

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

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Abstract

The leading explanation for the increase in the U.S. college premium over the last 40 years is aggregate skill biased technological change (SBTC). This explanation overlooks shifts in the economy's sectoral composition and excludes the possibility of different directions of technological biases in different sectors. I estimate a two-sector general equilibrium model which fits the U.S. aggregate and sectoral trends in relative wages, prices and employment during 1963-2005. Technological change is inferred by directly exploiting general equilibrium restrictions and optimality conditions. The estimates reveal that in the growing skill intensive services sector technological progress has been *unskilled* biased, i.e. average productivity of less skilled workers increased faster than it did for skilled workers. In the unskilled intensive goods sector in contrast, the opposite bias is estimated. Convolution of these two forces leads to inferring SBTC at the aggregate level, in spite of the diverging trends in goods and services. Faster productivity growth of unskilled versus skilled workers in services is consistent with a shift in the mix of occupations: unskilled workers in services have continuously re-allocated into more computer complementary occupations to a greater extent than skilled workers. In contrast, the occupational mix in the goods sector moderately shifted in the opposite direction, which is consistent with faster productivity growth for skilled workers. Taking explicitly into account the sectoral composition of the economy can change our view on the direction of technological change over the last 40 years.

Keywords: wage inequality, technological change, computerization, occupations, task requirements.

JEL classification: J23, J24, J31.

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1 Introduction

Over the last 40 years the U.S. labor market has experienced two important changes. The first is the substantial increase in the college premium in the face of growing supply of college graduates, documented in **Figure 1**. The leading explanation for this fact in the literature is a demand shift caused by aggregate skill biased technological change (SBTC).¹ This explanation relies on the aggregate elasticity of substitution between skilled and unskilled labor being greater than one. The second major change is the reallocation of employment towards the skill intensive service sector, documented in **Figure 2**. Most explanations of the increase in the college premium have overlooked the second fact. Moreover, they exclude the possibility of different directions of technological biases and different elasticities of substitution in different sectors. Allowing for this possibility may improve our understanding of the underlying mechanisms leading to the increase in the college premium.

In this paper I estimate a two-sector general equilibrium model designed to answer two questions. Do the goods and service sectors exhibit similar biases in technological change? And what is the role of the employment shift into the service sector in explaining the increase in the college premium? After answering these questions I introduce evidence on the mix of occupations which supports the estimates of technological change, and sheds more light on the mechanism that drives them. The methodological contribution of the paper is to directly exploit all of the general equilibrium restrictions and optimality conditions of the model to infer technological processes.

The estimation results are that the average productivity of less educated workers in services has increased *faster* than the productivity of college graduates, by 7 percent annually—i.e. we have witnessed *unskilled* biased technological change in the services sector. This *decreases* relative demand for less educated workers due to low substitutability in produc-

¹See 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. On trade-related explanations for the rise in the college premium see Wood (1994) and Wood (1995) for increased intergration of the global labor market, Leamer (1997) for trade, Feenstra and Hanson (1996) and Feenstra and Hanson (1997) for outsourcing. Krugman and Lawrence (1993) argue that the effect of international competition is likely to be of small magnitude. See Impullitti (2005) for a survey on, *inter alia*, how changes in labor market institutions and changes in social norms affect inequality. Krugman (2000a) argues that a switch in the signaling behavior of workers with high ability can increase wage inequality.

tion of services; the elasticity of substitution in services is estimated at 0.625, which is less than 1.² The relative productivity of college graduates in the goods sector has increased faster, by 2 percent annually, and there is high substitutability in production; the elasticity of substitution is estimated at 6.88. In both sectors biased technological change increases demand for college graduates and drives up the college premium, but for different reasons. In addition, I show that my results are consistent with inferring SBTC at the aggregate level, despite finding the opposite in the growing service sector.³

The estimates also show that the employment shift towards services is caused entirely by faster (Hicks neutral) productivity growth in the in goods sector, by 2 percent annually, combined with strong complementarity between goods and services in consumption. If productivity growth had been equal in both sectors, the employment share of services would actually decline slightly. However, the different pace of productivity growth hardly affects the relative wage of college graduates versus high school graduates.

