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

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Abstract

I fit a two-sector general equilibrium model to U.S. data in 1963–2005 in order to infer technological processes that affect the college premium. 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 economy. This indicates that technological change is more complex than what we observe at the aggregate level. The results are consistent with changes in occupational mixes: low-skill workers in services reallocate 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. Thus, theoretical treatments of the underlying mechanisms of skill biased technological change may be improved by taking into account occupational mixes within broad education-sector groups.

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

JEL classification: J23, J24, J31.

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1 Introduction

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 overlook 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. For example, as **Figure 3** shows, information technology (IT) capital shares have not increased at the same rate in both sectors.[4]

In this paper I argue that technological change is more complex than what we observe at the aggregate level. I reject the hypothesis that technological change operates in the same way in both sectors: In fact, I estimate opposite technological processes in the two sectors mentioned above. I then show that changes in occupational mixes are consistent with those estimates of technological processes and help interpret them. These results inform theoretical treatments of the underlying mechanisms of SBTC: They demonstrate that our understanding of technological change can be improved by taking into account occupational mixes within broad education-sector groups.

Specifically, 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

[1] For early work see Bound and Johnson (1992), Katz and Murphy (1992), Levy and Murnane (1992), Juhn, Murphy, and Pierce (1993). 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, as well as Autor, Katz, and Kearney (2008) and Acemoglu and Autor (2011) for up-to-date reports on empirical evidence and theoretical considerations. See also Card and DiNardo (2002) and Gordon (2009) for critical views 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).

[4] **Figure A1** in the online appendix shows that IT capital grows faster in services than in the goods sector in absolute terms, not only as a share of the total capital stock.

in the college premium? I find that factor augmenting technological change for college graduates in services progresses 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 substitution in services is estimated at 0.64, which is, critically, less than one.[5] 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 is skill biased: It increases relative demand for college graduates and drives up the college premium, but for different reasons. Importantly, I also 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 results imply faster Hicks neutral labor productivity growth in the goods sector and strong complementarity between goods and services in consumption. This entirely explains the employment shift towards services and the rise in the relative price of services (as in Baumol (1967)). If labor productivity growth had been equal in both sectors, the employment share of services would hardly change. The different rates of labor productivity growth increase the college premium by 15%. Thus, the rise of the college premium is mostly driven by intra-sectoral forces.[6]

As in most papers, technological change is usually indirectly inferred, not directly observed.[7] 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 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 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) are easily substituted by computers, because they can either be coded in soft-

[5] The intuition for this result 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 proportionately (while keeping relative demand in efficiency units unchanged).

[6] This is reminiscent of Berman, Bound, and Griliches (1994), who find that skill upgrading in manufacturing occurs mostly within 4-digit SIC industries, while industrial composition changes matter less.

[7] One notable exception is Xiang (2005), who uses new product definitions in U.S. manufacturing to identify technological progress directly. He then argues that new products are more skill intensitve.

ware or automated.[8] The diffusion of computers, automation and IT is one of the most important technological changes in the last 40 years. Moving out of computer substitutable occupations and into computer complementary occupations is expected to raise individual worker efficiency.

The estimation results are consistent with compositional changes. In services less-educated workers move out of occupations that are substitutable by computers into occupations that are complementary to computers. And they do so faster than college graduates. In contrast, the occupational mixes in the goods sector shift moderately in the opposite direction. These findings are also consistent with the changes in the IT shares: In **Figure 3** we see that IT capital shares increase much more in services than in the goods sector—from zero to 4% and to 12%, respectively. Indeed, we observe bigger changes in the occupational mix in services, as well as larger technological biases in absolute value.

In an important contribution, Lee and Wolpin (2006) also study the technological determinants of the increase in the college premium in the context of a two-sector model. This paper differs in two important ways. First, this paper contributes to the understanding and interpretation of estimated technological processes, whereas Lee and Wolpin (2006) 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 (2006) 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 results differ, it is due to the sectoral classification, not due to differences in methodology.

This paper is related to other work 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 de-

[8] See also Levy and Murnane (1996), Autor, Levy, and Murnane (2002), Bresnahan (1997) Bresnahan, Brynjolfsson, and Hitt (1999) and Autor, Katz, and Krueger (1998), but also the critique by DiNardo and Pischke (1997).

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

[10] Like Lee and Wolpin (2006), 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.

mand shifts, whereas my estimation procedure does. Beaudry and Green (2005) consider a model of organizational change, where a modern sector (with new mode of organization) emerges alongside a traditional one and thus increases relative demand for skill. However, they estimate reduced form equations, which do not impose general equilibrium restrictions.

Another related body of work addresses the recent "polarization" of employment and of the wage structure and its relation to the "routinization" hypothesis.[11] In recent years employment shares and wages have increased both at the top and at the bottom (although less so) of the skill distribution, while the opposite occurred in the middle—hence, polarization. This phenomenon is linked to the proliferation of computers and IT in the workplace, which replace the routine tasks that are performed most intensively by middle skill workers. While this is a plausible description of the cause and effect of recent changes in labor markets, one should keep in mind that changes in the distribution of employment shares and wages were of quite a different form in the 1980s and before, at least in the U.S. (Autor, Katz, and Kearney (2006)), and IT investment started long beforehand; polarization is something of the 1990s.[12] In contrast, this paper takes a longer view.

Another related paper is Autor and Dorn (2011), who focus on low education service occupations (jobs) and carefully distinguish them from service industries—while my paper addresses both. Consistent with their findings, my results show that low education workers in service industries have been shifting out of routine intensive occupations more rapidly than educated workers since 1980, and in addition juxtaposes this with the rest of the economy.

The rest of the paper is organized as follows. In the next section I present the model. In section 3 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 4 presents evidence on changes in occupational mixes. Section 5 concludes.

2 A two-sector model

The economy is populated by H skilled workers and L unskilled workers, who can work in two sectors, which are defined by two constant returns to scale technologies. Workers are freely mobile across sectors and the economy is closed. Since there is no investment, and therefore no

[11] See Goos and Manning (2007) for the U.K.; Autor, Katz, and Kearney (2006) and Firpo, Fortin, and Lemieux (2011) for the U.S.; and Goos, Manning, and Salomons (2009) and Michaels, Natraj, and Van Reenen (2011) for European and other developed countries.

[12] See Acemoglu and Autor (2011) for a model that is consistent with both periods of change in inequality.

inter-temporal dynamics, I drop time subscripts to ease the notation. All markets are perfectly competitive. The equilibrium evolves over time according to exogenous technological change and according to changes in the relative supply of skilled versus unskilled labor.

2.1 Demand

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

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

where φ is the (non negative) elasticity of substitution in demand. Due to homotheticity of U the economy can be treated as being populated by only one representative worker, who chooses $\{G, S\}$ to maximize U subject to the economy-wide budget constraint $G + pS \leq Lw_L + Hw_H$. This gives rise to the following relative demand function

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

where p is the relative price of services, and I set G as numeraire.

2.2 Supply

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

$$G = \left[(A_g L_g)^{(\sigma_g-1)/\sigma_g} + (B_g H_g)^{(\sigma_g-1)/\sigma_g}\right]^{\sigma_g/(\sigma_g-1)} \tag{2}$$

$$S = \left[(A_s L_s)^{(\sigma_s-1)/\sigma_s} + (B_s H_s)^{(\sigma_s-1)/\sigma_s}\right]^{\sigma_s/(\sigma_s-1)} , \tag{3}$$

where A_i and B_i are factor augmenting indices for low skilled labor (L) and high skilled labor (H), respectively, in sector $i \in \{g, s\}$. The (non negative) elasticities of substitution (EoS) σ_i need not be equal. Given (2), (3) and the competitive markets assumption, relative demand for skilled labor, or skill intensity, for each sector is given by

$$h_g = \omega^{-\sigma_g}\beta_g^{\sigma_g-1} \tag{4}$$

$$h_s = \omega^{-\sigma_s}\beta_s^{\sigma_s-1} , \tag{5}$$

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

$$\beta_i = B_i/A_i$$

is relative factor efficiency of skilled workers versus unskilled. Note that w_H, w_L and therefore ω are the same in both sectors due to perfect labor mobility.

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, $\sigma_i = 0$. In that case, if a factor becomes relatively more efficient, then less of it is required and relative demand for that factor falls.

Since σ_s need not equal σ_g there is no global ranking of skill intensity across sectors, giving rise to 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.

