. Moreover, skill intensive services are less capital intensive than the goods sector, and more of it is invested in structures, rather than equipment.[16] This may allow the goods sector more flexibility in employing skilled versus unskilled labor.

Beyond these arguments, it is also important to understand what features of the data

[16] However, this starts changing around 1980. Until 1980 the equipment share in the capital stock in skill intensive services is roughly 15% less than in the rest of the private sector; from 1980 it starts catching up; and by 2005 it catches up with the rest of the private sector. This reflects, *inter alia*, a more rapid increase in the IT share in the capital stock in skill intensive services. The data are from the fixed asset tables from the Bureau of Economic Analysis in constatnt 2000 prices.

give rise to this result in the estimation below. Two of the target moments in the estimation are the skill intensities. In the model they are determined in (5) and (6) by technological processes and the relative wage, where the latter is also a target for the estimation. Consider

$$\ln(h_{it}) = (\sigma_i - 1)\beta_{0,i} - \sigma_i \ln(\omega_t) + \left[(\sigma_i - 1)\beta_{1,i}\right]t + (\sigma_i - 1)u_t^i \ , \quad i \in \{g, s\} \ ,$$

which is obtained by taking logs of (5) and (6) and plugging in (12). Rewrite this as

$$\ln(h_{it}) = c_i - \sigma_i \ln(\omega_t) + \delta_i t + \varepsilon_t^i \ , \quad i \in \{g, s\} \ . \tag{14}$$

Figure 4 depicts detrended log skill intensities h_s and h_g plotted against the detrended log relative wage.[17] Both panels have the same scale. The picture is striking. The slope in services, 0.9, is much lower than the slope in goods, estimated at almost 10. Of course, the slopes are biased estimators of demand elasticities, due to the classic simultaneity problem. However, simultaneity biases notwithstanding, **Figure 4** would make us expect that $\sigma_s < \sigma_g$.

2.3 Estimation

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

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

which is a high dimensional integral, which will be evaluated by simulation, as detailed below.[18] It follows that

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

where $E(e|x) = 0$. I estimate θ by solving the following problem:

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

[17] By the Frisch-Waugh Theorem, the slopes of the linear predictions in **Figure 4** are exactly the OLS estimates of σ_i in (14).

[18] 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.

where W is a positive definite symmetric weighting matrix and Θ restricts the elasticities to non negative numbers. If $W = I$, then this is nonlinear least squares (non weighted). In practice, I use W =diag(yy'), which has the appealing feature of keeping all errors in the same percent units. This also addresses the concern that the time series in y are upward trending. Errors may be larger when values in y are larger in the latter part of the sample, and this will make the later observations more influential in the estimation. Translating the errors into percent terms solves this problem. Ultimately, this is a way to deal with potential heteroscedasticity. Nevertheless, results with $W = I$ are similar.[19]

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

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

   The estimator $\widehat{\theta}_0$ is biased, but it provides reasonable initial values for the true objective below. This objective function is well behaved, in the sense that $\widehat{\theta}_0$ is insensitive to initial values.

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

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

[19] 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.

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 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.[20]

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 $\widehat{\Sigma}_e = \widehat{e}\widehat{e}'$,

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

   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 and the average of those is used for $\Sigma_e(\Omega)$.

5. After obtaining $(\widehat{\theta}, \widehat{\Omega}_u)$ repeat steps 3-4 using these estimates to gain accuracy.

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

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

500 times, and computing the standard error(s) over all estimates, where each u_r is independently drawn from $F(\widehat{\Omega})$.[21]

[20] 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 $[4(T-1)] \times [4(T-1)]$.

[21] Standard errors for $\widehat{\theta}$ can also be computed using the delta method, which relies on asymptotic variances. But this method is known to underestimate standard errors.

2.4 Results

The estimates are reported in **Table 2**. The value of the objective function at the minimum is roughly 1, which implies that the simulated data deviates by 0.58 percent from each data point, on average ($1/(4 \times 43) \approx 0.0058$). **Figure 5** provides a visual fit. In Panel A the skill intensities seem to fit the data remarkably well. In Panel B the simulated skill premium misses the initial increase in the data series until 1973, after which it fits the data more tightly. This is not due to the log linear technological trends. When using piecewise linear or quadratic trends (in logs) I obtain a very similar result, without significant improvement of the objective function.

The model also misses the end of the sample in Panel C, where the price series declines, but the simulated series continues to increase. Most likely, the change in trend in the relative price data series stems from changes in the evaluation of services after the 2001 dot-com bubble burst.

I now discuss the estimates in **Table 2**.[22] The EoS in services is $\sigma_s = 0.625 < 1$ and $\beta_{1,s} = -0.07$. This means that factor augmentation has been faster for high school equivalents relative to college equivalents. This decreases relative demand for less skilled workers because the EoS in services is less than one. The EoS in the goods sector is $\sigma_s = 6.94 > 1$ and $\beta_{1,g} = 0.02$. This means that factor augmentation has been faster for college equivalents relative to high school equivalents. This increases relative demand for more skilled workers because the EoS in the goods sector is greater than one. The relative wage is determined in general equilibrium, but technological change contributes to its increase in both sectors. In addition, factor augmentation has been faster for high school equivalents in services relative to high school equivalents in the goods sector: $a_1 > 0$.

The sizes of the estimates of both elasticities are not unreasonable. Hamermesh (1993) (Table 3.7, pp. 110-111) surveys estimates of the elasticity of substitution between non-production (relatively skilled) workers and production (relatively unskilled) workers in U.S. manufacturing. These estimates lie between 0.5 and 6. In section 2.6 below I show that the combination of both estimates, together with inter-sector substitution, leads to estimates of an aggregate EoS that is in the range that is usually estimated.

[22] The stochastic process for u_t^h is simplified to iid normal. When it is allowed to be AR(1), ρ^h tends to revert to zero. When the initial value for search was zero, the numerical search stayed at zero.

The simulated college premium first decreases and then increases. Therefore aggregate relative demand is lagging behind supply until the 1980s and then grows faster than aggregate supply afterwards. This can be explained by a slowdown in supply of college equivalents, together with constant demand growth. A well documented fact is that the growth in the supply of college graduates decreased in the early 1980s.[23] The annualized growth rate of the aggregate skill abundance series used here slowed down to 2.1 percent per year in 1983-2005 from 6.7 percent per year in 1963-1981. All the model's exogenous technological variables grow at a constant rate. Thus, the slowdown in supply causes the college premium to increase because demand is still growing at the same rate.

Panel D in **Figure 5** reports relative labor productivity in services versus goods, which is defined as

$$\left(\frac{S}{L_s + H_s}\right) / \left(\frac{G}{L_g + H_g}\right) = \left(\frac{S}{G}\right) / \left(\frac{L_g + H_g}{L_s + H_s}\right) .$$

S/G is given in (8) and $(L_g + H_g) / (L_s + H_s)$ can be backed out from the relationship between h_s, h_g and h.[24] Treating the two types of labor as homogenous is the typical assumption maintained in productivity analyses. The estimates imply that average labor productivity in the service sector has declined relative to the goods sector by 60 percent over 42 years, or roughly 1.2 percent per year on average. This is close to what is obtained by aggregating industry estimates from Jorgenson and Stiroh (2000), using value added weights to aggregate to sectoral levels.

It is comforting to find results that are similar to a different study that uses a different methodology, although this is not one of the moments that are targeted. This contributes to the credibility of the results. Moreover, as mentioned in the discussion of the model assumptions, it helps alleviating the concerns for ignoring international trade.

The dynamics of the allocation of labor across sectors is almost identical to what is in the data. Recall that a_1 does not necessarily capture the sector bias in technological change in the Hicks neutral sense, because it always has a non-Hicks component unless β_g and β_s

[23] Card and Lemieux (2001) and Goldin and Katz (2008) argue that the slowdown in the growth of supply of college graduates plays an important role in increasing the college premium. The slowdown in the growth of the supply of college graduates is mainly due to the fact that two large cohorts finished college before the 1980s and were not replaced by similarly large younger cohorts. The first cohort is the Baby Boom. The second cohort is the Vietnam War veterans taking advantage of the G.I. Bill.

[24] Specifically, $(L_g + H_g) / (L_s + H_s) = \frac{h_s - h}{h - h_g} \frac{1 + h_g}{1 + h_s}$. This is always positive because either $h_g < h < h_s$, as is the case in the data, or $h_g > h > h_s$, which is ruled out by the data.

are fixed. One can see that even though $a_1 > 0$, relative labor productivity in the service sector has declined. This will be illustrated in the next section.

Table 2 also reports a very small elasticity in demand, φ. Note that the standard error is also very small, so this means that it is accurately estimated close to zero.[25] This implies that, holding constant μ, consumers demand an almost fixed ratio of services to goods.

I examine the ratio of services output to goods output in the data. To do this I construct a relative output series using real value added data from the BEA. 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, and further divided by the relative price of services, defined above in the text. I normalize the series to one in 1963. **Figure 6** presents the series graphically. The empirical output ratio fluctuates somewhat in the sample, but does not have a trend. Although it is not stable, the lack of trend is consistent with the estimation results.

2.5 The relative role of inter-sector bias

In order to gauge the role of the inter sector labor productivity shifts I simulate a counterfactual with zero relative Hicks neutral technological change and compare it to the fitted model. A_s/A_g captures relative Hicks neutral technological change only if β_g and β_s are fixed. Therefore, calculating intersectoral relative Hicks neutral technological change takes into account that β_g and β_s are changing. See Appendix C for details.

Figure 7 shows the difference between the fitted simulated series using estimated parameters and the simulated counterfactual series. In the latter case all other parameters are held at their estimated value. The sector bias explains 15% of the increase in the relative wage of college graduates. This is consistent with Lee and Wolpin (2006a), who also find that inter-sector relative productivity shifts do not play a major role in explaining wage inequality.

Not surprisingly, the effect on average labor productivity (Panel D) is large; instead of decreasing by 60%, it actually increases slightly, by 5%. Likewise, the effect on the relative

[25] Monte-Carlo simulations and "profiling" the objective function show that φ is indeed identified. "Profiling" means plotting the value of the objective function for various values of a specific parameter, while allowing the estimation procedure to optimize over all other parameters. If the value does not change for the specific parameter that is controlled for, then that parameter is not identified.

price is large; over the entire sample the relative price of services slightly falls from 1 to 0.93 instead of increasing by over 2.6. The employment shift into services is also explained by the dynamics of relative productivity. These shares remain roughly at their initial values of 1963. Notice that the skill intensities rise slightly more than in the fitted model because the skill premium rises slightly less.

The large role of the sector bias for relative employment and price is explained by the small estimated elasticity of demand, φ. Since consumers demand almost constant relative quantities of goods and services over time, the relative decline in labor productivity in the service sector in the fitted model is fully accommodated by employment shifts into services and it also keeps down the relative price of services.