Technological change is usually indirectly inferred, not directly observed, and this paper is no exception.⁴ However, I support the estimated trends in technological change with additional evidence on the occupational mix of workers in both sectors and education groups. This takes us a step closer to a better understanding of technological change because it describes what people actually do. Building on the ideas of Autor, Levy, and Murnane (2003), non-routine tasks (e.g. communication, planning and analytical thinking) are considered computer complementary, whereas routine tasks (e.g. filing and assembly) are easily substituted by computers, because they can either be coded in software or automated.⁵ Computerization, automation and IT encompass the main technological changes in the last 40 years.⁶ Given an increase in the use of computers, moving out of computer substitutable

²The 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 productivity of one factor (equivalently, a decrease in the unit factor requirement) will decrease its relative demand.

³The model has predictions for what a researcher would estimate if she misspecified the economy and thought that the data generating process is a one sector model. Using my estimates, and controlling for substitution across sectors, I derive a pseudo aggregate elasticity of substitution between skilled and unskilled labor greater than one. The value of the pseudo elasticity changes over time.

⁴One 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.

⁵On this topic see also Levy and Murnane (1996), Autor, Levy, and Murnane (2002), Bresnahan (1997) and Bresnahan, Brynjolfsson, and Hitt (1999).

⁶See Krueger (1993) and Autor, Katz, and Krueger (1998).

occupations and into computer complementary occupations raises individual worker productivity.

The evolution of occupational mixes is consistent with the estimated sectoral technological biases. Less educated workers in services have been moving out of occupations that are substitutable by computers, and into occupations that are complementary to computers. This, in turn, implies faster productivity gains for this class of workers. In contrast, the occupational mix in the goods sector moderately shifted in the opposite direction, which is consistent with faster productivity growth for skilled workers. These results can be viewed as supporting a different notion of bias in technological change: relative productivity has increased for workers who shifted into computer complementary occupations.

Technological determinants of the increase in the college premium have been previously investigated by Lee and Wolpin (2006a) using a two-sector model. My approach differs from theirs in one crucial way. I infer technological biases by directly exploiting general equilibrium restrictions and the implications of optimal demand in relative wage and employment data. Lee and Wolpin (2006a) do not close their goods markets, and their wage and price processes are not derived from optimality conditions. Therefore in their model biased technological change does not directly affect relative wages.⁷

This paper is related to other works that stress the sectoral composition of the economy in explaining the rise in the skill 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. Their empirical approach cannot identify whether demand shifts are caused by SBTC or by technological bias in the opposite direction, whereas my results show that the demand shifts in the skill intensive service and unskill intensive sectors are driven by opposite technological processes. 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 do not impose general equilibrium restrictions in their estimation, whereas I do.⁸ Krugman (2000b) highlights the role of sector biased technological change in explaining the skill premium in an international trade setup, but

⁷A less important difference between this paper and Lee and Wolpin (2006a) is that my concept of skill is education level (two, as typical in this literature), whereas they use (three) broad occupations.

⁸The theoretical implications that Beaudry and Green (2005) derive do rely on general equilibrium restrictions, but they do not carry these restrictions to the data.

does not conduct empirical analysis. My results show that the sector bias does not matter much for explaining the skill premium. Finally, I draw on the insights of Philippon and Reshef (2007), who find that changes in the mix of occupations are an important factor in explaining the evolution of productivity and wages in the financial services sector.

The rest of the paper is organized as follows. In the next section I present the model. Section 3 describes the data. Section 4 discusses estimation issues, presents the results and shows how previous aggregate results can be reconciled with mine. Section 5 gauges the relative role of sector bias in explaining the data. Section 6 provides a robustness check on the estimation results. Section 7 presents supporting evidence on occupations and task requirements. Section 8 concludes.

2 A two-sector model

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 make up the two sectors in the economy. Workers are freely mobile across sectors and the economy is closed. Time is discrete (each period corresponds to a year). 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. I now lay out the model in detail.

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

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

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

where A_i and B_i are factor augmenting productivity 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 .

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 $[(A_i L_i)^{\rho_i} + (B_i H_i)^{\rho_i}]^{1/\rho_i} \geq I$, where $I \in \{G, S\}$ and $i \in \{g, s\}$, respectively. This

yields the following unit cost functions

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

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

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.⁹

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

$$h_g = \omega^{-\sigma_g} \beta_g^{\sigma_g-1} \quad (5)$$

$$h_s = \omega^{-\sigma_s} \beta_s^{\sigma_s-1}, \quad (6)$$

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 productivity of skilled workers. Holding ω constant, changes in β_i capture the difference (bias) in changes in factor augmenting technological change.

The effect of biased technological change 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 $\partial h_i / \partial \beta_i < 0$.¹⁰ The intuition for the last result comes from the extreme case of zero substitutability, in a fixed proportions (Leontief) production function, in which $\sigma_i = 0$. In that case, if one factor of production becomes more productive we need less of it per unit of output, and relative demand for that factor falls. Alternatively, if there is sufficient

⁹Lee 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 not an unreasonable assumption.