Competition and constant returns to scale technologies require that the zero profit conditions must be satisfied: Unit costs equal unit prices. By using (4)–(5) in the zero profit conditions, the relative price of services can be written as

$$p = \frac{A_g \left(1 + (\omega/\beta_s)^{1-\sigma_s}\right)^{\frac{1}{1-\sigma_s}}}{A_s \left(1 + (\omega/\beta_g)^{1-\sigma_g}\right)^{\frac{1}{1-\sigma_g}}} . \tag{6}$$

Unit factor requirements are obtained by Shephard's lemma from unit costs. By using (4)–(5), unit factor requirements can be written as

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

Labor demand is given by multiplying the unit factor requirements by output for both sectors. Thus, labor market clearing is given by

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

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

$$\left[\frac{S}{G}\right]^s = \frac{A_s}{A_g}\left(\frac{h-h_g}{h_s-h}\right)\frac{(1+\omega h_g)^{\frac{\sigma_g}{1-\sigma_g}}}{(1+\omega h_s)^{\frac{\sigma_s}{1-\sigma_s}}} \ , \tag{7}$$

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

2.3 Equilibrium

To solve the model I equate relative demand (1) to relative supply (7) and plug in the expression for the relative price (6); using (4) and (5) again, this gives

$$\Phi\left(\omega, h, \beta_g, \beta_s, A_s/A_g\right) = \left(\frac{A_s}{A_g}\right)^{1-\varphi}\left(\frac{h-h_g}{h_s-h}\right)\frac{(1+\omega h_s)^{(\varphi-\sigma_s)/(1-\sigma_s)}}{(1+\omega h_g)^{(\varphi-\sigma_g)/(1-\sigma_g)}}$$

$$= \left(\frac{A_s}{A_g}\right)^{1-\varphi}\left(\frac{h-\omega^{-\sigma_g}\beta_g^{\sigma_g-1}}{\omega^{-\sigma_s}\beta_s^{\sigma_s-1}-h}\right)\frac{\left(1+\omega^{1-\sigma_s}\beta_s^{\sigma_s-1}\right)^{(\varphi-\sigma_s)/(1-\sigma_s)}}{\left(1+\omega^{1-\sigma_g}\beta_g^{\sigma_g-1}\right)^{(\varphi-\sigma_g)/(1-\sigma_g)}} - \left(\frac{\mu}{1-\mu}\right)^{\varphi}$$

$$= 0 \ . \tag{8}$$

This 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. All comparative statics can be computed by applying the implicit function theorem.[13] 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.

3 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 (1964–2006 surveys) for all wage and labor quantities. For the relative price of services versus goods I use data from the Bureau of Economic Analysis. The definitions of 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.

[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.

I follow the exact methodology of Katz and Murphy (1992) to construct wage and employment series.[14] Constraining myself to a predetermined sample construction methodology avoids making choices that may affect the results and, facilitates comparing my aggregate results to theirs.[15]

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. Individuals who are not college graduates or high school graduates exactly (less than 12 years of schooling and 13–15 years) are allocated 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.

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. The wage series construction scheme neutralizes compositional changes in gender and experience, since it uses a time-fixed vector of weights to compute wages for each cell.

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 $p = p_s/p_g$, and is normalized to one in 1963; it is increasing throughout almost the entire sample, as can be seen in Panel C of **Figure 4** (dashed line).

[14] To make sure that my understanding of their documentation is correct, I replicate their main tables and figures.

[15] A complete and detailed description of the data can be found in the online appendix. **Figure A2** and **Figure A3** in the online appendix plot employment shares and real wages, respectively, of all four groups.

3.1 Model specification and estimation

The main specification of the technology processes is log linear. I also experiment with 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 the more flexible technology processes are estimated as almost log linear. 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.

Four exogenous processes—h, β_g, β_s and A_s/A_g—determine ω in (8) and therefore determine all other endogenous variables at any point in time. These are given by

$$h(t) = h\_data(t) \cdot \exp\{u_t^h\} \tag{9}$$

$$\beta_i(t) = \frac{B_i}{A_i}(t) = \exp\left\{\beta_{0,i} + \beta_{1,i} t + u_t^i\right\} \ , \ i \in \{g, s\} \tag{10}$$

$$\frac{A_s}{A_g}(t) = \exp\left\{a_0 + a_1 t + u_t^a\right\} \ . \tag{11}$$

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 $\mu = 1/2$.[16]

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 concentrates all the parameters of the model: Elasticities and technology trend parameters. The time index in G_t makes it explicitly dependent on time. Stacking all exogenous and endogenous variables, as well as structural shocks, allows writing the model as

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

Denote the vector of parameters that govern the stochastic processes by Ω, i.e. $u \sim F(\Omega)$.

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

The main identification assumption is that the aggregate relative supply of skilled labor (skill abundance) is exogenous. If this assumption is violated, then the estimator of the elasticities of substitution σ_i and of technology trend parameters $\beta_{1,i}$ will be biased towards zero.[17] However, this bias is likely to be small for the following reasons. Typically, individuals decide to go to college when young. Shocks that affect relative wages may affect contemporaneous investment in education (a flow) but will have a relatively small effect on aggregate relative supply (a stock), which includes individuals with up to 40 years of potential experience. Moreover, college investment today will show up in supply only four years later. Thus, relative supply can be thought of as quasi-fixed.[18]

I estimate the model using a weighted nonlinear least squares estimator. Let

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

This is a high dimensional integral, which is evaluated by simulation.[19] It follows that

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

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

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

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

In order to deal with potential heteroskedasticity I use $W = \text{diag}(yy')$, which transforms all errors into percent units. The time series in y are upward trending. Therefore errors may be larger when values in y are larger in the latter part of the sample; this might make the later observations more influential in the estimation. Translating the errors into percent terms solves this problem. However, results with $W = I$ are similar because the model tracks the data well.[20]

In order to estimate θ, one must evaluate $G^* (x, \theta)$ by simulation (this is not feasible analyti-

[17] The direction of the bias to the estimator of φ is less clear, and is affected by the relative sizes of each sector.

[18] A discussion of other modeling assumptions can be found in the online appendix.

[19] 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.

[20] 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.

cally), which requires knowing Ω or an estimate of Ω. Although it is possible to jointly estimate θ and Ω, it is computationally taxing. Instead, I apply an estimation procedure that resembles feasible generalized least squares (albeit nonlinear). I start with an imperfect estimate of θ, assuming $u = 0$ (but not necessarily $e = 0$). This initial estimate is used to obtain an initial estimate of Ω. The latter is used to re-estimate θ. I then re-estimate Ω. Finally, standard errors are computed by parametric bootstrapping. See online appendix for complete details.

3.2 Results

The estimates are reported in **Table 2**. The value of the problem 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 4** provides a visual fit. In Panel A the skill intensities fit the data remarkably well. As a consequence, employment shares also fit the data equally well. In Panel B the simulated skill premium misses the initial increase until 1973. 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. The model also misses the end of the sample in Panel C. 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.[21] In services $\beta_{1,s} = -0.07$: Factor augmentation is faster for high school equivalents relative to college equivalents. This decreases relative demand for less skilled workers because $\sigma_s = 0.625 < 1$. In the goods sector $\beta_{1,g} = 0.02$: Factor augmentation is faster for college equivalents relative to high school equivalents. This increases relative demand for more skilled workers because $\sigma_g = 6.94 > 1$. In addition, factor augmentation is faster for high school equivalents in services relative to high school equivalents in the goods sector: $a_1 = 0.02 > 0$.

What features of the data give rise to these estimates? Consider estimating

$$\ln(h_{it}) = c_i - \sigma_i \ln(\omega_t) + \delta_i t + \varepsilon_t^i \ , \quad i \in \{g, s\} \ , \tag{12}$$

which is obtained by taking logs of (4) and (5) and plugging in (10). **Table 3** reports results for estimating (12) by OLS and then using the Prais-Winsten estimator, which corrects for AR(1) errors. In addition—although not used in the structural estimation—the table uses sector-specific college relative wages.[22] All estimators yield a much larger elasticity in the goods sector. The

[21] u_t^h is simplified to i.i.d. normal; when it is allowed to be AR(1), ρ^h tends to revert to zero.

[22] The latter are constructed using the same methodology as the aggregate relative college wage—the same weights are used within education cells—except that the calculation uses wages from each sector separately.

Prais-Winsten point estimate for σ_s is less than one. Of course, these are biased estimators, which do not take into account general equilibrium effects. However biased, **Table 3** makes us expect $\sigma_s < \sigma_g$.

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 3.4 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.

One way to rationalize the estimates of the elasticities is by using the concept of scale effects. To develop this idea take logs of (4)–(5) and drop subscripts to ease notation: $\ln h = -\sigma \ln \omega + (\sigma - 1)\ln \beta$. We expect the same technological improvement with the same bias (an increase in β)—say, IT investment—to invoke a larger effect on relative demand for skill (h) where this technology has a larger impact on scale effects for skilled workers, i.e. when σ is larger. I expect scale effects to be larger in the goods sector, which in my classification includes manufacturing, retail and wholesale trade, etc. In this sector we see lower skill intensity (see **Figure 2**), which implies that a smaller number of skilled workers plan, manage and participate in production.[23]

A complementary argument involves the organizational structure of the industries involved, which makes me expect to find a higher degree of complementarity between skilled and unskilled in the services sector. For example, while a new medical innovation can make surgery more effective (or a new surgery available), the surgeon still needs the anesthesiologist, nurses and cleaners to perform the procedure, in similar proportions. Similarly, in education, innovation and investments in IT seem not to change much the nature of how this service is delivered. Notice that services are relatively skill intensive, but the change in skill in logs is much smaller, relative to the goods sector.