2.6 Relationship to previous aggregate results

There is a tension between finding a small (less than one) EoS in services and the general finding of a much larger aggregate EoS. Most theories of SBTC rely on an aggregate elasticity that is larger than one. Taking this as given, researchers have built models that generate faster factor augmentation for skilled workers and, hence, higher demand for their labor services; e.g. Acemoglu (1998) and Thoenig and Verdier (2003). In this section I relieve this tension, which is methodologically important, since it lends credibility to the estimation results.

Autor and Katz (1999) report that estimates of the aggregate elasticity of substitution are in the range of 0.5 and 3 but argue that it is likely close to 1.4.[26] But they also point out that the interpretation of an aggregate elasticity is not straightforward. As Acemoglu (2002) notes, the aggregate elasticity "...combines substitution both within and across industries." [pp. 20]. And there is a lot of substitution across industries: witness the growth of the employment share in services. Do the estimation results predict a large *aggregate* elasticity? And is its value stable over time?

To address these questions I use the two-sector model to characterize a "pseudo" aggregate elasticity of substitution. Suppose that the data generating process of the world is

[26] Johnson (1970) estimates the aggregate EoS between college and high-school graduates at 1.34 and Katz and Murphy (1992) estimate it at 1.4. More recent estimates are reported by Heckman, Lochner, and Taber (1998) at 1.44, and Krusell, Ohanian, Rios-Rull, and Violante (2000) at 1.67. Polgreen and Silos (2005) find that using the methodology of Krusell, Ohanian, Rios-Rull, and Violante (2000) with longer series and different data yields much higher estimates, between 2 and 9.

the two-sector model. If a researcher misspecified the data generating process and thought that it is a one-sector model, what would she get? In particular, one can ask what would be the estimate of σ from a regression of the type

$$\log(\omega_t) = c - \frac{1}{\sigma}\log(h_t) + \delta t + \varepsilon_t \ . \tag{15}$$

To answer this question I use the function Φ given in (10). By the implicit function theorem $dh/d\omega = -\Phi_\omega/\Phi_h$ and the pseudo aggregate EoS is given by

$$\widetilde{\sigma} = -\frac{dh}{d\omega}\cdot\frac{\omega}{h} = \frac{\omega\Phi_\omega}{h\Phi_h} \ .$$

This yields the following expression

$$\widetilde{\sigma} = \sigma_g \frac{h_g(1+\omega h)(h_s-h)}{h(1+\omega h_g)(h_s-h_g)} + \sigma_s \frac{h_s(1+\omega h)(h-h_g)}{h(1+\omega h_s)(h_s-h_g)} + \varphi \frac{\omega(h-h_g)(h_s-h)}{h(1+\omega h_g)(1+\omega h_s)} \ . \tag{16}$$

This is a convex combination of the elasticities in production, σ_g and σ_s, and the elasticity of demand, φ.[27] This illustrates that indeed the aggregate elasticity combines substitution both within and across industries. The coefficients to the elasticities may change over time with the changes in relative employment and relative skill intensities in the two sectors. This implies that the notion of a stable aggregate elasticity is tenuous.[28]

Using (16) and the parameter values from the estimation in **Table 2** I calculate $\widetilde{\sigma}$ for every year in the sample. As can be seen in **Figure 8**, $\widetilde{\sigma}$ increases from 1.04 in 1963 to 3.9 in 1982 and then decreases to 3.2 in 2005. The evolution of $\widetilde{\sigma}$ in the first part of the sample is dominated by a faster increase in h_g relative to h_s, which overwhelms the gradual increase in the share of services in employment (which is reflected in a decline of $(h_s - h)/(h - h_g)$). The simple average of $\widetilde{\sigma}$ for the 1963-2005 sample is 3.13 and for the 1963-1987 sample of Katz and Murphy (1992) the average is 2.84. One can also fit (15) using the simulated ω series. The estimate of σ from that regression in 1963-2005 is 2.17. For the 1963-1987 sample it is 1.87. Thus, the small elasticity in services and large one in the goods sector are consistent with previous aggregate estimates.

The estimates of δ in (15) are always positive. This would lead us to conclude that at

[27] If $h_i = h$, then $\widetilde{\sigma} = \sigma_i$, i.e. the economy is one "i" sector, regardless of the value of φ.

[28] One could agrue the same thing for each of the sectorial elasticities, because they too are composed of smaller sub-sectors and industries. However, this does not invalidate the last point, which is that the value of the aggregate elasticity changes with changes in employment shares.

the aggregate level factor augmentation has been faster for college graduates than for less skilled workers, since $\delta = (\sigma - 1)\,\beta_1$, where β_1 is the aggregate analogue of $\beta_{1,i}$. But this conclusion is misleading, because it is based on very different technological processes, in particular in services. This raises concerns for theories of SBTC that uniformly generate faster factor augmentation for skilled labor.

3 Robustness checks

3.1 Alternative technological processes

I estimate the model under alternative specifications of (13)-(12). In one specification I allow for a piecewise linear technological process (in logs), where the slopes (a_1 and $\beta_{1,i}$) may change at some year between 1980 and 1985 (1980, 1983 or 1985). This choice follows from the abrupt change in trend in the college premium around those years, which is visible in **Figure 1**. The results show that the trends (in logs) are very similar before and after the break year. In another alternative specification I allow for a log quadratic technological processes. The estimated log linear trends are very similar to those reported in **Table 2** and the quadratic components were extremely small and not statistically different from zero. These alternative specifications hardly affect the objective function.[29]

3.2 Alternative production functions

I use an alternative specification of the production functions to solve the model and re-estimate the parameters of interest:

$$G = Z_g \left[(1-\alpha_g)\, L_g^{\rho_g} + \alpha_g H_g^{\rho_g} \right]^{1/\rho_g} \tag{17}$$

$$S = Z_s \left[(1-\alpha_s)\, L_s^{\rho_s} + \alpha_s H_s^{\rho_s} \right]^{1/\rho_s} \ . \tag{18}$$

Other than that change, all else remains the same, in particular workers' preferences. I now present the main differences between the two versions of the model.[30]

[29] All these results are available upon request.

[30] See the appendix for complete details on the derivation.

Using (17) and (18) the expressions for skill intensities change to

$$h_g = \omega^{-\sigma_g}\gamma_g^{\sigma_g} \tag{19}$$

$$h_s = \omega^{-\sigma_s}\gamma_s^{\sigma_s} \ , \tag{20}$$

where $\gamma_i = \alpha_i / (1-\alpha_i)$. I obtain a similar expression for the equilibrium implicit function

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

The expression in square brackets is equal to A_s/A_g in (10). The other terms are identical to those in (10), but their underlying functions are different.

The exogenous processes are given by

$$\begin{aligned}
h(t) &= h_data(t) \cdot \exp\{u_t^h\} \\
\gamma_i(t) &= \frac{\alpha_i}{1-\alpha_i}(t) = \exp\left\{\gamma_{0,i} + \gamma_{1,i}t + u_t^i\right\} \ , \ i \in \{g, s\} \\
\frac{Z_s}{Z_g}(t) &= \exp\left\{z_0 + z_1 t + u_t^z\right\} \ .
\end{aligned}$$

As above, u_t^i are AR(1) processes. Despite the fact that I am still using constant growth rates for the exogenous technology processes, this representation of the dynamics is not equivalent to the previous one. 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 is not constant, since $Z_i = A_i\left(1+\beta_i^{\rho_i}\right)^{1/\rho_i}$.[31]

The estimation follows the same steps as described above in section 2.3 and the results are reported in **Table 3**. The estimates of the elasticities are on the same order of magnitude as before. In particular, $\sigma_s = 0.53 < 1$ and $\sigma_g = 5.57$. Ignoring the shocks, one can back out the implied β_i from γ_i: $\widetilde{\beta}_{1,i} = \gamma_{1,i}\sigma_i / (\sigma_i - 1)$. These are $\widetilde{\beta}_{1,g} = 0.024$ and $\widetilde{\beta}_{1,s} = -0.056$, which are very similar to what was estimated above. Here too the results indicate falling

[31] See the appendix for details.

relative productivity in services in the Hicks neutral sense ($z_1 = -0.02 < 0$), which is consistent with the fall in average labor productivity estimated above.

The value of the objective function at the minimum is roughly 1.19, which implies that the simulated data deviates by 0.7 percent from each data point, on average ($1.1878/(4 \times 43) \approx 0.007$). The main results provide a better fit. Despite this, and the different specification of the dynamics, the main results are robust: a low elasticity and faster factor augmentation for high school equivalents in services; and a high elasticity and faster factor augmentation for college graduates in goods.

4 Evidence on changes in occupational mixes

As Krugman (2000) argues, technological explanations for the increase in the skill premium are too much of a *deus ex machina*. Can the estimated technological processes be supported by evidence that is external to the analysis above? Methodologically, this is an important thing to do, because it contributes to the validity to the estimation results. Moreover, it can shed light on the underlying mechanism that gives rise to the results.

The estimation results imply that (1) factor augmentation in services is faster for high school equivalents than for college equivalents ($\beta_{1,s} < 0$) and that (2) the opposite is happening in the goods sector ($\beta_{1,g} > 0$). In addition, (3) factor augmentation has been faster for high school equivalents in services relative to high school equivalents in the goods sector ($a_1 > 0$). The following section aims to support these findings with data on changes in the occupational mix of the four groups of workers in the model: skilled and unskilled in both sectors. In what follows, I demonstrate that the estimated technological processes are consistent with empirical changes in the occupational mixes.

4.1 Accounting for the occupational mix

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

$$Q = [(AL)^{\rho} + (BH)^{\rho}]^{1/\rho} \ .$$

For now focus on BH, which is the sum of labor services supplied by skilled workers, in efficiency units. Let hrs_n denote hours worked by worker n and let e_n denote her efficiency units. Then

$$BH = \sum_n hrs_n e_n = \left(\sum\nolimits_n \frac{hrs_n}{H} e_n \right) H = \left(\sum\nolimits_n \lambda_n e_n \right) H \ ,$$

where λ_n is the share of hours worked by individual n; H is the sum of hours worked by skilled workers, $H = \sum_n hrs_n$; and B is their weighted average supply of efficiency units, $B = \sum_n \frac{hrs_n}{H} e_n = \sum_n \lambda_n e_n$. The summation over n is for individuals in the relevant group, in this case skilled workers.