¹⁰Holding ω constant, if $\sigma_i > 1$, then an increase in β_i captures skill-biased technological change. In terms of labor saving, this is an unskilled-labor saving technological change (Hicks (1932)). The opposite is true if $\sigma_i < 1$.

substitutability in production ($\sigma_i > 1$), then (holding the relative wage fixed) an increase in the relative productivity of one factor will induce an increase in relative demand for that factor, because production is "flexible" enough to shift towards that factor.

Notice that since σ_s need not equal σ_g we do not have a global ranking of skill intensity across sectors (factor intensity reversals). In the data we have $h_s > h_g$, i.e. services are relatively more skill intensive. Imposing this does not change the theoretical analysis. We can proceed, while taking note that in the empirical estimation our estimates will maintain this condition.

Competition and CRS production require that the zero profit conditions must be satisfied. I focus only on interior solutions. I normalize the price of goods to one and rewrite (3)-(4) to get unit cost functions

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

in goods and services, which are set equal to 1 and p , respectively. This satisfies the zero profit conditions. Take the ratio and use (5) and (6) to get the relative price of services

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

Unit factor requirements were obtained by taking the derivative of the unit cost functions with respect to the wage. By using (5)-(6) we can write them as follows

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

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

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

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

output

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

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

Workers of both types supply labor inelastically and get paid 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 we can treat the economy as having 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

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

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

Plugging (8) and (7) into the expression for relative demand (9), together with (5)-(6), we get

$$\begin{aligned} \Phi(\omega, h, \beta_g, \beta_s, A_s/A_g) &= \left(\frac{A_s}{A_g} \right)^{1-\varphi} \left(\frac{h - h_g}{h_s - h} \right) \frac{(1 + \omega h_s)^{(\varphi - \sigma_s)/(1 - \sigma_s)}}{(1 + \omega h_g)^{(\varphi - \sigma_g)/(1 - \sigma_g)}} - \left(\frac{\mu}{1 - \mu} \right)^\varphi \\ &= \left(\frac{A_s}{A_g} \right)^{1-\varphi} \left(\frac{h - \omega^{-\sigma_g} \beta_g^{\sigma_g - 1}}{\omega^{-\sigma_s} \beta_s^{\sigma_s - 1} - h} \right) \frac{(1 + \omega^{1 - \sigma_s} \beta_s^{\sigma_s - 1})^{(\varphi - \sigma_s)/(1 - \sigma_s)}}{(1 + \omega^{1 - \sigma_g} \beta_g^{\sigma_g - 1})^{(\varphi - \sigma_g)/(1 - \sigma_g)}} \\ &\quad - \left(\frac{\mu}{1 - \mu} \right)^\varphi = 0. \end{aligned} \quad (10)$$

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. The goods market is in equilibrium, since the economy can be scaled up or down, and by Walras' law the labor market is also in equilibrium. Actual quantities produced are determined by the labor resource constraints.¹¹ By totally differentiating (10) we can get all the comparative statics for relative wages as a function of biases in technology. It can be shown that the derivative

¹¹This is a manifestation of the Non-Substitution Theorem.

of ω with respect to either one of the β 's depends on the elasticities of substitution and changes signs around a threshold ω^* .

Note that changes in A_s/A_g affect the equilibrium (unless $\varphi = 1$), but this does not capture the sector bias in technological change in the Hicks neutral sense unless we fix β_g and β_s . When we evaluate the role of sector bias we will address this issue in detail.

After briefly describing the data I turn to estimation of the model. The function Φ plays a prominent role in the estimation, as it determines all equilibrium outcomes.

3 Data

I create a sample of labor supplies, wages and prices for 1963-2005. 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).¹² 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 A**.

I follow the exact 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, and their estimate of the aggregate elasticity of substitution to a good degree of accuracy.¹³ 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. Moreover, it makes my aggregate results directly comparable to KM.

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. 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

¹²I obtained the data from Unicon Research, <http://www.unicon.com>, by license to the Department of Economics at New York University.

¹³Specifically, I replicate their estimate of equation 19, which fits the following regression $\log(\omega_t) = c - (1/\sigma)\log(h_t) + \delta \cdot t$, where ω is the relative wage of college graduates versus high-school graduates, and h is their relative supply. Their estimate for $\hat{\sigma} = 1.41$, together with $\hat{\delta} = 0.033$, implies SBTC: $\hat{\beta} = \hat{\delta}\hat{\sigma}/(\hat{\sigma} - 1) = 0.11 > 0$.

obtained from wage regressions which embody the assumption that high school dropouts and people with some college education are linear combinations of high school and college graduates in terms of their productivity.