Table 2 reports a very small elasticity in demand, φ. The standard error is also very small, so this means that it is accurately estimated close to zero.[24] With a constant μ, estimating zero substitutability is consistent with a rising relative price of services in the face of fixed (or very stable)

[23] Scale effects may be larger in finance, which may be different in this respect from other services, but finance is a small fraction of services employment; on this see Philippon and Reshef (2012).

[24] "Profiling" the objective function shows that φ is indeed identified. By "profiling" I mean 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. Buera and Kaboski (2009) also find that the best fit to the data is zero substitutability.

relative output of services. Indeed, empirically, the ratio of services to goods output fluctuates in the sample, but does not have a trend.[25]

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 or increasing demand growth. Indeed, 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.[26]

Panel D in **Figure 4** reports relative labor productivity in services versus goods, given by

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

S/G is given in (7) and $(L_g + H_g) / (L_s + H_s)$ can be backed out from the relationship between h_s, h_g and h.[27] 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).[28] It is comforting that the estimates imply similar results to a study that uses a different methodology, especially because this is not one of the moments that are targeted.[29]

3.3 The 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.[30] **Figure**

[25] This uses data from the BEA. See **Figure A4** in the online appendix.

[26] 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 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.

[27] 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.

[28] I use real value added weights to aggregate to sectoral levels. When computing industry productivities, Jorgenson and Stiroh (2000) use only one kind of labor input, and include capital services, intermediate inputs in their calculation. Note also that more IT investment in services (**Figure 3**) is not commensurate with faster labor productivity growth, a result that is reminiscent of Jorgenson and Stiroh (1999).

[29] Moreover, as mentioned in the discussion of the model assumptions in the online appendix, it helps alleviating concerns for ignoring international trade.

[30] A_s/A_g captures relative Hicks neutral technological change only if β_g and β_s are fixed. Therefore the calculation takes into account that β_g and β_s are changing. See complete details in the online appendix.

5 shows the difference between the fitted model and the simulated counterfactual series. The sector bias explains 15% of the increase in the relative wage of college graduates. This is consistent with findings in Lee and Wolpin (2006).

The effect on relative average labor productivity (Panel D) is large; instead of decreasing by 60%, it actually increases slightly, by 5%. Likewise, the effect on the relative price is large; over the entire sample the relative price of services slightly falls from 1 to 0.93 instead of increasing to 2.6 in the fitted model. The employment shift into services is also explained by the dynamics of relative productivity. The skill intensities rise slightly more than in the fitted model because the skill premium rises slightly less; the effect on the goods sector is larger due to the larger elasticity of substitution there. The large role of the relative decline in labor productivity in the service sector for relative employment and relative price is explained by the small estimated elasticity of demand φ, just as in the classic analysis of unbalanced growth in Baumol (1967).

3.4 Relationship to aggregate results

There is a tension between finding a small—and less than one—EoS in services, which is increasing its employment share, and the general finding of a much larger aggregate EoS. Most models of the *mechanics* of SBTC rely on an aggregate elasticity that is larger than one and faster factor augmentation for skilled workers, and, hence, higher demand for their labor services.[31]

Autor and Katz (1999) report that estimates of the aggregate EoS are in the range of 0.5 and 3 but argue that it is likely close to 1.4.[32] 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?

I use the function Φ given in (8) to answer these questions. By the implicit function theorem

[31] See, for example, Acemoglu (1998) and Thoenig and Verdier (2003).

[32] 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.

$dh/d\omega = -\Phi_\omega/\Phi_h$. Define the aggregate EoS by

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

Some algebra yields the following expression

$$\overline{\sigma} = \sigma_g \frac{h_g \left(1+\omega h\right)\left(h_s - h\right)}{h\left(1+\omega h_g\right)\left(h_s - h_g\right)} + \sigma_s \frac{h_s \left(1+\omega h\right)\left(h - h_g\right)}{h\left(1+\omega h_s\right)\left(h_s - h_g\right)} + \varphi \frac{\omega \left(h - h_g\right)\left(h_s - h\right)}{h\left(1+\omega h_g\right)\left(1+\omega h_s\right)} \ , \qquad (13)$$

which is a convex combination of the elasticities in production and the elasticity of demand.[33] Indeed, the aggregate elasticity combines substitution both within and across industries. The coefficients to the elasticities change over time with relative employment and relative skill intensities in the two sectors. This implies that the notion of a *stable* aggregate elasticity is tenuous.[34]

I use (13) and the estimation results to calculate $\overline{\sigma}$ for every year in the sample. $\overline{\sigma}$ increases from 1.04 in 1963 to 3.9 in 1982 and then decreases to 3.2 in 2005.[35] The average $\overline{\sigma}$ in 1963–2005 is 3.13 and for the 1963–1987 sample of Katz and Murphy (1992) it is 2.84.

In regressions of the type $\ln(\omega_t) = c - (1/\overline{\sigma})\ln(h_t) + \delta t + \varepsilon_t$ the estimate of $\overline{\sigma}$ is typically greater than one, and the estimate of δ is always positive. This would lead us to conclude that at the aggregate level factor augmentation is faster for college graduates than for less skilled workers, since $\delta = (\sigma - 1)\beta_1$, where β_1 is the aggregate analogue of $\beta_{1,i}$. The two sector estimation results cast doubt on this conclusion, and raise concerns for theories of SBTC that treat workers within skill types *uniformly*, regardless of sector (and occupation; see Section 4 below).

3.5 Robustness checks

I estimate the model under alternative specifications of the technological processes (9)–(11). 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. The trends (in logs) are very similar before and after the break year. A second specification allows for a log

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

[34] 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.

[35] See **Figure A5** in the online appendix. The evolution of $\overline{\sigma}$ 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 $(h_s - h)/(h - h_g)$).

quadratic technological processes. The estimated quadratic components were extremely small and not statistically different from zero. These two alternative specifications have a similar fit as in **Table 2**.

A third specification uses an alternative specification of the production functions:

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

Other than that change, all else remains the same, in particular workers' preferences. Here the expressions for skill intensities change to

$$\begin{aligned} h_g &= \omega^{-\sigma_g} \gamma_g^{\sigma_g} \\ h_s &= \omega^{-\sigma_s} \gamma_s^{\sigma_s} \ , \end{aligned}$$

where $\gamma_i = \alpha_i / (1-\alpha_i)$. I derive a similar expression to (8) for the equilibrium, which is reported in the online appendix. The exogenous processes are given by

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

$$\gamma_i(t) = \frac{\alpha_i}{1-\alpha_i}(t) = \exp\left\{\gamma_{0,i} + \gamma_{1,i} t + u_t^i\right\} \ , \ i \in \{g, s\}$$

$$\frac{Z_s}{Z_g}(t) = \exp\{z_0 + z_1 t + u_t^z\} \ .$$

As above, u_t^i are AR(1) processes. This representation of the dynamics is not equivalent to the previous one, because a constant growth rate for β_i and A_s/A_g does not yield a constant growth rate of Z_s/Z_g, since $Z_i = A_i \left(1 + \beta_i^{\rho_i}\right)^{1/\rho_i}$ ($\rho_i = (\sigma_i - 1)/\sigma_i$).[36]

The estimation follows the same procedure as described above and the results are reported in **Table 4**. The estimates of the elasticities are on the same order of magnitude as in **Table 2**. In particular, $\sigma_s = 0.53 < 1$ and $\sigma_g = 5.57$. Ignoring the shocks, one can back out the implied β_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 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, so the main

[36] See the online appendix for complete details.

results provide a better fit. Overall, the qualitative results are the same: 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*. In this section I present evidence on changes in occupational mixes that support the validity of the estimates of the technological processes, and shed light on the underlying mechanism.

I argue that the underlying force for changes in occupational mixes is investment in IT (see **Figure 3**) and its differential effects in the two sectors. However, endogenizing occupational choice is beyond the scope of this paper.[37] In Section 2 I assume that all workers within a class of skill are paid the same wage. So within that framework they do not care which occupation they work in. Clearly, this is unrealistic. But this is part of the identifying assumptions in the estimation; and it is the result of this estimation procedure that I wish to understand better here.

4.1 Accounting for the occupational mix

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

$$Q = \left[(AL)^{(\sigma-1)/\sigma} + (BH)^{(\sigma-1)/\sigma} \right]^{\sigma/(\sigma-1)} .$$

For now focus on BH, which is the sum of labor services supplied by skilled workers, in efficiency units. Let hrs_n and e_n denote hours worked and efficiency units per hour of worker n. 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, $H = \sum_n hrs_n$ and $B = \sum_n \frac{hrs_n}{H} e_n = \sum_n \lambda_n e_n$.