Each individual n works in an occupation o. Therefore,

$$B = \sum_n \lambda_n e_n = \sum_o \sum_{n \in \langle o \rangle} \lambda_n e_{o_n} \ ,$$

where $n \in \langle o \rangle$ means that n has occupation o and o_n denotes n's occupation. Assume that all individuals with occupation o supply the same efficiency units. This means that $e_{o_n} = e_o$. Then

$$B = \sum_o \sum_{n \in \langle o \rangle} \lambda_n e_{o_n} = \sum_o \sum_{n \in \langle o \rangle} \lambda_n e_o = \sum_o e_o \sum_{n \in \langle o \rangle} \lambda_n = \sum_o \lambda_o e_o \ ,$$

where $\lambda_o = \sum_{n \in \langle o \rangle} \lambda_n$ is the share of hours worked in occupation o.[32] Define the occupational mix as the set of λ_o's, denoted $\{\lambda_o\}$. Eventually,

$$BH = \left(\sum\nolimits_o \lambda_o^H e_o \right) H \ . \tag{21}$$

And repeating the same derivation for AL,

$$AL = \left(\sum\nolimits_o \lambda_o^L e_o \right) L \ . \tag{22}$$

Adding superscripts to λ differentiates the occupational mix for L and H. In the model there are two sectors, so (21) and (22) will also be indexed by sector.

This allows relating occupational composition to average efficiency units: given e_o, changes in $\{\lambda_o^L\}$ and $\{\lambda_o^H\}$ affect the average efficiencies A and B.

[32] The expression $B = \sum_o \lambda_o e_o$ implictly assumes that all occupations within a sector and class of skill are perfect substitutes. This is consistent with the working assumption in the construction of the data hitherto, which maintained perfect substitutability among workers within a sector and class of skill.

4.2 Occupational efficiency units and tasks: a conceptual framework

I build on the ideas of Autor, Levy, and Murnane (2003): computers are complementary to tasks that are non-routine and can substitute tasks that are routine. Routine tasks can be coded into software (e.g. filing) or automated by robots (e.g. assembly). Non-routine tasks can be made more efficient by use of computers (e.g. analytical thinking, planning, communication).

I characterize each occupation o by routine task intensity, R_o, and non-routine task intensity, N_o. Suppose that efficiency per hour worked in occupation o is given by

$$e_o = e\left(R_o, N_o, C\right) = \left(R_o + C\right)^{1-\delta} N_o^{\delta} \ ,$$

where C is computer capital and $\delta \in (0,1)$. The important features of this specification are that N_o and R_o are not perfect substitutes and that R_o is more substitutable by C than N_o is.[33]

Now suppose that technological change induces computerization and use of information technology. A fall in the relative price of computing power will induce more use of computer inputs. This makes all occupations more efficient since

$$\frac{\partial e_o}{\partial C} = (1-\delta)\left(R_o + C\right)^{-\delta} N_o^{\delta} > 0 \ .$$

The increase in efficiency is larger for relatively non-routine task intensive occupations

$$\frac{\partial^2 e_o}{\partial N_o \partial C} = \delta (1-\delta)\left(R_o + C\right)^{-\delta} N_o^{\delta-1} > 0 \ ,$$

and smaller for occupations that are more routine task intensive

$$\frac{\partial^2 e_o}{\partial R_o \partial C} = -\delta (1-\delta)\left(R_o + C\right)^{-\delta-1} N_o^{\delta} < 0 \ .$$

Therefore, computerization increases the relative efficiency of occupations that have higher non-routine task intensities and lower non-routine task intensities.

It follows that if a high school graduate works in an occupation that has a relatively low

[33] Another way to say this is that there is computer-non-routine task complementarity, which is reminiscent of capital-skill complementarity (Griliches (1969)). Any function with this feature will do; this specification is just a simplest example. In principle, δ could have also varied by occupation, but this is not important for what follows.

non-routine task intensity and relatively high routine task intensity, then computerization will increase her occupational efficiency by less than for a college graduate. But if high school graduates are reallocating into occupations that are relatively more non-routine task intensive, i.e. occupations which are more computer complementary, then this will increase their average occupational efficiency input as a group. And if the reallocation is large enough in that direction, then the increase in average efficiency can be even larger than the increase in average efficiency that college graduates experience as a group.

I formalize these ideas using (21) and (22). Suppose that the impetus for changes in B and A over time is the use of computers. Then

$$\frac{dB}{dC} = \sum\nolimits_o \frac{\partial \lambda_o^H}{\partial C} e_o + \sum\nolimits_o \lambda_o^H \frac{\partial e_o}{\partial C}$$

and

$$\frac{dA}{dC} = \sum\nolimits_o \frac{\partial \lambda_o^L}{\partial C} e_o + \sum\nolimits_o \lambda_o^L \frac{\partial e_o}{\partial C} \ .$$

Changes in average task intensity reflect changes both in $\{\lambda_o\}$ and in $\{e_o\}$. An increase in average non-routine task intensity reflects a shift in $\{\lambda_o\}$ towards computer complementary occupations. A decrease in average routine task intensity reflects a shift in $\{\lambda_o\}$ away from computer substitutable occupations. Both lead to increases in average efficiency input per worker.

But in order to say whether A increases more than B, changes in $\{e_o\}$ must also be taken into account:

$$\frac{dA}{dC} - \frac{dB}{dC} = \sum\nolimits_o \left[\frac{\partial \lambda_o^L}{\partial C} - \frac{\partial \lambda_o^H}{\partial C} \right] e_o + \sum\nolimits_o \left[\lambda_o^L - \lambda_o^H \right] \frac{\partial e_o}{\partial C} \ .$$

Unfortunately, this is not possible without taking a stand on the function e_o and estimating it. This is beyond the scope of this paper. The empirical analysis addresses the first sum; it indicates that it is positive and large in services, but not so in the goods sector. In the data, $\lambda_o^L < \lambda_o^H$ in occupations that are categorized as more computer complementary (and vice versa for computer substitutable occupations). Then what matters for the second sum is how strongly does $\partial e_o / \partial C$ correlate with computer complementary across occupations. Given diminishing marginal returns (as above), this correlation may not be very strong. If this is the case, i.e. the effect of computerization on the efficiency of occupations is not too high, and the differences between λ_o^L and λ_o^H are not too large, then $dA/dC - dB/dC$ will be likely positive when the first sum is positive.

The three estimates of technological trends can be cast against three hypotheses about changes in occupational mixes. Not rejecting these hypotheses is consistent with these technological trends and offers an interpretation:

(**H1**) *In services the occupational mix of low skilled workers,* $\{\lambda_o^{L,s}\}$*, shifts towards computer complementary occupations more than the occupational mix of high skilled workers,* $\{\lambda_o^{H,s}\}$ *(consistent with* $\beta_{1,s} < 0$*).*

(**H2**) *In the goods sector the occupational mix of low skilled workers,* $\{\lambda_o^{L,g}\}$*, shifts towards computer complementary occupations less than the occupational mix of high skilled workers,* $\{\lambda_o^{H,g}\}$ *(consistent with* $\beta_{1,g} > 0$*).*

(**H3**) *The occupational mix of low skilled workers in services,* $\{\lambda_o^{L,s}\}$*, shifts towards computer complementary occupations more than the occupational mix of low skilled workers in the goods sector,* $\{\lambda_o^{L,g}\}$ *(consistent with* $a_1 > 0$*).*

4.3 The evolution of task indices

Testing H1-H3 hypotheses requires a mapping from occupations to tasks. For each occupation and gender, five task intensities from the Dictionary of Occupational Titles are used to reflect computer complementarity and substitutability.[34] The task intensities capture routine and non-routine tasks, which can be either manual or cognitive; see **Table 4**.[35]

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) captures analytical thinking, and *PLAN* (direction, control and planning) captures decision making and communication skills—both of which are non-routine cognitive tasks. **Table A** in the appendix provides more details and examples and **Table B** reports summary statistics. The task intensities vary over the [0,10] interval. I calculate task indices for high school and college equivalents

[34] I am greatful to David Autor for sharing this data with me. See appendix for complete documentation.

[35] Spitz-Oener (2006) reports the evolution of similar task indices by education level in the German economy, but not in different sectors. Although her task measures are different in nature, she finds similar patterns to those documentted by Autor, Levy, and Murnane (2003) for the U.S. economy.

in goods and services sectors for 1967-2001. The shorter sample is due to comparability issues before 1967 and after 2001.[36]

After matching the task intensities with individuals' occupations in the CPS sample, I aggregate by sector, college equivalents and high school equivalents. For each generic task and sector there are $TASK_{s,HS}$ and $TASK_{s,COL}$ in each year, where $TASK \in \{DEX$, $COORD$, $STAND$, $MATH$, $PLAN\}$ and $s \in \{goods, services\}$. The task indices are in units of percentiles in the 1967 distribution of each task. The benefit of this transformation is twofold. First, it makes the task indices comparable in magnitude, since they are now all in percentile terms. Second, it assigns smaller weight to extreme values which are found in ranges that are less dense in 1967. The results are qualitatively the same if I use weighted averages instead of using the 1967 distribution. See the appendix for complete documentation of the construction of these indices.

In order to test the first two hypotheses listed above, I construct an index of relative task intensity of high school versus college equivalents for each sector

$$\Delta TASK_{s,t} = (TASK_{s,HS,t} - TASK_{s,HS,1971}) - (TASK_{s,COL,t} - TASK_{s,COL,1971}) \ .$$

By construction $\Delta TASK_{s,t}$ is equal to zero in $t = 1971$. The choice of 1971 as base year facilitates the graphical exposition, since the indices are somewhat noisy before 1971.

Figure 9 plots all five $\Delta TASK_{s,t}$ separately for goods and services. Both panels in the figure have the same scale. A few features stand out. First, the changes in $\Delta TASK$ are much larger in services than in the goods sector. Second, ΔDEX, $\Delta STAND$ and $\Delta COORD$ move in opposite directions in services and goods. Thirdly, $\Delta MATH$ and $\Delta PLAN$ increase substantially more in services relative to the goods sector.

Table 5 reports the differences in $\Delta TASK$ from 1971 to 2001. In services, routine manual task intensity (ΔDEX) and routine cognitive task intensity ($\Delta STAND$) substantially decrease (by 8.6% and 11.5%, respectively) for high school relative to college equivalents. The goods sector exhibits small increases. In services, both analytical non-routine cognitive task intensity ($\Delta MATH$ and $\Delta PLAN$) increase for high school versus college equivalents (6% and 6.3%, respectively). These increases are larger than in the goods sector (3.3% and

[36] Although a consistent occupation classification is used for the entire sample, it does not perform well for separate sectors outside of the 1967-2001 sample. See appendix for details.

4%, respectively). Most of the changes in the relative task intensities stem from changes in the numerator, i.e. in the mix of occupations of high school equivalents. After all, college graduates have always predominantly held non-routine intensive occupations, and this has not changed much since 1967.[37]

The changes in the occupational mixes all point in the same direction. High school equivalents in services have dramatically shifted out of occupations that are relatively more computer substitutable, and into occupations that are relatively more computer complementary. They have done so to a greater extent than college equivalents. The opposite pattern is observed in the goods sector. Thus, the first two hypotheses are supported by the data.