Aggregate skill abundance, h , is the ratio of total college equivalents to high school equivalents in the U.S. sample. Sector skill intensities, h_s and h_g , are calculated in a similar way, using the ratio of college equivalents to high school equivalents in the relevant sector. I use the same equivalence weights for all labor supply series to keep the accounting consistent.¹⁴

The wage concept is average weekly wage. 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. All wages are deflated using the implicit personal consumption expenditures deflator from the NIPAs, which is calculated using data obtained from the Bureau of Economic Analysis.

The Bureau of Economic Analysis (BEA) provides chain-type price indices for value added by 1-digit industries (starting in 1947). The industries roughly correspond to the industrial classification of the CPS which is described in the top panel of **Table A**. 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. 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. The relative price of services to goods, p , is increasing throughout almost the entire sample, as can be seen in **Figure 3**.

4 Estimation

In this section I discuss the specification of the exogenous technological processes, present the estimation technique and report the results.

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

4.1 Evolution of exogenous parameters

As we saw above, (10) completely determines the equilibrium in the economy. We need to specify how the exogenous parameters in (10) evolve over time, which will determine how the equilibrium evolves. The exogenous variables are h , β_g , β_s and A_s/A_g . Without loss of generality I set $\mu = 1/2$, since it is not separately identified.¹⁵ I drop time indices where there is no confusion.

First, h is the aggregate skill abundance in the economy and it evolves exactly according to the data. The technological parameters are all assumed to grow at constant rates with a shock. Specifically,

$$A_s/A_g = \exp \{a_0 + a_1 t + \varepsilon_t^a\} \quad (11)$$

$$\beta_i = \exp \{\beta_{0,i} + \beta_{1,i} t + \varepsilon_t^i\}, \quad i \in \{g, s\}, \quad (12)$$

where ε_t^i are i.i.d. normal with zero mean and variance v_i^2 , $i \in \{a, g, s\}$. 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 a la Katz and Murphy (1992).¹⁶ Adding shocks to the technological trends allows the equilibrium to evolve stochastically around those trends.

4.2 Motivation for different elasticities

The model allows different magnitudes of σ_s for σ_g , but should we expect them to be very different empirically? In this section I provide some motivation for a much smaller elasticity in services than in goods. It is important to understand what features of the data 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

¹⁵This paper focuses on productivity trends. For a demand-based explanation for the rise of the service sector see Buera and Kaboski (2006).

¹⁶Card and DiNardo (2002) claim that wage inequality actually stabilized in the 1990s and that the driving forces for the rise in wage inequality in the 1980s were episodic. They stress the role of the declining real value of the minimum wage and declining bargaining power of workers. However, **Figure 1** is evidence against this conclusion, since the college premium continues to rise at a relatively constant rate throughout the 1981-2005 subsample. Autor, Katz, and Kearney (2007) also argue that wage inequality has continued to rise throughout the 1990s and stress long run driving forces. See also Card (1992) Freeman (1993) Freeman and Katz (1995) and Lemieux (2007). Acemoglu, Aghion, and Violante (2001) argue that SBTC might actually induce de-unionization by altering the incentives for being a member of a union.

are determined in (5) and (6) by the technological bias and relative wage, where the latter is also a target for the estimation. Consider

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

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

$$\ln(h_{it}) = c_i - \sigma_i \ln(\omega_t) + \delta_i t, \quad i \in \{g, s\}. \quad (13)$$

Heuristically, controlling for a particular time trend, δ_i , a larger response of h_i to ω implies a larger σ_i .¹⁷

In order to illustrate this, **Figure 4** depicts detrended log skill intensities h_s and h_g plotted against the detrended log relative wage. Both panels in the figure have the same scale. The picture is striking. The "response" of the detrended h_s to changes in detrended ω in services is much lower than the "response" in goods. Of course, these responses are not demand effects, since the demand curve is not identified.¹⁸ However, simultaneity biases notwithstanding, the figure would make us expect that $\sigma_s < \sigma_g$, which is what is estimated below.

4.3 Simulated method of moments

I estimate the parameters of the model by simulated method of moments. Specifically, I simulate the college premium ω , skill intensities $\mathbf{h}_g$ and $\mathbf{h}_s$ and the relative price of services to goods, $\mathbf{p}$ and minimize the distance between them and their empirical counterparts during 1963-2005 (43 years). I denote vectors of data or simulated series in boldface.