Each individual n works in an occupation o. Therefore, $B = \sum_o \sum_{n \in \langle o \rangle} \lambda_n e_{o_n}$, where $n \in \langle o \rangle$ means that individual n has occupation o and o_n denotes n's occupation. Assume that all

[37] See Acemoglu and Autor (2011) and Autor and Dorn (2011) for models that address occupational choice in the context of technological change.

individuals with occupation o supply the same efficiency units. Then $e_{o_n} = e_o$ and so

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

where $\lambda_o = \sum_{n \in \langle o \rangle} \lambda_n$.[38] Define the occupational mix as the set of λ_o's, denoted $\{\lambda_o\}$. We can write

$$BH = \left(\sum\nolimits_o \lambda_o^H e_o \right) H \ . \tag{14}$$

And repeating the same derivation for AL,

$$AL = \left(\sum\nolimits_o \lambda_o^L e_o \right) L \ . \tag{15}$$

Adding superscripts to λ differentiates the occupational mix for L and H. In the model there are two sectors, so (14) and (15) are also be indexed by sector. This formulation assumes that skilled and unskilled workers who have the same occupation have the same efficiency units. The focus is on how occupational mixes change, so this simplification is not so important. It allows relating occupational composition to average efficiency units: Given e_o, changes in $\left\{\lambda_o^L\right\}$ and $\left\{\lambda_o^H\right\}$ affect the average efficiencies A and B.

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). See **Table 5** for a taxonomy of tasks. 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

$$e_o = e(R_o, N_o, C) = (R_o + C)^{1-\delta} N_o^{\delta} \ , \quad \delta \in (0,1) \ ,$$

where C is computer capital. 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.[39]

[38] 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.

[39] 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

Now suppose that a fall in the relative price of computing power induces more use of computer capital and information technology. This makes all occupations more efficient since

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

The increase in efficiency is larger for relatively non-routine task intensive occupations and smaller for occupations that are more routine task intensive:

$$\begin{aligned} \frac{\partial}{\partial N_o}\left(\frac{\partial e_o}{\partial C}\right) &= \delta\,(1-\delta)\,(R_o + C)^{-\delta}\,N_o^{\delta-1} > 0 \\ \frac{\partial}{\partial R_o}\left(\frac{\partial e_o}{\partial C}\right) &= -\delta\,(1-\delta)\,(R_o + C)^{-\delta-1}\,N_o^{\delta} < 0\ . \end{aligned}$$

It follows that if a high school graduate works in an occupation that has a relatively low non-routine task intensity and relatively high routine task intensity, then computerization increases her occupational efficiency by less than for a college graduate.

But computerization may do something more: According to the "routinization" hypothesis, computerization may completely eliminate jobs that are routine-intensive. If high school graduates reallocate 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 by using (14) and (15). Let

$$\begin{aligned} \frac{dB}{dC} &= \sum\nolimits_o \frac{\partial \lambda_o^H}{\partial C} e_o + \sum\nolimits_o \lambda_o^H \frac{\partial e_o}{\partial C} \\ \frac{dA}{dC} &= \sum\nolimits_o \frac{\partial \lambda_o^L}{\partial C} e_o + \sum\nolimits_o \lambda_o^L \frac{\partial e_o}{\partial C}\ . \end{aligned}$$

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.

simplest example. In principle, δ could have also varied by occupation, but this is not important for what follows.

In order to say whether A increases more than B we must consider

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

Changes in $\{e_o\}$ must also be taken into account. Unfortunately, this is not possible without taking a stand on the function e_o and estimating it, which is beyond the scope of this paper. The empirical analysis focuses on the first sum; it indicates that it is positive and large in services, but not so in the goods sector. As shown in **Table 6**, high school equivalents have higher employment shares in occupations that are categorized as more computer complementary versus college equivalents—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, 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.

I cast the estimates of technological trends against three hypotheses about changes in occupational mixes:

(**H1**) *In services the occupational mix of low skill workers* $\left\{\lambda_o^{L,s}\right\}$ *shifts towards computer complementary occupations more than the occupational mix of high skill workers* $\left\{\lambda_o^{H,s}\right\}$ *(consistent with faster efficiency gains for low skill workers in the services sector,* $\beta_{1,s}<0$*).*

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

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

Not rejecting these hypotheses is consistent with the estimated technological trends.

4.3 The evolution of task indices

Testing H1–H3 requires a mapping from occupations to tasks. I use five task intensities from the Dictionary of Occupational Titles to reflect computer complementarity and substitutability.[40] The task intensities capture routine and non-routine tasks, which can be either manual or cognitive; see **Table 5**.[41] *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.[42] I calculate task indices for high school and college equivalents in goods and services sectors for 1967–2001. The shorter sample is due to comparability issues before 1967 and after 2001.[43]

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.[44] **Table 6** reports the levels of each task across skill levels and sectors in 1971 and 2001, as well as changes from 1971 to 2001. The choice of 1971 facilitates the graphical exposition below, since the indices are somewhat noisy before 1971.[45]

I construct relative task intensities of high school versus college equivalents for each sector

$$\Delta TASK_{s,t} = \left(TASK^{HS}_{s,t} - TASK^{HS}_{s,1971}\right) - \left(TASK^{COL}_{s,t} - TASK^{COL}_{s,1971}\right) \ .$$

By construction, $\Delta TASK_{s,t}$ is equal to zero in $t = 1971$. **Figure 6** plots all five $\Delta TASK_{s,t}$ separately for goods and services. A few features stand out. First, the changes in $\Delta TASK$ are

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

[41] 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.

[42] **Table A1** in the online appendix provides more details and examples and **Table A2** reports summary statistics.

[43] 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 discussion in the online appendix.

[44] 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 online appendix for complete documentation of the construction of these indices.

[45] **Figure A8** in the online appendix plots all task indices for all groups over time.

much larger in services than in the goods sector. Second, ΔDEX, $\Delta STAND$ and $\Delta COORD$ move in opposite directions in services and goods. Third, $\Delta MATH$ and $\Delta PLAN$ increase substantially more in services relative to the goods sector.

Panel A of **Table 7** reports the changes in $\Delta TASK$ from 1971 to 2001. In services, ΔDEX and $\Delta STAND$ substantially decrease (by 8.6% and 11.5%, respectively); in the goods sector they increases slightly. In services, $\Delta MATH$ and $\Delta PLAN$ increase (by 6% and 6.3%, respectively); these increases are larger than in the goods sector (3.3% and 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.

The changes in the occupational mixes imply that high school equivalents in services have 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 data are consistent with H1 and H2.

To test H3 I construct relative task intensities for high school equivalents in services:

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

Panel B of **Table 7** reports the changes in $\Delta TASK^{HS}$ 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. Finally, $\Delta COORD^{HS}$ increases by 1.35%.[46] 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 is consistent with H3.

In order to support my argument—admittedly, not providing outright proof—for the importance of changes in the occupational mixes $\{\lambda_o\}$ versus within-occupation changes in $\{e_o\}$, I offer the following observations. As **Table 6** shows, the difference in task intensity levels between skill groups is similar within both sectors. But the efficiency gains that are implied by the estimation are very different. The large compositional changes for high school equivalents in services can help

[46] This is consistent with Autor and Dorn (2011), where computers drive unskilled workers out of routine intensive occupations and into non-routine manual service occupations.

reconcile these differences: Relative routine task intensity of high school equivalents ($\Delta STAND$ and $\Delta COORD$) decreases sharply in services, but increases in the goods sector.

To further support the argument, note that high school equivalents in services and in the goods sector both exhibit similar (albeit not identical) task intensities in all dimensions in 1971 (see **Table 6**), so the within occupation changes in $\{e_o\}$ are likely to be the same. Yet high school equivalents in services gain efficiency faster than high school equivalents in the goods sector (see **Table 2**: $a_1 = 0.02 > 0$): It is the compositional changes that are bigger for high school equivalents in services, and are consistent with the relative efficiency gains.

To strengthen the interpretation of the results I revisit **Figure 3**: The IT share increases much more in services than in goods. This supports the notion that the shift into computer complementary occupations helps explaining the relative changes in factor efficiency. Autor, Levy, and Murnane (2003) also find faster growth of computer complementary task intensities in industries that invested more in computers and the opposite for computer substitutable task intensities.[47] Moreover, they find larger changes in task intensities for workers with less than college degree.

Although the task indices summarize occupational mixes, some examples are useful. Consider first workers with less than a four-year college degree in services. The employment share of secretaries and of personal and household service occupations (relatively routine occupations) among these workers drops from 9% in 1971 to 5% 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. 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 have similar routine and non routine task intensities.