To test the third hypothesis, I construct relative task intensity indices for high school equivalents in services versus goods:

$$\Delta TASK_{HS,t} = (TASK_{serv,HS,t} - TASK_{serv,HS,1971}) - (TASK_{good,HS,t} - TASK_{good,HS,1971}) \ .$$

Here I only report the changes from 1971 to 2001. Both $\Delta MATH_{HS}$ and $\Delta PLAN_{HS}$ increase by 4.3%, while $\Delta STAND_{HS}$ and ΔDEX_{HS} decrease by 1.6% and 2.4%, respectively ($\Delta COORD_{HS}$ increases by 1.35%).

High school equivalents in services have shifted their occupational mix out of occupations that are relatively more computer substitutable, and into occupations that are relatively more computer complementary—much more than high school equivalents in the goods sector. This supports the last hypothesis.

To strengthen the interpretation of these results, I calculate the share of IT in the capital stock in each sector.[38] The IT share increases much faster in services than in the goods sector. This supports the conclusion that the shift into computer complementary occupations has been behind the relative changes in factor efficiency. Indeed, Autor, Levy, and Murnane (2003) find faster growth of computer complementary task intensities in industries that invested more in computers; they find the opposite for computer substitutable task intensities. Moreover, they find larger changes in task intensities for workers with less than

[37] Non-routine manual task intensity ($\Delta COORD$) increases in services whereas it decreases in the goods sector, although this probably is not affected directly by computers.

[38] I use data from the fixed asset tables from the Bureau of Economic Analysis to construct IT shares in constatnt 2000 prices.

college degree. My results are consistent with these findings.

Although the task indices summarize all the relevant information on occupational mixes, some examples are useful. To simplify, consider first workers with less than a 4 year college degree in services (not high school equivalents).[39] The employment share of secretaries and of personal and household service occupations (relatively routine occupations) among these workers drops from 9% in 1971 to 4.8% in 2001 and from 22.7% to 10%, respectively. The same group increases its employment share of information clerks (which include, e.g., call centers) and of managers (relatively non routine occupations) from 1.5% in 1971 to 3.6% in 2001 and from 7% to 12.3%, respectively. These shifts are among those that drive the change in the task indices for unskilled in services. Considering the same education group in the goods sector, the share of managers hardly changes over this period (it fluctuates around 7.8%). The change in the occupational composition of college graduates' in services is almost entirely explained by a shift away from teaching and into management and other professional occupations, all of which are not very dissimilar in their routine and non routine task intensities.

5 Conclusions

This paper demonstrates that our understanding of technological change can be improved by taking into account occupational mixes within broad education-sector groups. By directly exploiting the general equilibrium restrictions and optimality conditions of a two sector model I estimate that factor augmenting technological change has operated in opposite directions in the skill intensive services sector versus the rest of the private sector. Both processes drive up relative demand for college graduates, but for different reasons. In the goods sector relative demand shifts towards college graduates because they become relatively more efficient and can easily substitute high school graduates. In the services sector relative demand shifts towards college graduates because of their strong complementarity with high school graduates, who become relatively more efficient. Overall, relative demand for unskilled workers falls relative to their supply, commensurate with a decline in their

[39] In the calculation of high school equivalents, the weight for high school dropouts is 1.11 and for workers with more than high school but less than a 4 year college degree the weight is 0.93. For college equivalents, the weight for high school dropouts is -0.16 and for workers with more than high school but less than a 4 year college degree the weight is 0.14.

relative wage.

These opposite technological processes are consistent with shifts in occupational mixes, which help interpret the estimates of technological processes. Many routine tasks have been replaced by computers, e.g. filing. In services, the occupational composition of unskilled workers has shifted away from routine task intensive occupations, and towards non routine task intensive occupations. This shift may be large enough to explain how their average efficiency growth outpaced that of college graduates in services. In contrast, in the goods sector unskilled workers have not shifted into computer complementary occupations as much as in skill intensive services. This is consistent with a decline in their relative efficiency.

One may wonder why the goods sector behaves so differently. One reason for the opposite trend in the goods sector may be that everything that could be automated has already been automated by the beginning of the sample.[40]

The results of the analysis inform theoretical treatments of the underlying mechanisms of SBTC and provide support for the framework of Autor, Levy, and Murnane (2003). However, they raise concerns for aggregate, uniform explanations of the increase in the college premium, e.g. Acemoglu (1998) and Thoenig and Verdier (2003). These explanations rely on an aggregate elasticity of substitution between skilled and unskilled labor greater than one and on uniformity of workers within education groups, where the same forces operate on all workers of the same group, regardless of sector. However, the estimation results are at odds with this approach and changes in occupational mixes seem to be consistent with the estimated technological trends. Therefore, it appears that a more appropriate understanding of technological change would rely not only on characterizing levels of education, but also on characterizing occupations and how they are affected by the main inventions of the period considered.

[40] See also Michaels (2007) for an analysis of an IT revolution in the begining of the 20th century, which affected demand for clerks.

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Appendix

A 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 New York University.

The CPS is a monthly survey of about 50,000 households conducted by the Bureau of the Census for the Bureau of Labor Statistics. Currently, there are more than 65,000 participating households. 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 famous 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 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

$$hrs_{ct} = \frac{\sum_{n \in \langle c \rangle} \lambda_{nt} hrs_{nt}}{\sum_{n} \lambda_{nt} hrs_{nt}} \ , \tag{23}$$

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

$$w_{ct} = \frac{\sum_{n\in\langle c\rangle} w_{nt}\lambda_{nt} hrs_{nt}}{\sum_n \lambda_{nt} hrs_{nt}} , \tag{24}$$

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.

B 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 (23). 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

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

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

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

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 $\omega = w_{16}/w_{12}$.

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.

C Calculating fixed Hicks neutral technology path

Recall that 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 are changing. To do this I proceed as follows. An alternative representation of the production technologies (1) and (2) is

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

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:

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

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

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

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. I use this path to simulate the model using all other estimated parameters to see how the equilibrium path changes.

D An α-Z specification of the model

I briefly report here the complete derivation of the equilibrium using the alternative 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. Each firm in sector i chooses inputs $\{L_i, H_i\}$ to minimize costs $C = w_L L_i + w_H H_i$, such that $Z_i\left[(1-\alpha_i)L_i^{\rho_i}+\alpha_i H_i^{\rho_i}\right]^{1/\rho_i} \geq Q_i$, where $Q_g = G$ and $Q_s = S$. This yields the following unit cost functions

$$c_g = \frac{1}{Z_g}\left[(1-\alpha_g)^{\sigma_g} w_L^{1-\sigma_g} + \alpha_g^{\sigma_g} w_H^{1-\sigma_g}\right]^{\frac{1}{1-\sigma_g}} \quad (25)$$

$$c_s = \frac{1}{Z_s}\left[(1-\alpha_s)^{\sigma_s} w_L^{1-\sigma_s} + \alpha_s^{\sigma_s} w_H^{1-\sigma_s}\right]^{\frac{1}{1-\sigma_s}} \ , \quad (26)$$

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, so w_L and w_H are not indexed by sector.

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

$$h_g = \omega^{-\sigma_g}\gamma_g^{\sigma_g} \quad (27)$$

$$h_s = \omega^{-\sigma_s}\gamma_s^{\sigma_s} \ , \quad (28)$$

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. Restrict attention to interior solutions. Normalize the price of goods to one and rewrite (25)-(26) to get

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

Take the ratio and use (27) and (28) to get the relative price of services

$$
p=\frac{Z_g}{Z_s}\frac{\left(1-\alpha_g\right)^{\frac{\sigma_g}{\sigma_g-1}}}{\left(1-\alpha_s\right)^{\frac{\sigma_s}{\sigma_s-1}}}\frac{\left[1+\omega h_s\right]^{\frac{1}{1-\sigma_s}}}{\left[1+\omega h_g\right]^{\frac{1}{1-\sigma_g}}}\ . \tag{29}
$$

Unit factor intensities were obtained by taking the derivative of the unit cost functions with respect to the wage. By using (27)-(28)

$$
\begin{aligned}
L_i^1 &= \frac{1}{Z_i\left(1-\alpha_i\right)^{\frac{\sigma_i}{\sigma_i-1}}}\left[1+\omega h_i\right]^{\frac{\sigma_i}{1-\sigma_i}} \\
H_i^1 &= \frac{1}{Z_i\alpha_i^{\frac{\sigma_i}{\sigma_i-1}}}\left[1+\left(\omega h_i\right)^{-1}\right]^{\frac{\sigma_i}{1-\sigma_i}}\ .
\end{aligned}
$$

Full employment is given by multiplying the unit factor intensities for both sectors,

$$
L = SL_s^1+GL_g^1=S\frac{1}{Z_s\left(1-\alpha_s\right)^{\frac{\sigma_s}{\sigma_s-1}}}\left[1+\omega h_s\right]^{\frac{\sigma_s}{1-\sigma_s}}+G\frac{1}{Z_g\left(1-\alpha_g\right)^{\frac{\sigma_g}{\sigma_g-1}}}\left[1+\omega h_g\right]^{\frac{\sigma_g}{1-\sigma_g}} \tag{30}
$$

$$
H = SH_s^1+GH_g^1=S\frac{1}{Z_s\alpha_s^{\frac{\sigma_s}{\sigma_s-1}}}\left[1+\left(\omega h_s\right)^{-1}\right]^{\frac{\sigma_s}{1-\sigma_s}}+G\frac{1}{Z_g\alpha_g^{\frac{\sigma_g}{\sigma_g-1}}}\left[1+\left(\omega h_g\right)^{-1}\right]^{\frac{\sigma_g}{1-\sigma_g}} \tag{31}
$$

By manipulating (30)-(31) the following expression for relative output is obtained

$$
\frac{S}{G}=\frac{Z_s}{Z_g}\frac{\left(1-\alpha_s\right)^{\frac{\sigma_s}{\sigma_s-1}}}{\left(1-\alpha_g\right)^{\frac{\sigma_g}{\sigma_g-1}}}\left(\frac{h-h_g}{h_s-h}\right)\frac{\left(1+\omega h_g\right)^{\frac{\sigma_g}{1-\sigma_g}}}{\left(1+\omega h_s\right)^{\frac{\sigma_s}{1-\sigma_s}}}\ , \tag{32}
$$

where $h=H/L$ is the relative skill abundance of the economy.