The estimation proceeds as follows. I draw $R = 500$ sets of vectors of standard normal shocks $\mathbf{z}_r^i$ for the three technological processes, $i \in \{a, g, s\}$, $r = 1, 2, \dots, R$, where it is understood that each $\mathbf{z}_r^i$ is a 43-by-1 vector of shocks. Denote the vector of unknown parameters by θ ,

$$\theta = \{\sigma_s, \sigma_g, \beta_{0,s}, \beta_{1,s}, \beta_{0,g}, \beta_{1,g}, a_0, a_1, \varphi, v_s, v_g, v_a\}.$$

¹⁷Likewise, controlling for a particular level of responsiveness of h_i to ω , σ_i , the bias in technology will be given by the residual trend in h_i , since $\delta_i = (\sigma_i - 1)\beta_{1,i}$.

¹⁸By the Frisch-Waugh Theorem, the slopes of the linear predictions in **Figure 4** are exactly the OLS estimates of σ_i in (13). Of course, these estimates do not identify σ_i due to the classic demand-supply identification problem.

Start with an initial guess for θ . For each set of draws r , multiply all $\mathbf{z}_r^i$ shocks by their corresponding standard deviations, v_i , to get the model's structural shocks, ε_t^i , $i \in \{a, g, s\}$. Solve for the equilibrium path of $\boldsymbol{\omega}(\theta)$ using (10). Then, using $\boldsymbol{\omega}(\theta)$, simulate $\mathbf{h}_g(\theta)$ and $\mathbf{h}_s(\theta)$ and $\mathbf{p}(\theta)$. Minimize the objective function—which will be described shortly below—using a numerical optimization method. Store the estimation results as $\hat{\theta}_r$. In the end compute the averages and standard errors of the estimates, $\hat{\theta} = \frac{1}{R} \sum_{r=1}^R \hat{\theta}_r$ and $\hat{\sigma}_\theta = \left[\frac{1}{R-1} \sum_{r=1}^R (\hat{\theta}_r - \hat{\theta})^2 \right]^{1/2}$, where $\hat{\sigma}_\theta$ is calculated separately for each element of θ .¹⁹

The objective function for the numerical optimization method in each draw is

$$\Psi = [\hat{\mathbf{x}}(\theta, \mathbf{h}, \mathbf{z}_r) - \mathbf{x}]' W [\hat{\mathbf{x}}(\theta, \mathbf{h}, \mathbf{z}_r) - \mathbf{x}],$$

where

$$\mathbf{x} = \begin{bmatrix} \boldsymbol{\omega} \\ \mathbf{h}_s \\ \mathbf{h}_g \\ \mathbf{p} \end{bmatrix},$$

$\mathbf{z}_r$ represents the three vectors of standard normal shocks, and W is a weighting matrix, the choice of which I discuss currently. As in all method of moments estimation, results may depend on the choice of the weighting matrix. Since I do not have sampling error in the target time series, an optimal weighting matrix cannot be computed. One important consideration for the choice of W is that the data is trending. Therefore, I opt for minimizing percent deviations. This maintains the same distance concept no matter what the magnitude of the target series is. It amounts to a particular weighting matrix: $W = \text{diag}(\mathbf{x}\mathbf{x}')$. Operationally, the algorithm chooses θ to minimize

$$\Psi = [\ln \hat{\mathbf{x}}(\theta, \mathbf{h}, \mathbf{z}_r) - \ln \mathbf{x}]' [\ln \hat{\mathbf{x}}(\theta, \mathbf{h}, \mathbf{z}_r) - \ln \mathbf{x}]. \quad (14)$$

Results with no weighting scheme ($W = I$) are very similar.²⁰

¹⁹I do not weight the results by some function of their fit. Results that get a better fit do not contain additional information on the "true" parameters—their fit is just by luck of the draw.

²⁰In 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.

4.4 Results

The estimates are reported in **Table 1**. The average objective value is $\Psi = 0.97$. The standard deviations of the technological shocks are small and not accurately identified. See **Figure 5** for a visual fit, which uses the average parameter estimates and no shocks. In Panel A we see that 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. The model also misses the end of the sample in Panel C, where the price series declines, but the simulated series continues to increase.