5 Conclusions

In this paper 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. Consistent with SBTC, both processes drive up relative demand for college graduates, but for different reasons. In

[47] While Autor, Levy, and Murnane (2003) find higher computer investment in less skill intensive industries, at the more aggregate level I find that the IT capital share, which is a stock value, increased more in the skill intensive service sector. If indeed IT is the driver for substitution between non-routine and routine tasks, then the share is a more appropriate measure of IT intensity.

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 relative wage.

The 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. I argue that this shift can help 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.[48]

The analysis informs theoretical treatments of the underlying mechanisms of SBTC. Previous technological explanations of the increase in the college premium—e.g. Acemoglu (1998) and Thoenig and Verdier (2003)—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 uniform approach; and changes in occupational mixes are consistent with the estimated technological trends. Therefore, it appears that a more appropriate understanding of SBTC 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.[49]

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

[49] See Acemoglu and Autor (2011), who make a major step in this direction.

References

Acemoglu, D. (1998): "Why Do New Technologies Complement Skills? Directed Technical Change and Wage Inequality," *The Quarterly Journal of Economics*, 113(4), 1055–1089.

——— (2002): "Technical Change, Inequality and the Labor Market," *Journal of Economic Literature*, 40(1), 7–72.

Acemoglu, D., and D. Autor (2011): "Skills, tasks and technologies: Implications for employment and earnings," in *Hanbook of Labor Economics*, ed. by O. Ashenfelter, and D. Card, vol. 4b. North Holland.

Altonji, J. G., and L. M. Segal (1996): "Small-Sample Bias in GMM Estimation of Covariance Structures," *Journal of Business and Economic Statistics*, 14(3), 353–366.

Autor, D., L. Katz, and A. Krueger (1998): "Computing Inequality: Have Computers Changed the Labor Market?," *The Quarterly Journal of Economics*, 113(4), 1169–1214.

Autor, D. H., and D. Dorn (2011): "The Growth of Low Skill Service Jobs and the Polarization of the U.S. Labor Market," Working Paper, MIT.

Autor, D. H., and L. F. Katz (1999): "Changes in the Wage Structure and Earnings Inequality," in *Handbook of Labor Economics*, ed. by J. B. Taylor, and M. Woodford, vol. 3A. Elsevier Science, North Holland.

Autor, D. H., L. F. Katz, and M. S. Kearney (2006): "The Polarization of the U.S. Labor Market," *The American Economic Review, AEA Papers and Proceedings*, 96(2), 189–194.

——— (2008): "Trends in U.S. Wage Inequality: Revising the Revisionists," *The Review of Economics and Statistics*, 90(2), 300–323.

Autor, D. H., F. Levy, and R. J. Murnane (2002): "Upstairs, Downstairs: Computers and Skills on Two Floors of a Large Bank," *Industrial and Labor Relations Review*, 55(3), 432–447.

——— (2003): "The Skill Content of Recent Technological Change: An Empirical Exploration," *The Quarterly Journal of Economics*, 118(4), 1279–1333.

Baumol, W. J. (1967): "Macroeconomics of Unbalanced Growth: The Anatomy of Urban Crisis," *The American Economic Review*, 57(3), 415–426.

Beaudry, P., and D. Green (2005): "Changes in U.S. wages, 1976-2000: Ongoing Skill Bias or Major Technological Change?," *Journal of Labor Economics*, 23(3), 609–648.

Berman, E., J. Bound, and Z. Griliches (1994): "Changes in the Demand for Skilled Labor Within U.S. Manufacturing: Evidence from the Annual Survey of Manufactures," *The Quarterly Journal of Economics*, 109(2), 367–397.

Blundell, R., L. Pistaferri, and I. Preston (2006): "Consumption Inequality and Partial Insurance," Working Paper, Standford.

Bound, J., and G. Johnson (1992): "Changes in the Structure of Wages in the 1980s: An Evaluation of Alternative Explanations," *The American Economic Review*, 82(3), 371–392.

Bresnahan, T. F. (1997): "Computerization and Wage Dispersion: An Analytical Reinterpretation," Working Paper, Stanford University.

Bresnahan, T. F., E. Brynjolfsson, and L. M. Hitt (1999): "Information Technology, Workplace Organization and the Demand for Skilled Labor: Firm-Level Evidence," Working Paper, Stanford University.

Buera, F. J., and J. P. Kaboski (2006): "The Rise of the Service Economy," Working Paper, Northwestern University.

——— (2009): "Can Traditional Theories of Structural Change Fit the Data?," *Journal of the European Economic Association*, 7(2-3), 469–477.

Card, D., and J. E. DiNardo (2002): "Skill Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles," *Journal of Labor Economics*, 20(4), 733–783.

Card, D., and T. Lemieux (2001): "Can Falling Supply Explain the Rising Return to College for Younger Men? A Cohort-Based Analysis.," *The Quarterly Journal of Economics*, 116(2), 705–746.

DiNardo, J. E., and J.-S. Pischke (1997): "The Returns to Computer Use Revisited: Have Pencils Changed the Wage Structure Too?," *The Quarterly Journal of Economics*, 112(1), 291–303.

Firpo, S., N. M. Fortin, and T. Lemieux (2011): "Occupational Tasks and Changes in the Wage Structure," Working Paper, University of British Columbia.

Goldin, C., and L. F. Katz (2008): *The Race Between Education and Technology*. Belknap Harvard University Press, Cambridge.

Goos, M., and A. Manning (2007): "Lousy and Lovely Jobs: The Rising Polarization of Work in Britain," *The Review of Economics and Statistics*, 89(1), 118–133.

Goos, M., A. Manning, and A. Salomons (2009): "Job Polarization in Europe," *The American Economic Review, AEA Papers and Proceedings*, 99(2), 58–63.

Gordon, R. J. (2009): "Misperceptions About the Magnitude and Timing of Changes in American Income Inequality," NBER Working Paper No. 15351.

Griliches, Z. (1969): "Capital-Skill Complementarity," *Review of Economics and Statistics*, 51(4), 465–468.

Hamermesh, D. S. (1993): *Labor Demand*. Princeton University Press.

Haskel, J. E., and M. J. Slaughter (2002): "Does the Sector Bias of Skill-Biased Technological Change Explain Changing Skill Premia?," *European Economic Review*, 46, 1757–1783.

Heckman, J. J., L. Lochner, and C. Taber (1998): "Explaining Rising Wage Inequality: Explorations with a Dynamic General Equilibrium Model of Labor Earnings with Heterogenous Agents," *Review of Economic Dynamics*, 1, 1–58.

Hornstein, A., P. Krusell, and G. L. Violante (2005): "The Effects of Technical Change on Labor Market Inequalities," in *Handbook of Economic Growth*, ed. by P. Aghion, and S. Durlauf, vol. 1, pp. 1275–1370. Elsevier Science, North Holland.

Johnson, G. (1970): "The Demand for Labor by Educational Category," *Southern Economic Journal*, 37, 190–204.

Jorgenson, D. W., and K. J. Stiroh (1999): "Information Technology and Growth," *The American Economic Review, AEA Papers and Proceedings*, 89(2), 109–115.

——— (2000): "U.S. Economic Growth at the Industry Level," *The American Economic Review, AEA Papers and Proceedings*, 90(2), 161–167.

Juhn, C., K. M. Murphy, and B. Pierce (1993): "Wage Inequality and the Rise in Returns to Skill," *Journal of Political Economy*, 101(3), 410–442.

Katz, L. F., and K. M. Murphy (1992): "Changes in Relative Wages, 1963-1987: Supply and Demand Factors," *The Quarterly Journal of Economics*, 107(1), 35–78.

Krugman, P. R. (2000): "And Now For Something Completely Different: An Alternative Model of Trade, Education and Technology," in *The Impact of International Trade on Wages*, ed. by R. C. Feenstra. The University of Chicago Press, NBER conference report.

Krusell, P., L. E. Ohanian, J.-V. Rios-Rull, and G. L. Violante (2000): "Capital-Skill Complementarity and Inequality: A Macroeconomic Analysis," *Econometrica*, 68(5), 1029–1053.

Lee, D., and K. I. Wolpin (2006): "Accounting for Wage and Employment Changes in the U.S. from 1968-2000: A Dynamic Model of Labor Market Equilibrium," Mimeo, New York University.

Levy, F., and R. J. Murnane (1992): "U.S. Earnings Levels and Earnings Inequality: A Review of Recent Trends and Proposed Explanations," *Journal of Economic Literature*, 30(3), 1333–1381.

——— (1996): "With What Skills Are Computers a Complement?," *The American Economic Review, AEA Papers and Proceedings*, 86(2), 258–262.

Michaels, G. (2007): "The Division of Labor, Coordination, and the Demand for Information Processing," CEPR Discussion Paper 6358.