Using the same preferences as above, I get the same expression for relative demand

$$
\frac{S}{G}=p^{-\varphi}\left(\frac{\mu}{1-\mu}\right)^{\varphi}\ .
$$

Using this together with (32) and (27)-(28) the following equilibrium condition is obtained

$$\begin{aligned}
&\Phi\left(\omega, h, \gamma_g, \gamma_s, Z_s/Z_g\right) \\
= &\left[\frac{Z_s}{Z_g}\frac{(1-\alpha_s)^{\frac{\sigma_s}{\sigma_s-1}}}{(1-\alpha_g)^{\frac{\sigma_g}{\sigma_g-1}}}\right]^{(1-\varphi)}\left(\frac{h-h_g}{h_s-h}\right)\frac{(1+\omega h_s)^{(\varphi-\sigma_s)/(1-\sigma_s)}}{(1+\omega h_g)^{(\varphi-\sigma_g)/(1-\sigma_g)}} \\
= &\left[\frac{Z_s}{Z_g}\frac{(1-\alpha_s)^{\frac{\sigma_s}{\sigma_s-1}}}{(1-\alpha_g)^{\frac{\sigma_g}{\sigma_g-1}}}\right]^{(1-\varphi)}\left(\frac{h-\omega^{-\sigma_g}\gamma_g^{\sigma_g}}{\omega^{-\sigma_s}\gamma_s^{\sigma_s}-h}\right)\frac{\left(1+\omega^{1-\sigma_s}\gamma_s^{\sigma_s}\right)^{(\varphi-\sigma_s)/(1-\sigma_s)}}{\left(1+\omega^{1-\sigma_g}\gamma_g^{\sigma_g}\right)^{(\varphi-\sigma_g)/(1-\sigma_g)}} \\
= &\left(\frac{\mu}{1-\mu}\right)^{\varphi} . \qquad (33)
\end{aligned}$$

Note that the only differences between (33) and (10) are in the expressions for sectoral productivity in brackets and the functions for skill intensities.

E Relationship between α-Z and A-B specifications

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

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

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 $A_i = Z_i \left(1+\gamma_i\right)^{-1/\rho_i}$.

F 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 A** 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 B** 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 $F(TASK_{i,e,g})$ to aggregate by sector and education level

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

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 $F(TASK_{i,e,g})$ 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 (22), 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 collage 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.

Table 1: Definition of Goods and Services Industries

	Goods	Services
1963-2001	Agriculture, forestry, & fisheries	Finance, insurance & real estate
	Mining	Business & repair services
	Construction	Personal services
	Manufacturing, nondurable goods	Entertainment & recreation services
	Manufacturing, durable goods	Health services
	Transportation (including USPS)	Educational services
	Communications & other public utilities	Other professional & related services
	Wholesale trade	
	Retail trade	
2002-2005	Agriculture, forestry, fishing & hunting	Finance & insurance
	Mining	Real estate, & rental & leasing
	Construction	Arts, entertainment, & recreation
	Manufacturing	Accommodation & food services
	Transportation & warehousing	Health care & social assistance
	Utilities	Educational services
	Information	Professional, scientific, & technical services
	Wholesale trade	Management of companies & enterprises
	Retail trade	Administrative, support & waste management
		Other services (except public administration)

Notes: The table lists the 1-digit industries in each sector, as they are named in the Current Population Survey. In 2002 there was a major revision of industrial classifications. The public sector is excluded in all years.

Table 2: Estimates

Elasticities			
	Services	Goods	Demand
	$\sigma(s)$	$\sigma(g)$	ϕ
	0.64	6.94	0.003
	(0.005)	(0.083)	(0.002)

Technological Processes			
	Services	Goods	Intersectoral
Rate of change	$\beta(1,s)$	$\beta(1,g)$	$a(1)$
	-0.07	0.02	0.021
	(0.001)	(0.0002)	(0.0005)
Initial value	$\beta(0,s)$	$\beta(0,g)$	$a(0)$
	1.811	-0.127	2.146
	(0.017)	(0.0076)	(0.016)

Stochastic Processes			
Relative Supply	Services	Goods	Intersectoral
$\rho(h)$	$\rho(s)$	$\rho(g)$	$\rho(a)$
-	0.55	0.68	0.3
$v(h)$	$v(s)$	$v(g)$	$v(a)$
0.004	0.002	0.001	0.001

Fit (sum squared deviations): 1.0034

Notes: Estimates are obtained by weighted nonlinear least squares, applying the method of simulated moments. See text for details. Standard errors in parentheses are calculated using parametric bootstrapping, with 500 simulations. The technological processes are for the relative productivity of skilled versus unskilled labor in services $\beta(s,t)=exp\{\beta(0,s)+\beta(1,s)t+u(s)\}$, in the goods sector $\beta(g,t)=exp\{\beta(0,g)+\beta(1,g)t+u(g,t)\}$, and for the relative productivity of unskilled in services versus unskilled in the goods sector $As/Ag(t)=exp\{a(0)+a(1)t+u(a,t)\}$. All $u(i,t)$ shocks are AR(1) with coefficient $\rho(i)$ and iid shock with standard deviation $v(i)$. An additional shock to aggregate relative supply is iid. The fit of 1.0034 implies that the simulated data deviates by 0.58 percent from each data point, on average (1.0034/(4*43) = 0.0058).

Table 3: Estimates of Alternative Specification

Elasticities

	Services	Goods	Demand
	σ(s)	*σ(g)*	*ϕ*
	0.53	5.57	0.0001
	(0.004)	(0.064)	(0.00001)

Technological Processes

	Services	Goods	Intersectoral
Rate of change	*γ(1,s)*	*γ(1,g)*	*z(1)*
	0.05	0.02	-0.02
	(0.003)	(0.0024)	(0.001)
Initial value	*γ(0,s)*	*γ(0,g)*	*z(0)*
	-1.37	-0.264	0.896
	(0.008)	(0.008)	(0.019)

Stochastic Processes

Relative Supply	Services	Goods	Intersectoral
ρ(h)	*ρ(s)*	*ρ(g)*	*ρ(a)*
-	0.47	0.36	0.48
v(h)	*v(s)*	*v(g)*	*v(a)*
0.0085	0.0142	0.0095	0.0087

Fit (sum squared deviations): 1.1878

Implied β's	*β(1,s)*	*β(1,g)*
	-0.056	0.024

Notes: Estimates are obtained by weighted nonlinear least squares, applying the method of simulated moments. See text for details. Standard errors in parentheses are calculated using parametric bootstrapping, with 500 simulations. The errors are identical to those drawn in **Table 1**, but their standard deviations are optimized separately. The technological parameters are for the ratio of distribution parameters of skilled versus unskilled labor $(\alpha/(1-\alpha))$ in services $\gamma(s,t)=exp\{\gamma(0,s)+\gamma(1,s)t+u(s,t)\}$, in the goods sector $\gamma(g,t)=exp\{\gamma(0,g)+\gamma(1,g)t+u(g,t)\}$, and for the relative Hicks-neutral productivity in services versus the goods sector $Zs/Zg(t)=exp\{z(0)+z(1)t+u(z,t)\}$. All $u(i,t)$ shocks are AR(1) with coefficient $\rho(i)$ and iid shock with standard deviation $v(i)$. An additional shock to aggregate relative supply is iid. The implied biases in technological change are calculated as $\beta(1,i) = \gamma(1,i)*\sigma(i)/(\sigma(i)-1)$, where $i=s$ or g . The fit of 1 implies that the simulated data deviates by 0.7 percent from each data point, on average (1.878/(4*43) = 0.007).

Table 4: Dictionary of Occupational Titles Task Intensities

	Manual	Cognitive
Routine	*DEX* (assembly)	*STAND* (filing)
Non-Routine	*COORD* (diamond cutting)	*MATH, PLAN* (solving models, manager)

Notes: Task intensities are from the Dictionary of Occupational Titles. *DEX* : Finger-dexterity, *COORD* : eye-hand-foot coordination, *STAND* : set limits, tolerances and standards, *MATH* : math aptitude, *PLAN* : direction, control and planning. Examples of tasks are given in parentheses.

Table 5: Changes in Relative DOT Task Intensities: 1971-2001

	Services	Goods
DEX	-8.6%	0.8%
STAND	-11.5%	1.3%
COORD	3.3%	-2.3%
MATH	5.9%	3.3%
PLAN	6.3%	4.0%

Notes: The table reports changes from 1971 to 2001 of *ΔTASK* , which is the relative task intensity of high-school versus college equivalents for each *TASK.* The units are percentiles in the 1967 distribution of each task. Task intensities are 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.

Appendix Table A: 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).

Appendix Table B: DOT Tasks Summary Statistics

A. Sample Statistics

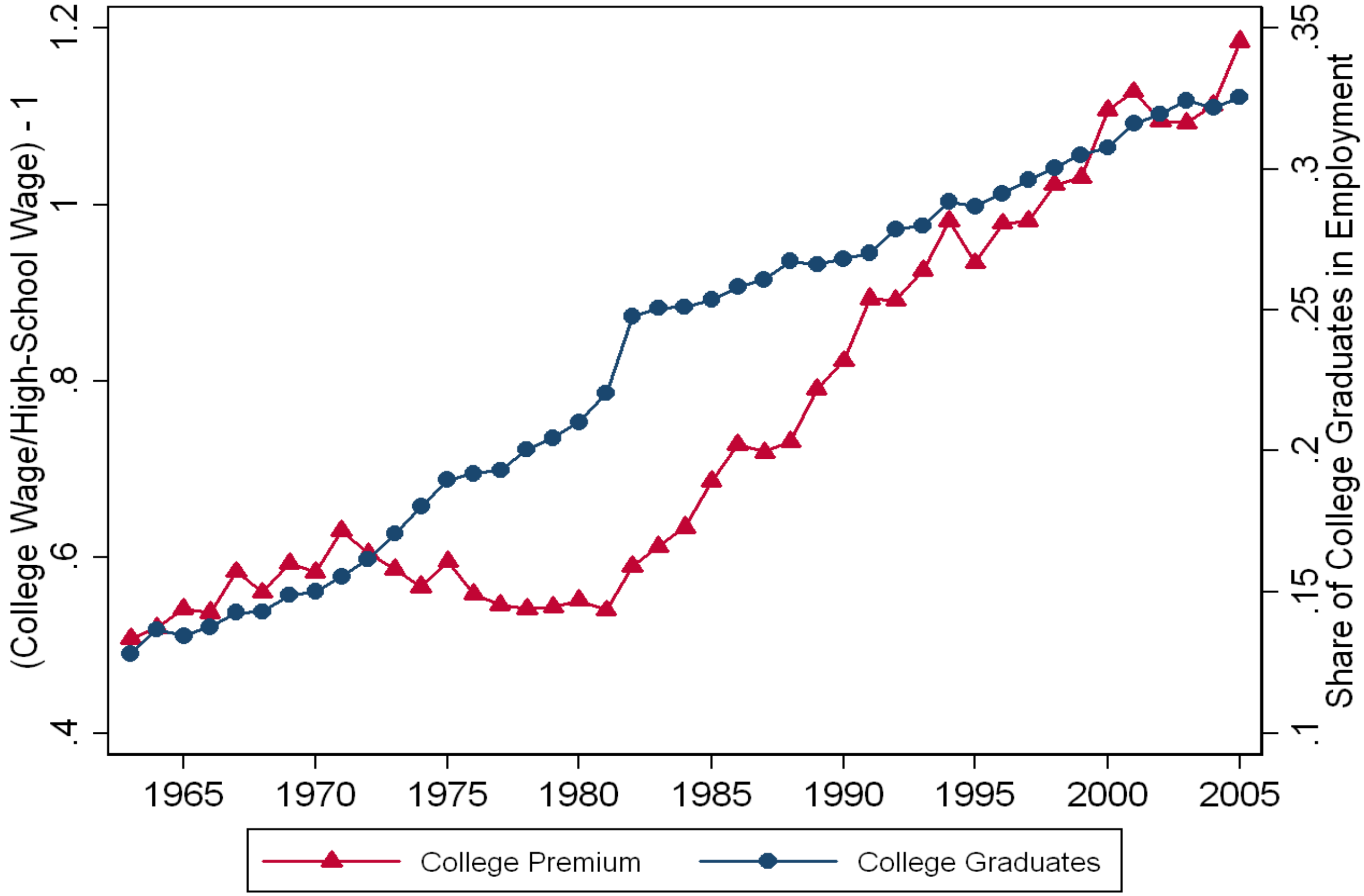
	Median	Mean	S.D.	Min	Max
FINGDEX	3.8	3.9	1.3	0	9
COORD	0.77	1.2	1.4	0	10
STAND	5.8	5.1	3.8	0	10
MATH	3.5	3.8	2.3	0	10
PLAN	0.5	2.3	3.2	0	10