I now discuss the average estimates in **Table 1**. The EoS in services is $\sigma_s = 0.625 < 1$ and the bias in technological change in services is towards the less skilled workers, $\beta_{1,s} = -0.07$. This means that high school equivalents have been increasing their productivity faster than college equivalents. This decreases demand for less skilled workers and contributes to their falling relative wage because the estimate of the EoS in services is less than one. Of course, the relative wage is determined in general equilibrium, but the technological bias in services contributes to its increase. The EoS in the goods sector is $\sigma_g = 6.88 > 1$ and the bias in technological change in this sector is towards the skilled workers, $\beta_{1,g} = 0.02$.²¹ This means that college equivalents have been increasing their productivity faster than high school equivalents in the goods sector.

The sizes of the estimates of both elasticities are reasonable. In **Section 5** 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.

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 growth in technological biases. A well documented fact is that the growth in the supply of college graduates decreased in the early 1980s.²² The

²¹Hamermesh (1993) (Table 3.7, pp.110-111) surveys works that estimate 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. Fallon and Layard (1975) estimate the elasticity of substitution between workers with at least 8 years of education and those with less in four industries (mining, manufacturing, construction and utilities) in a cross-section of 16 countries. Their estimates are low, between 0.63 and 1.66, but are not comparable to my estimates due to the very different definition of skill and the international aspect of the data.

²²Card and Lemieux (2001) argue that the slowdown in the growth of supply of college graduates plays

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 .²³ Treating the two types of labor as homogenous is the typical assumption maintained in productivity analyses. We can see 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. Although this is not one of the moments that are targeted, it is on the same order of magnitude that Jorgenson and Stiroh (2000) find, who document slower average labor productivity growth in services relative to the rest of the private sector in 1958-1996.

The dynamics of the allocation of labor across sectors is almost identical to what is in the data, since it can be represented as a function of h_s , h_g and h , as demonstrated above. 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 we fix β_g and β_s .²⁴ One can see that even though $a_1 > 0$, i.e. the productivity of unskilled labor in services has increased faster than in the goods sector, relative labor productivity in the service sector has declined. This will be illustrated in the next section.

Table 1 also reports a very small elasticity in demand, φ . It is not implausible that goods and services are strong complements in consumption. This implies that consumers

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. See Freeman (1976).

²³It can be shown that $(L_g + H_g) / (L_s + H_s) = \frac{h_s - h}{h - h_g} \frac{1 + h_g}{1 + h_s}$. 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.

²⁴To see this last point re-write the generic production function $Y = [(AL)^\rho + (BH)^\rho]^{1/\rho}$ as $Y = A(1 + \beta^\rho)^{1/\rho} \left[\frac{1}{1 + \beta^\rho} L^\rho + \frac{\beta^\rho}{1 + \beta^\rho} H^\rho \right]^{1/\rho}$. Only when β is fixed does A capture Hick-neutral technological change.

demand an almost fixed ratio of services to goods. The actual quantity cannot be identified in the model because μ is not identified. Nevertheless, we would like to know whether the ratio of services output to goods output remains the same in the data.

To test this I construct a relative output series using 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. **Figure 6** presents the series graphically.

The empirical output ratio increases from 1966 to 1975, then fluctuates until 1991, then declines back to the original level of 1963 by the end of the sample. The model fails to capture these changes in relative output. However, I do not find that the ratio has a trend in 1963-2005. Fitting a regression of relative real output to the relative price of services (and a constant) gives a very small, statistically insignificant coefficient, which is consistent with the low estimate of φ in the SMM results.²⁵ Therefore, the failure of the model to capture the shifts in relative output does not likely affect the long run trends in technological bias.

4.5 Reconciling previous aggregate results

In this section I reconcile my results with previous work that has estimated a large aggregate elasticity of substitution and thus SBTC. 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].

It is important to remember that there is a lot of substitution across sectors, i.e. relative employment in the service sector is growing. If the elasticity of substitution is less than one

²⁵Of course, this regression does not identify the demand schedule.

²⁶Johnson (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): 1.44, and Krusell, Ohanian, Rios-Rull, and Violante (2000): 1.67. In a recent contribution, 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. Fallon and Layard (1975) estimate the aggregate elasticity of substitution between workers with at least 8 years of education and those with less in a cross-section of 22 countries (their Table 1). Their estimates are low, between 0.3 and 0.58, but are not comparable to my estimates due to the very different definition of skill and the international aspect of the data.

in services, then this might imply that the aggregate elasticity will decrease over time.²⁷ SBTC relies on an aggregate elasticity that is larger than one. Does the model predict such a magnitude? Moreover, is that value stable over time?