Michaels, G., A. Natraj, and J. Van Reenen (2011): "Has ICT Polarized Skill Demand Evidence from Eleven Countries over 25 Years," Working Paper, London School of Economics and Political Science.

Philippon, T., and A. Reshef (2012): "Human Capital in the U.S. Financial Sector: 1909-2006," *The Quarterly Journal of Economics*, Forthcoming.

Polgreen, L., and P. Silos (2005): "Capital-Skill Complementarity and Inequality: A Sensitivity Analysis," Federal Reserve Bank of Atlanta Working Paper 2005-20.

Spitz-Oener, A. (2006): "Technical Change, Job Tasks and Rising Educational Demands: Looking Outside the Wage Structure," *Journal of Labor Economics*, 24(2), 235–270.

Stern, S. (1997): "Simulation-Based Estimation," *Journal of Economic Literature*, 35, 2006–2039.

Thoenig, M., and T. Verdier (2003): "A Theory of Defensive Skill-Biased Innovation and Globalization," *The American Economic Review*, 93, 709–728.

Xiang, C. (2005): "New Goods and the Relative Demand for Skilled Labor," *Review of Economics and Statistics*, 87(2), 285–298.

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, & fisheries	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

	Services	Goods	Demand
Elasticities			
	σ(s)	*σ(g)*	*ϕ*
	0.64	6.94	0.003
	(0.005)	(0.083)	(0.002)
Technological Processes	Services	Goods	Intersectoral
Rate of change	*β(1,s)*	*β(1,g)*	*a(1)*
	-0.07	0.02	0.021
	(0.001)	(0.0002)	(0.0005)
Initial value	*β(0,s)*	*β(0,g)*	*a(0)*
	1.811	-0.127	2.146
	(0.017)	(0.0076)	(0.016)
Stochastic Processes			
Relative Supply	Services	Goods	Intersectoral
ρ(h)	*ρ(s)*	*ρ(g)*	*ρ(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: Reduced Form Estimates of Elasticities

Estimated Equation: $ln(h_t) = c - \sigma ln(\omega_t) + \delta t + \varepsilon_t$

	h = skill intensity in goods				*h* = skill intensity in services			
Estimator:	OLS	OLS	PW	PW	OLS	OLS	PW	PW
Ln(college relative wage):								
Aggregate (ω)	-6.66***		-5.02***		-1.10***		-0.81***	
	(0.964)		(1.302)		(0.192)		(0.280)	
Goods (ω^{goods})		-7.07***		-3.20**				
		(1.457)		(1.409)				
Services ($\omega^{services}$)						-1.19***		-0.67**
						(0.237)		(0.277)
Time (t)	0.13***	0.12***	0.12***	0.09***	0.03***	0.03***	0.03***	0.03***
	(0.009)	(0.011)	(0.013)	(0.011)	(0.002)	(0.002)	(0.003)	(0.003)
Observations	43	43	43	43	43	43	43	43
R-squared	0.92	0.89	0.89	0.87	0.96	0.96	0.93	0.92
Durbin-Watson	0.42	0.41			1.04	1.04		
Implied AR(1)	0.79	0.80			0.48	0.48		

Notes: PW is the Prais-Winsten AR(1) regression estimator. The dependent variable (h) is the log of skill intensity, which is the ratio of college equivalents to high school equivalents (as in **Figure 2**). The college relative wage (ω) is the ratio of college wages to high school wages, either at the aggregate level (as in **Figure 1**), within the goods sector (ω^{goods}), or within services ($\omega^{services}$). These series are reported in **Figure A7** in the online appendix, which also provides complete details on series construction. A constant was included in all regressions and is not reported. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Estimates of Alternative Specification

	Elasticities		
	Services	Goods	Demand
	$\sigma(s)$	$\sigma(g)$	ϕ
	0.53	5.57	0.0001
	(0.004)	(0.064)	(0.00001)

	Technological Processes		
	Services	Goods	Intersectoral
Rate of change	$\gamma(1,s)$	$\gamma(1,g)$	$z(1)$
	0.05	0.02	-0.02
	(0.003)	(0.0024)	(0.001)
Initial value	$\gamma(0,s)$	$\gamma(0,g)$	$z(0)$
	-1.37	-0.264	0.896
	(0.008)	(0.008)	(0.019)

	Stochastic Processes		
Relative Supply	Services	Goods	Intersectoral
$\rho(h)$	$\rho(s)$	$\rho(g)$	$\rho(a)$
-	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	$\beta(1,s)$	$\beta(1,g)$
	-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 5: 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 6: DOT Task Intensities

	1971	2001	Change from 1971 to 2001
A. High school equivalents, goods sector			
DEX	42.4%	38.0%	-4.4%
STAND	49.3%	45.1%	-4.2%
COORD	67.5%	65.9%	-1.6%
MATH	40.3%	42.7%	2.5%
PLAN	50.2%	56.3%	6.1%
B. High school equivalents, services sector			
DEX	50.0%	43.2%	-6.8%
STAND	43.2%	37.4%	-5.8%
COORD	53.5%	53.3%	-0.2%
MATH	45.7%	52.6%	6.8%
PLAN	46.1%	56.5%	10.4%
C. College equivalents, goods sector			
DEX	34.6%	29.4%	-5.2%
STAND	37.3%	31.8%	-5.5%
COORD	49.4%	50.2%	0.8%
MATH	81.1%	80.2%	-0.9%
PLAN	79.9%	82.0%	2.2%
D. College equivalents, services sector			
DEX	29.4%	31.2%	1.8%
STAND	17.1%	22.8%	5.7%
COORD	52.9%	49.3%	-3.6%
MATH	86.6%	87.5%	0.9%
PLAN	77.0%	81.1%	4.1%

Notes: Each panel reports task indices for either high-school or college equivalents in the goods or services sector, 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.

Table 7: Changes in Relative DOT Task Intensities: 1971-2001

A. High school versus college equivalents

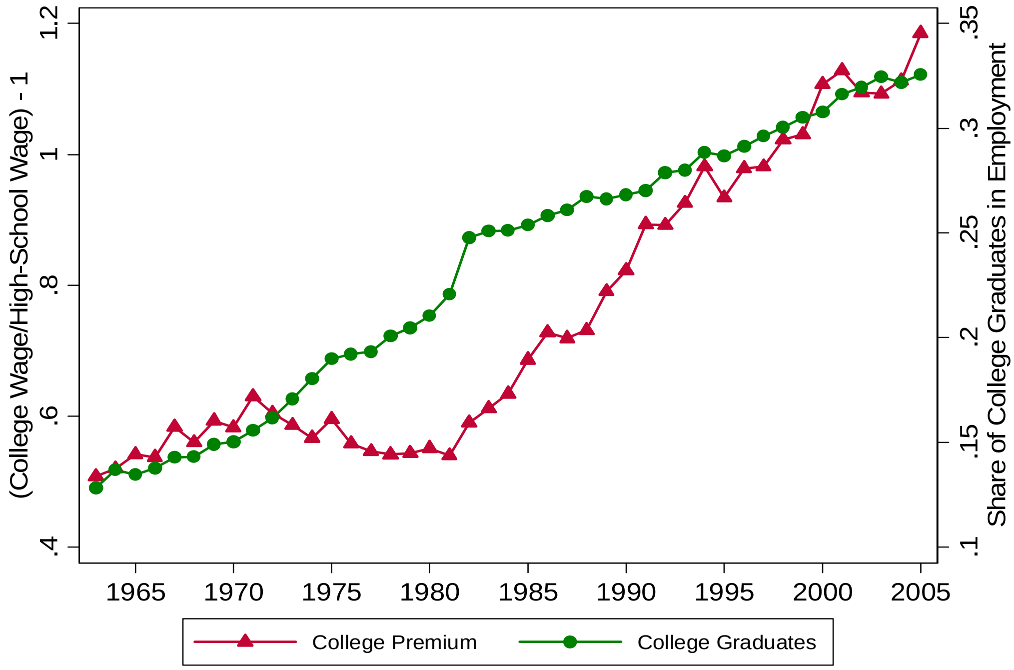
	Services	Goods
ΔDEX	-8.6%	0.8%
ΔSTAND	-11.5%	1.3%
ΔCOORD	3.3%	-2.3%
ΔMATH	5.9%	3.3%
ΔPLAN	6.3%	4.0%

B. High school equivalents in services versus goods

ΔDEX^{HS}	-2.4%
$\Delta STAND^{HS}$	-1.6%
$\Delta COORD^{HS}$	1.4%
$\Delta MATH^{HS}$	4.3%
$\Delta PLAN^{HS}$	4.3%