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

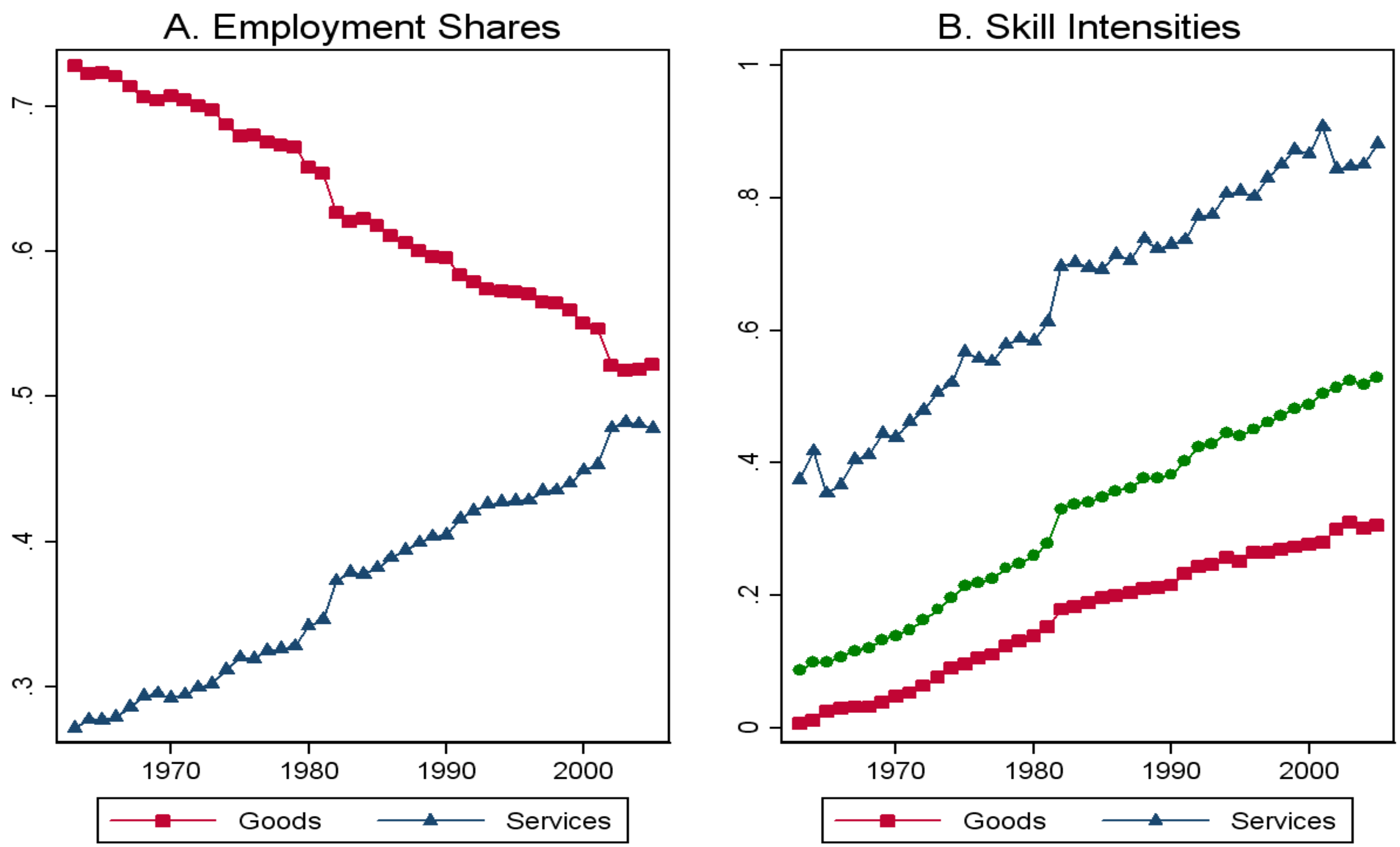
Notes: Statistics are calculated for 746 observations by occupation and gender. * denotes 5% statistical significance level.

Figure 1: College Premium and Relative Supply of College Graduates



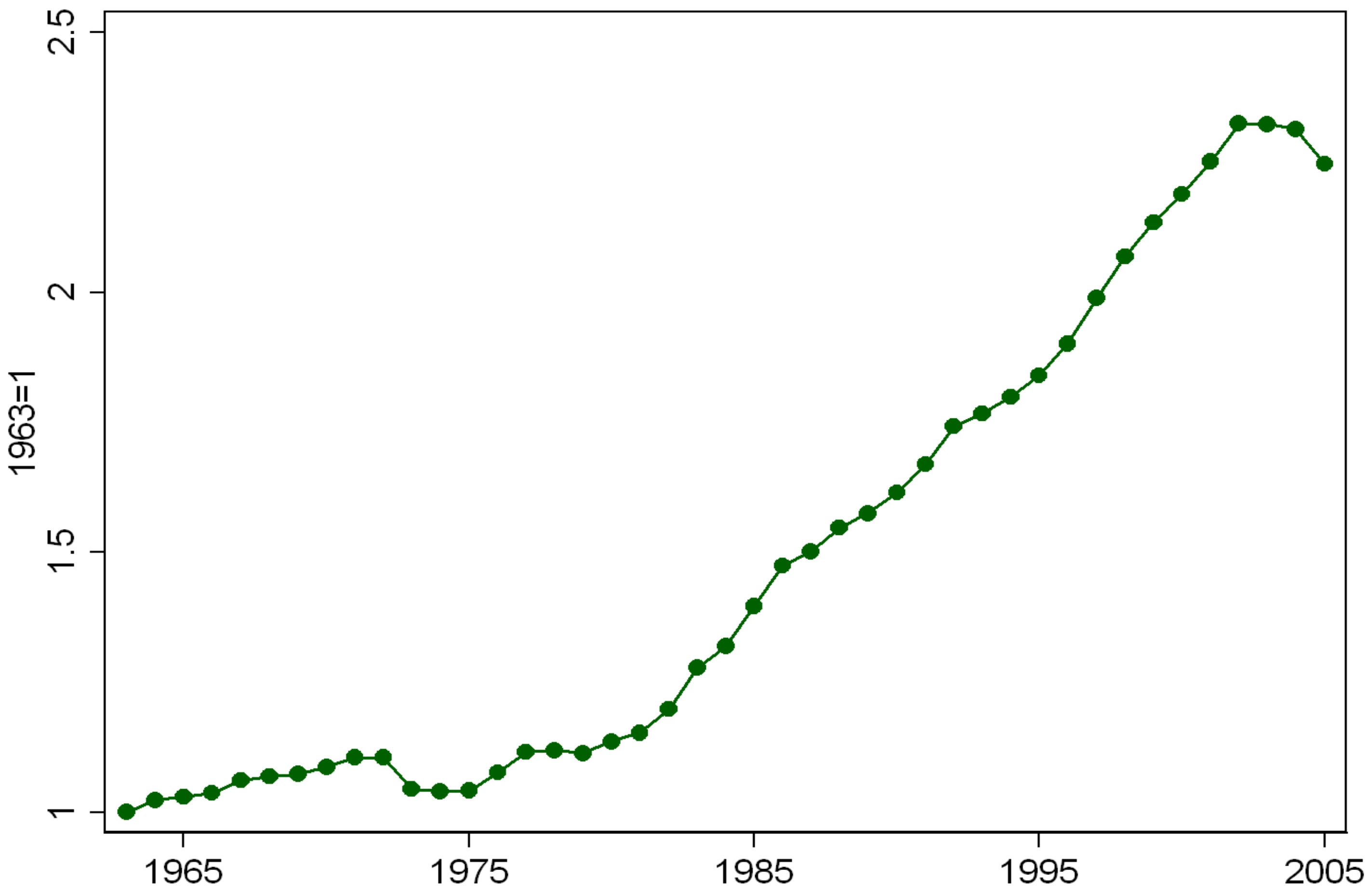
Notes: The College Premium is equal to the ratio of the average weekly wage of college graduates to average weekly wage of high-school graduates, minus one. College graduates are reported as their percent of the labor force. Source: March CPS 1964-2006.