To address these questions I use the two-sector model to characterize a "pseudo" aggregate elasticity of substitution, which captures relative factor substitution at the aggregate level. Using the estimates of the model, the pseudo aggregate elasticity of substitution turns out to be larger than one and in the range that aggregate EoS is usually estimated. However, it varies quite a bit over time. I now present this result formally.

Suppose that the data generating process (DGP) of the world is indeed the model above. If a researcher misspecified the DGP and thought that it is a one-sector model, what would she get? In particular, what should the estimate of σ from a regression

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

be?

To answer this question I use the function Φ given in (10). Recall that Φ is a function of all exogenous variables and the endogenous relative wage. Fix all technology parameters and totally differentiate Φ with respect to ω and h . By the implicit function theorem,

$$\frac{d\omega}{dh} = -\frac{\Phi_h}{\Phi_\omega}$$

and the pseudo aggregate EoS is given by

$$\tilde{\sigma} = -\frac{d \ln(h)}{d \ln(\omega)} = -\frac{dh/h}{d\omega/\omega} = \frac{\omega \Phi_\omega}{h \Phi_h}.$$

This yields the following expression

$$\tilde{\sigma} = \sigma_g \frac{h_g (1 + \omega h) (h_s - h)}{h (1 + \omega h_g) (h_s - h_g)} + \sigma_s \frac{h_s (1 + \omega h) (h - h_g)}{h (1 + \omega h_s) (h_s - h_g)} + \varphi \frac{\omega (h - h_g) (h_s - h)}{h (1 + \omega h_g) (1 + \omega h_s)}, \quad (16)$$

where I write h_i to conserve space, but the reader should remember that h_i are functions of ω and β_i .²⁸

This expression is always positive; it is a weighted average of the elasticities in production, σ_g and σ_s , and the elasticity in demand, φ . This illustrates that indeed the aggregate

²⁷In the limit, the two-sector economy will converge to a one-sector services economy.

²⁸See the **Appendix** for complete details on the derivation of $\tilde{\sigma}$.

elasticity combines substitution both within and across industries. But the weights change over time with the changes in relative employment in the two sectors. This implies that the notion of a stable aggregate elasticity is tenuous.²⁹ It can easily be verified that if $h_i = h$, then $\tilde{\sigma} = \sigma_i$ (the economy is one sector). The closer h_i is to h , the closer $\tilde{\sigma}$ is to σ_i .

Using (16) and the parameter values from the estimation in **Table 1** I calculate $\tilde{\sigma}$ for every year in the sample, which is depicted in **Figure 8**. Although the share of the service sector has been increasing throughout the sample, $\tilde{\sigma}$ increases from 1.05 in 1963 to 3.9 in 1983. The increase in $\tilde{\sigma}$ in the beginning of the sample is driven by the rapid expansion in supply of skills. After 1983 $\tilde{\sigma}$ declines to 3.25 in 2005. This is driven by the slowdown in the growth of the supply of skills and a higher share of services.

The simple average of $\tilde{\sigma}$ for the 1963-2005 sample is 3.16 and for the 1963-1987 sample of Katz and Murphy (1992) the average is 2.9. One can also fit (15) using the simulated ω series. The estimate of σ from that regression in 1963-2005 is 2.35. For the 1963-1987 sample it is 1.9. Given that the estimate of δ in (15) is positive, this implies that technological change at the aggregate level is biased towards skilled workers, since $\delta = (\sigma - 1)\beta_1$, where β_1 is the pseudo-aggregate bias in technological change (analogous to $\beta_{1,i}$ at the sector level).

Thus, the small elasticity in services and large one in the goods sector are consistent with previous aggregate estimates.

5 The relative role of inter-sector bias: a counterfactual

In this section I gauge the relative role of inter sector productivity shifts versus the role of intra-sector biases in explaining the rise in the relative wage of college graduates. To do this I simulate a counterfactual and compare it to the fitted model. The counterfactual imposes the condition that the relative Hicks neutral technological change in both sectors is the same, i.e., no sector bias; all other things are equal.

Recall that A_s/A_g does not capture relative Hicks neutral technological change unless we fix β_g and β_s . Since the latter are changing, I take this into account when calculating the role

²⁹One could argue 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.

of inter sector productivity shifts. To do this I use a slightly different representation of the production functions (1) and (2) that will allow me to separate Hicks neutral technological change from intra-sector biases. I drop time indices where there is no confusion.