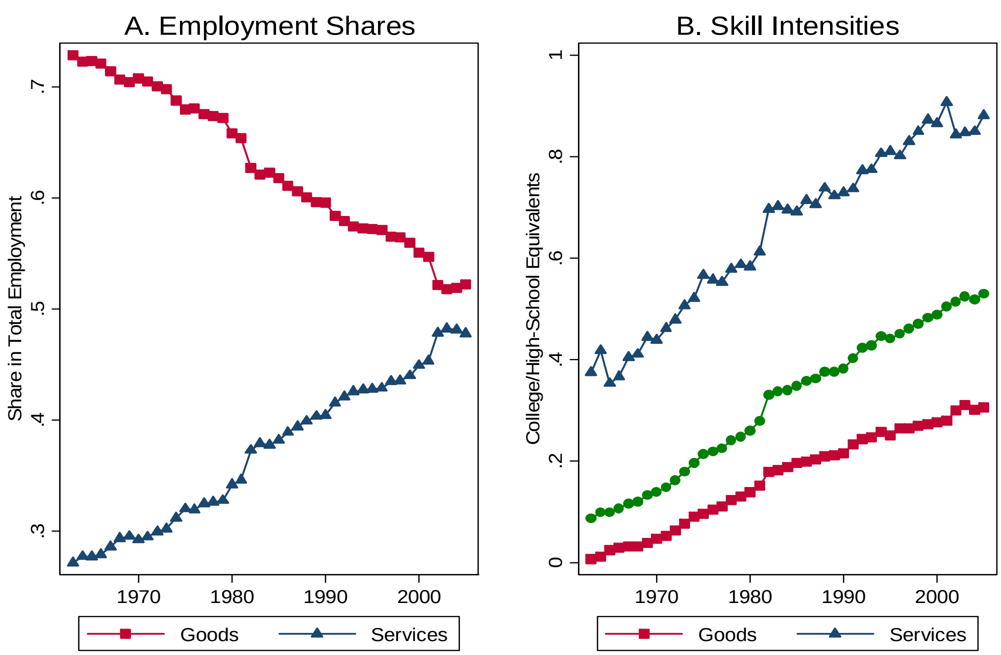
Notes: Panel A reports changes from 1971 to 2001 of *ΔTASK*, which is the difference between a task intensity of high-school and that of college equivalents for each *TASK*. Panel B reports changes from 1971 to 2001 of $\Delta TASK^{HS}$, which is the difference between a task intensity of high-school equivalents in services and that of high-school equivalents in goods for each *TASK*. The units are percentiles in the 1967 distribution of each task. The indices are normalized to zero in 1971. 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.

Figure 1: College Premium and Relative Supply of College Graduates



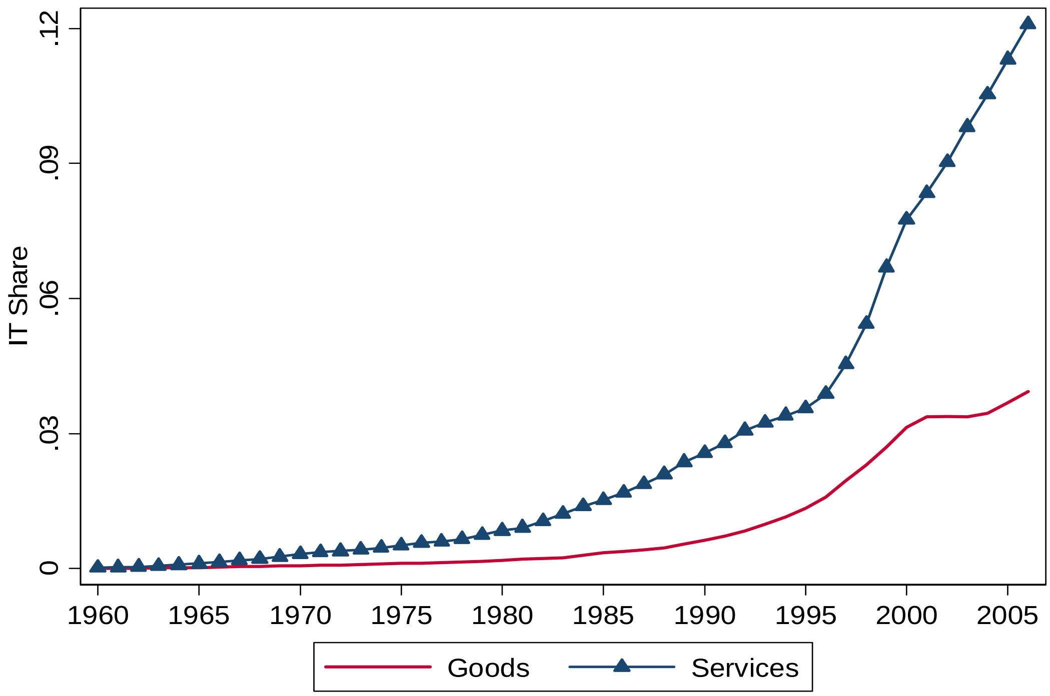
Notes: The College Premium is equal to the ratio of the average weekly wage of college graduates to average weekly wage of high-school graduates, minus one. College graduates are reported as their share of the labor force. Source: March CPS 1964-2006.

Figure 2: Employment Shares and Skill Intensities



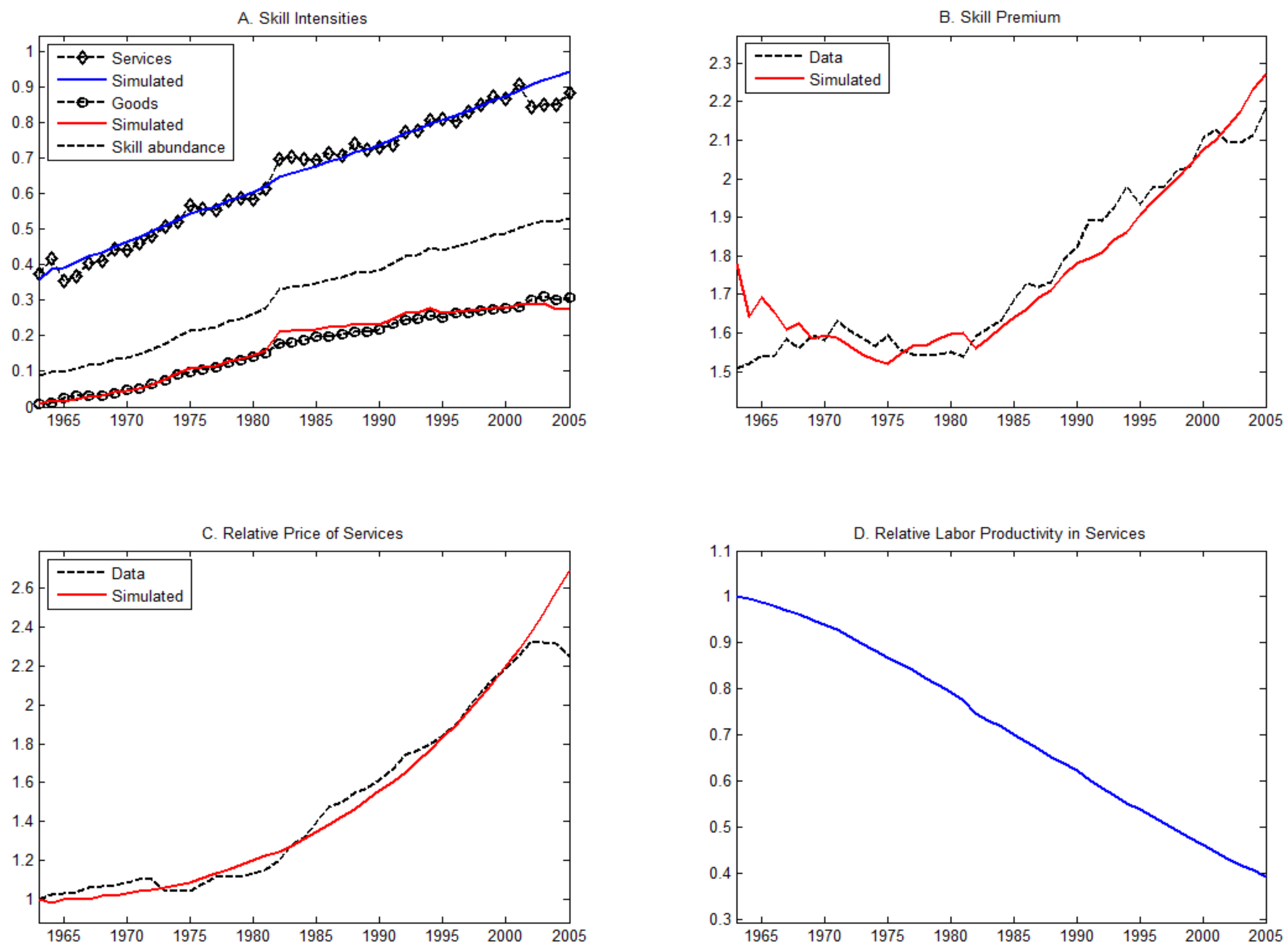
Notes: Employment is measured in annual hours times CPS sampling weights as a fraction of total private sector employment. Sectors are defined in **Table 1**. The breaks in the series in 1981-1982 and in 2001-2002 are due to industry reclassifications in the CPS. A reallocation procedure was used in order to make 1-digit industry classifications after 2001 consistent with the classification until 2001. The reallocation procedure is based on information from Census Bureau (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. Source: March CPS 1964-2006. See text for complete details on construction of series.