Figure 2: Employment Sahers and Skill Intensities



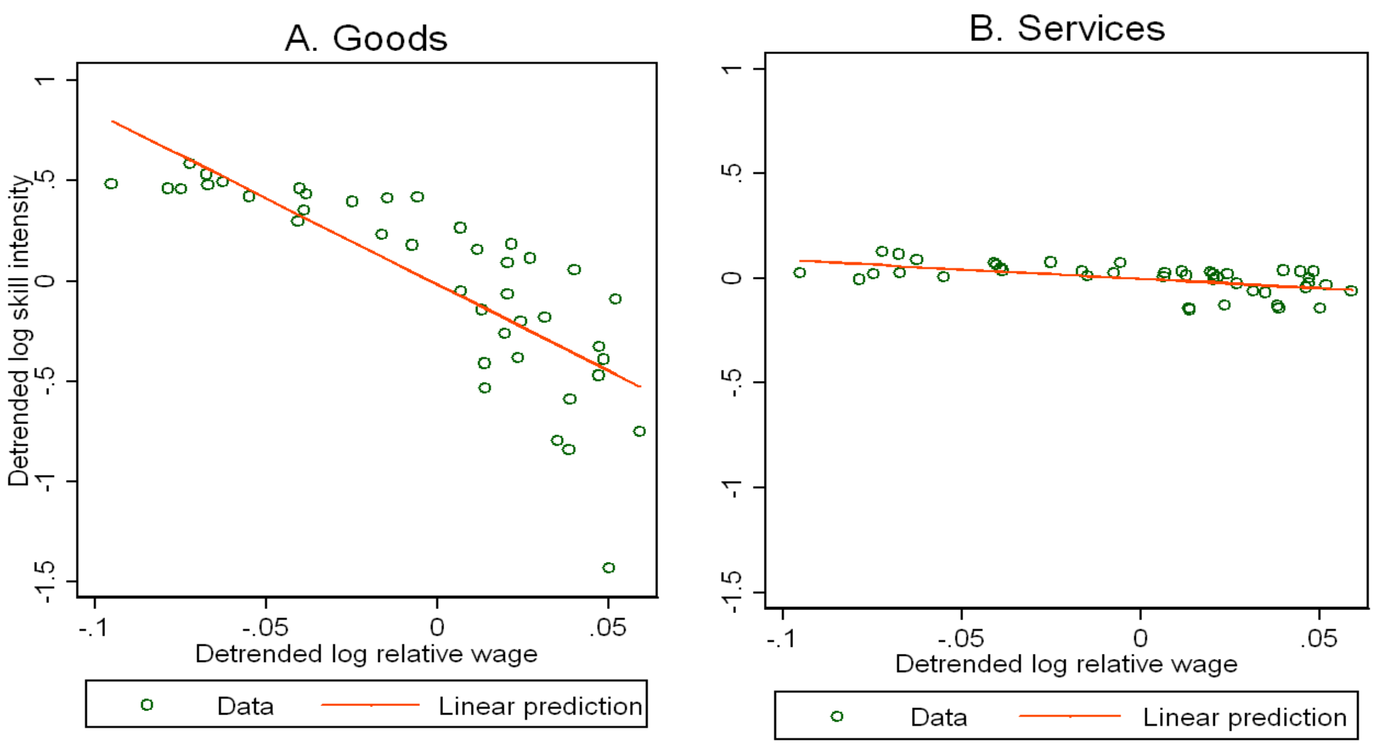
Notes: Employment is measured in annual hours times CPS sampling weights as a fraction of total private sector employment. Sectors are defined in **Table 1**. The breaks in the series in 1981-1982 and in 2001-2002 are due to industry reclassifications in the CPS. For the 2001-2002 break a reallocation procedure was used in order to make 1-digit classifications after 2001 consistent with the classification until 2001. The reallocation is based on information from the Census Bureau's 2003 Technical Paper 65. Skill intensities are ratios of college equivalents to high school equivalents. The unmarked series in panel B is aggregate skill abundance, which is the ratio of college equivalents to high school equivalents in the private sector. Source: March CPS 1964-2006. See text for complete details on construction of series.

Figure 3: Relative Price of Skill-Intensive Services versus Goods



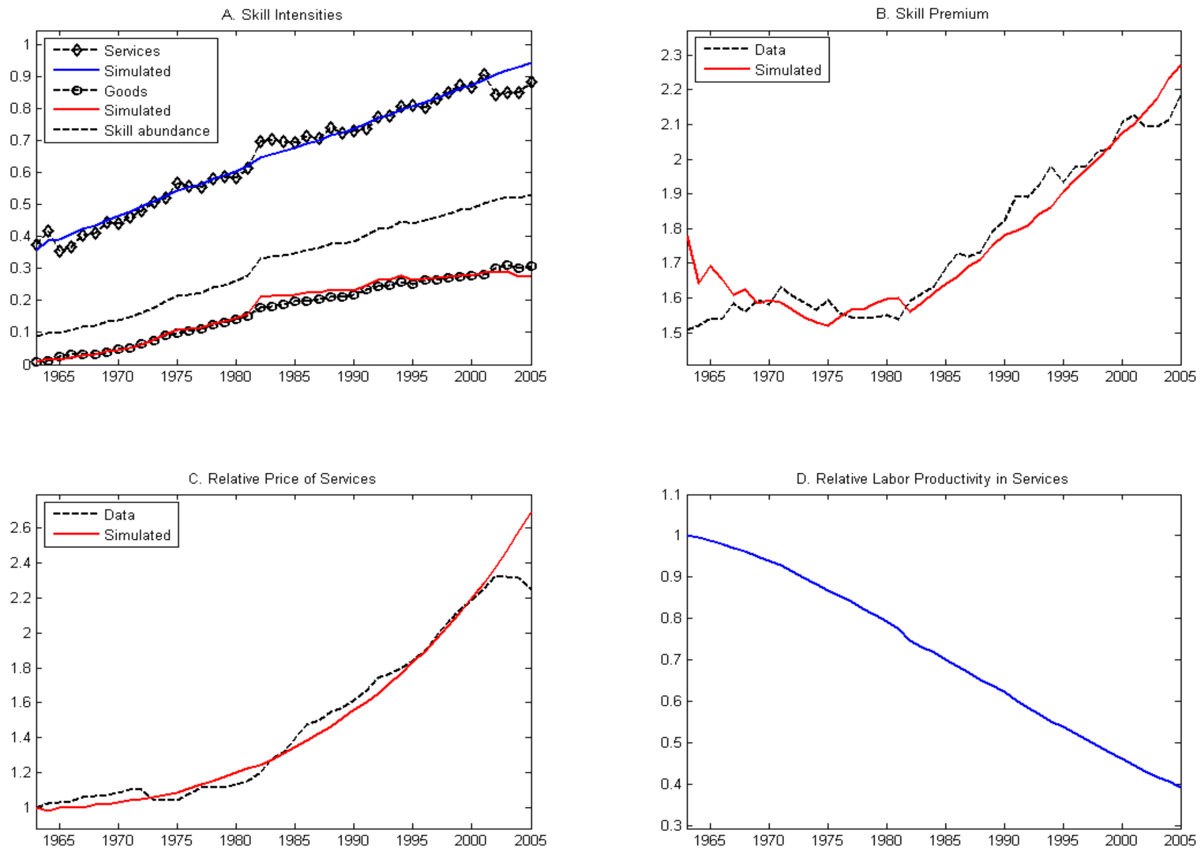
Notes: The price for the skill-intensive and goods sectors in each year is a weighted average of chain-type prices of industries that fall in that sector, where the weights are value added. The relative price of services versus goods is their ratio, which is normalized to one in 1963. Sectors are defined in **Table 1**. Source: Bureau of Economic Analysis.

Figure 4: Relative Wage and Skill Intensity



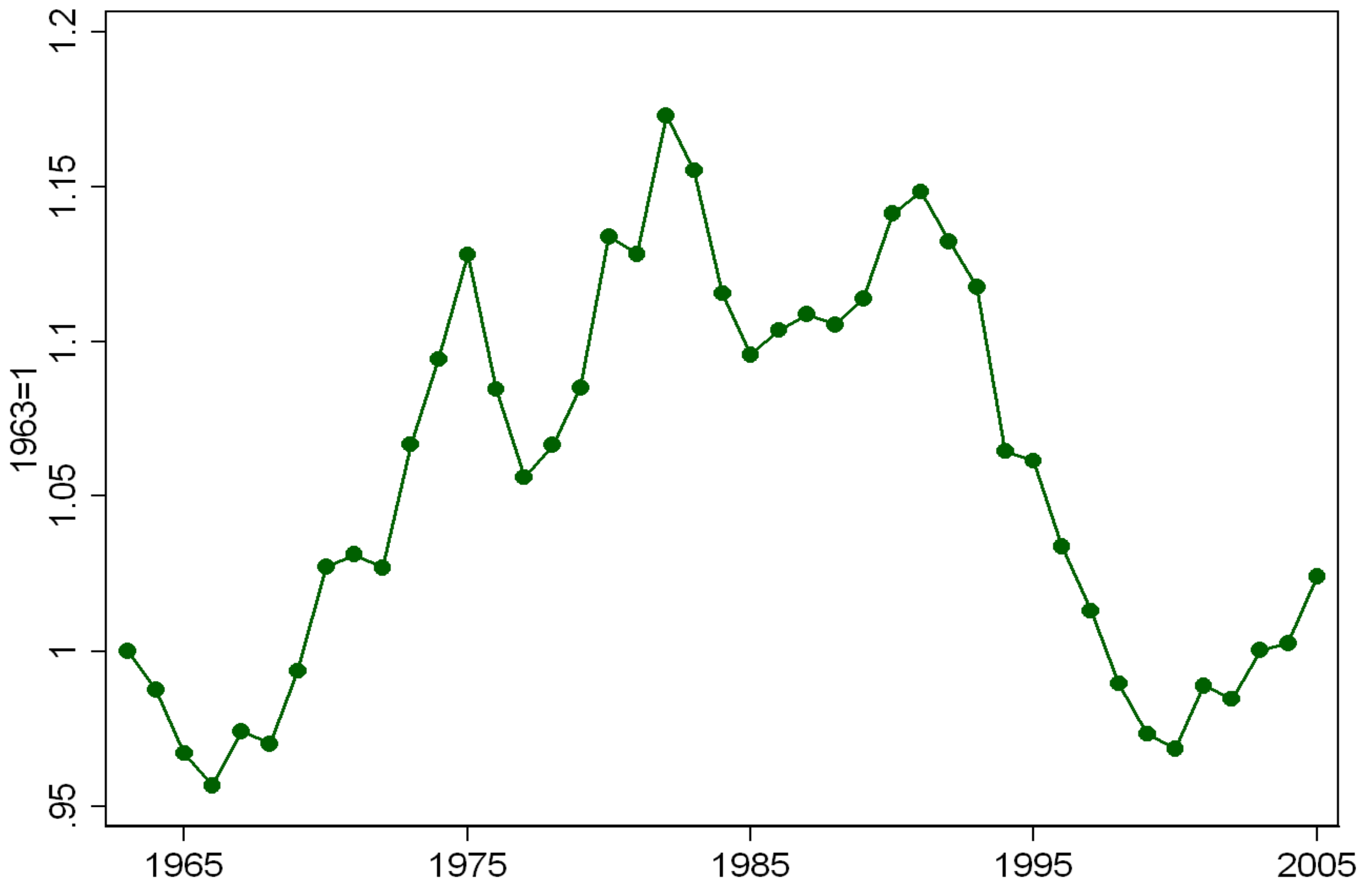
Notes: The relative wage is for college graduates versus high-school graduates in the entire economy. Skill intensities are the ratio of college to high-school equivalents in the goods and services sectors. Sectors are defined in **Table 1**. All detrended series are residuals from a regression of the original series in logs on a time trend and a constant. The scales are the same in both panels.

Figure 5: Fit of the Model



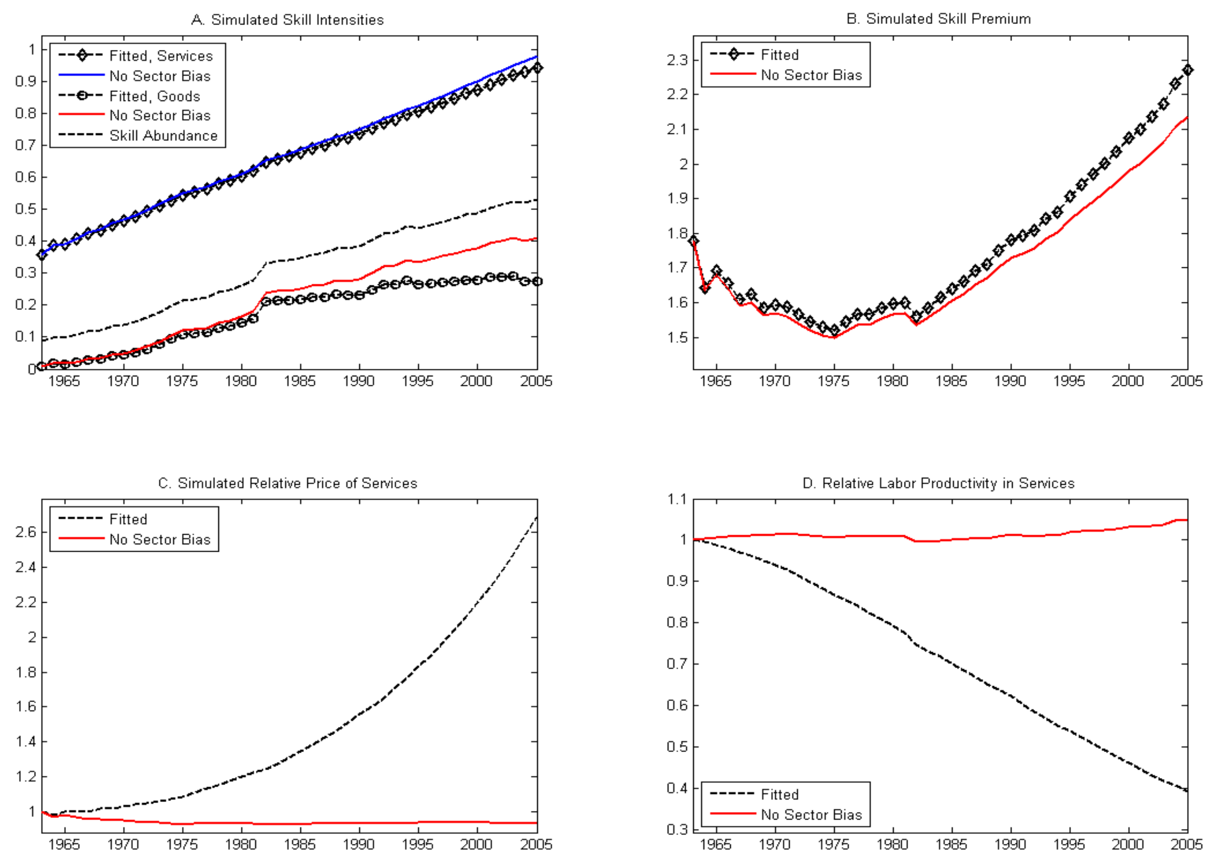
Notes: The figure shows the data that was used for the simulated method of moments estimation and the simulated series with the optimal parameters.

Figure 6: Relative Output of Services versus Goods



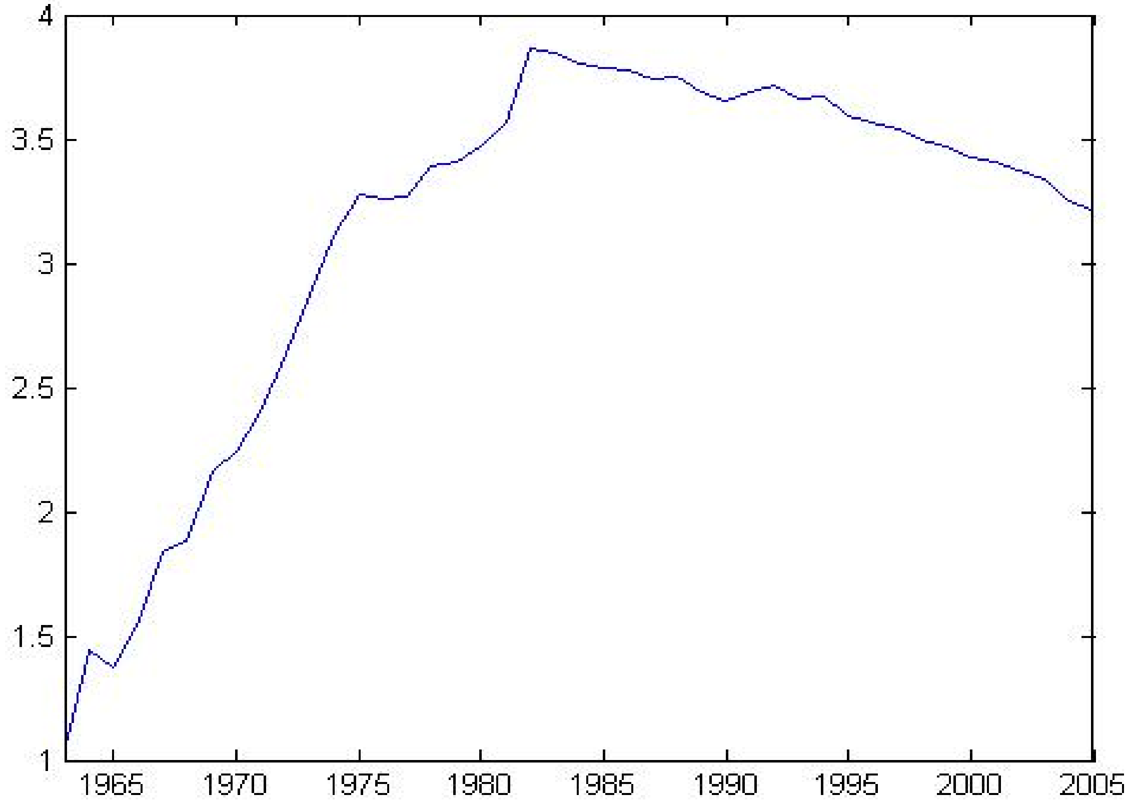
Notes: Relative output in skill-intensive services versus goods is calculated as the ratio of value-added in the service sector divided by value-added in the goods sector, further divided by the relative price of services, defined above in the text. The ratio is normalized to one in 1963. Sectors are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

Figure 7: Fixed Inter-Sector Productivity



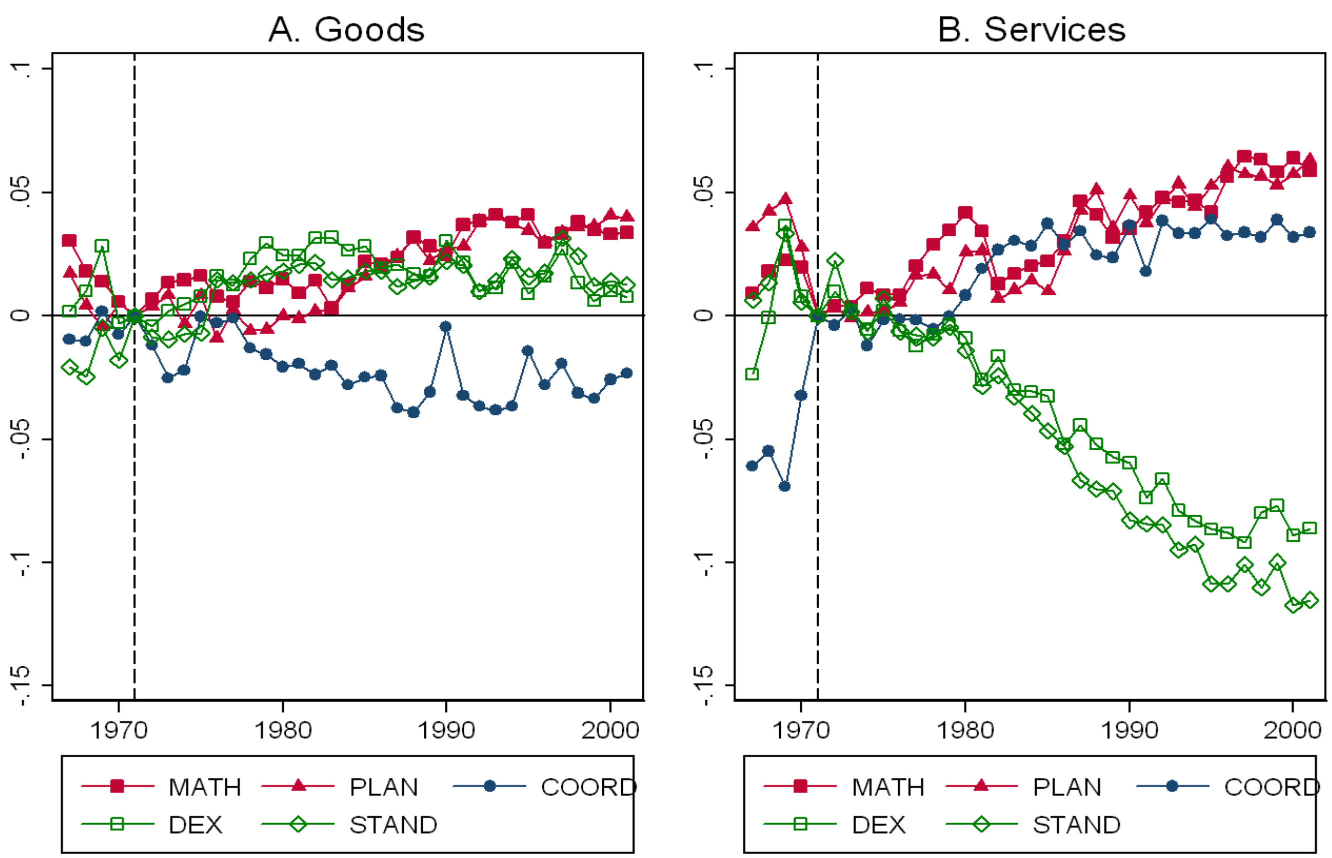
Notes: Fitted series are simulated using the estimated parameters from the estimation. No Sector Bias series are simulated while keeping the Hicks-neutral relative productivity of services versus goods fixed. In that case all other parameters are held at the estimated values.

Figure 8: Pseudo Aggregate Elasticity of Substitution



Notes: The pseudo 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 calcualted using the estimates of the model from **Table 2**.

Figure 9: Relative DOT Task Indices, High-School versus College Equivalents



Notes: Each task index is the relative task intensity of high-school versus college equivalents for each *TASK*. 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. The Dashed lines indicate the base year 1971, in which all indices are equal to zero, by construction.