Figure 3: IT Capital Shares



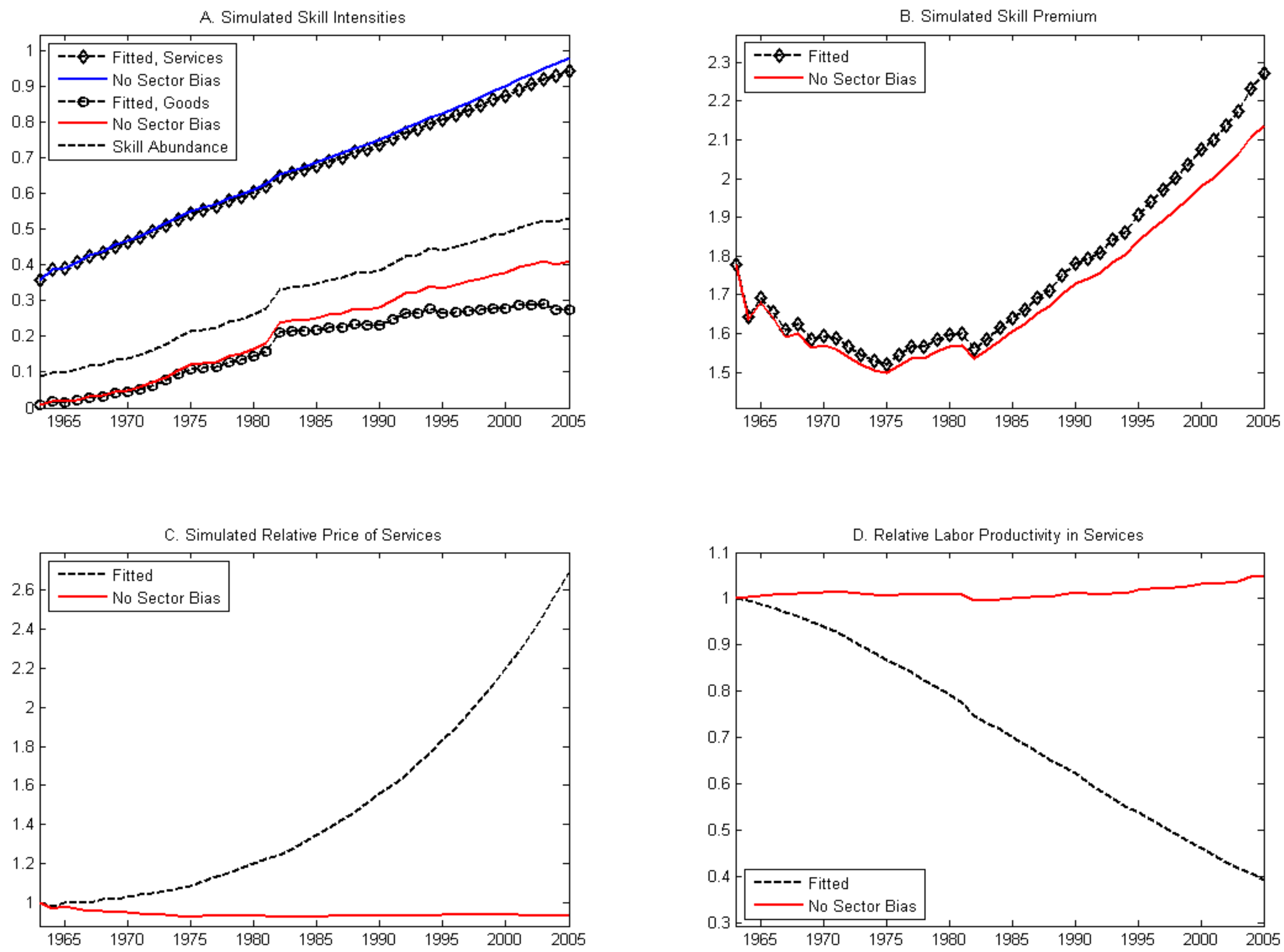
Notes: The IT capital share is computed using chain-type quantity indices and 2000 prices. Aggregation to goods and services sectors follows the classification used throughout the paper. Sectors are defined in Table 1. See online appendix for complete details. Data source: BEA Fixed Assets Tables.

Figure 4: Fit of the Model



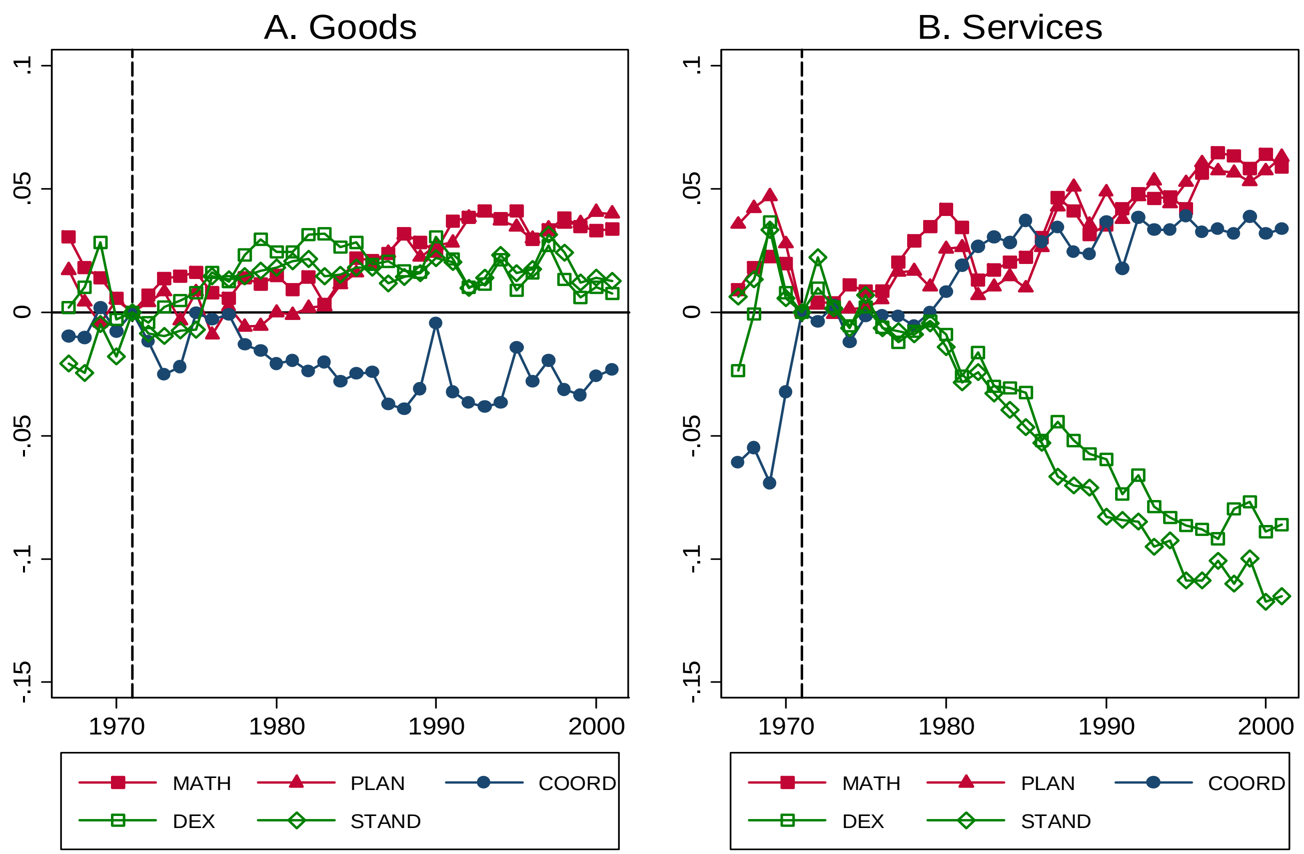
Notes: Panels A-C display the data that was used for the simulated method of moments estimation and the simulated series with the optimal parameters. Panel D displays simulated relative labor productivity in services.

Figure 5: Fixed Inter-Sector Productivity Simulation



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 othe parameters are held at the estimated values.

Figure 6: Relative DOT Task Indices, High-School versus College Equivalents



Notes: Each index is the difference between a task intensity of high-school and that of college equivalents for each TASK. The units are percentiles in the 1967 distribution of each task. The indices are normalized to zero in 1971. 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.