An alternative representation of the production technologies (1) and (2) is

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

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

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

$$\begin{aligned} \alpha_i &= \frac{\beta_i^{\rho_i}}{1 + \beta_i^{\rho_i}} \\ Z_i &= A_i (1 + \beta_i^{\rho_i})^{1/\rho_i}. \end{aligned}$$

This clarifies why A_s/A_g does not capture relative Hicks neutral technological change when β_g and β_s are changing. Given the estimates in **Table 1**, we can calculate the inter-sector ratio of Hicks neutral sector productivities.

In order to gauge the relative role of inter-sector productivity shifts, I calculate an 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 of the Hicks neutral productivity ratio according the estimation results. Define this initial value as z_1

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

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

$$\frac{A'_s(t)}{A'_g(t)} \equiv z_1 \frac{(1 + \beta(t)_g^{\rho_g})^{1/\rho_g}}{(1 + \beta(t)_s^{\rho_s})^{1/\rho_s}}$$

where z_1 is defined above and where β_g and β_s evolve according to the estimation results without shocks. $A'_s(t)/A'_g(t)$ 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.

Figure 7 shows the difference between the fitted simulated series using estimated parameters and the simulated counterfactual series that use A'_s/A'_g . In the latter case all other parameter values are held at their estimated values. The effect on the relative wage of college graduates is very small. Instead of going up to 2.27, it reaches 2.14.³⁰

Perhaps not surprisingly, the effect on average labor productivity (Panel D) is also large; instead of decreasing by 60 percent, it actually increases slightly by 5 percent. 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 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 (see **Figure 2**). Notice that the skill intensities rise more than in the fitted model because the skill premium rises less. The differences are visually small, but they are enough to change the dynamics of sectoral employment shares³¹.

Recall that one of the estimation results above is a small elasticity in demand, φ . This explains the large role of the sector bias for relative employment and price. Since consumers demand (almost) constant relative amounts 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 drives up the relative price of services.

6 Robustness check

Although the production functions (1) and (2) are the most natural way to think about biased technological change, a problem arises as σ_i approaches 1. In that case output approaches infinity.³² This causes the objective function to be averse of $\sigma_i = 1$.

To make sure that my low estimate of σ_s does not follow from this problem, and as a robustness check for the other estimates, I use the production specification in (17) and (18) to solve the model all over and re-estimate the parameters of interest. Other than that

³⁰Lee and Wolpin (2006a) also find that inter-sector relative productivity shifts do not play a major role in explaining wage inequality.

³¹Recall that $(L_g + H_g)/(L_s + H_s) = \frac{h_s - h}{h - h_g} \frac{1 + h_g}{1 + h_s}$, so employment shares are given by the relationship between skill intensities, h_s and h_g , and skill abundance, h .

³²In terms of (17) and (18), as ρ_i approaches zero (σ_i approaches one) α_i approaches 1/2 and Z_i approaches infinity.

change, all else remains the same, including preferences. I now present the main differences between the two versions of the model.³³

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

$$h_g = \omega^{-\sigma_g} \gamma_g^{\sigma_g} \quad (19)$$

$$h_s = \omega^{-\sigma_s} \gamma_s^{\sigma_s}, \quad (20)$$

where $\gamma_i = \alpha_i / (1 - \alpha_i)$. Going through the same steps as we did above, we get a similar expression for the equilibrium implicit function

$$\begin{aligned} & \tilde{\Phi}(\omega, h, \gamma_g, \gamma_s, Z_s/Z_g) \\ &= \left[\frac{Z_s (1 - \alpha_s)^{\frac{\sigma_s}{\sigma_s - 1}}}{Z_g (1 - \alpha_g)^{\frac{\sigma_g}{\sigma_g - 1}}} \right]^{(1-\varphi)} \left(\frac{h - h_g}{h_s - h} \right) \frac{(1 + \omega h_s)^{(\varphi - \sigma_s)/(1 - \sigma_s)}}{(1 + \omega h_g)^{(\varphi - \sigma_g)/(1 - \sigma_g)}} - \left(\frac{\mu}{1 - \mu} \right)^\varphi \\ &= \left[\frac{Z_s (1 - \alpha_s)^{\frac{\sigma_s}{\sigma_s - 1}}}{Z_g (1 - \alpha_g)^{\frac{\sigma_g}{\sigma_g - 1}}} \right]^{(1-\varphi)} \left(\frac{h - \omega^{-\sigma_g} \gamma_g^{\sigma_g}}{\omega^{-\sigma_s} \gamma_s^{\sigma_s} - h} \right) \frac{(1 + \omega^{1 - \sigma_s} \gamma_s^{\sigma_s})^{(\varphi - \sigma_s)/(1 - \sigma_s)}}{(1 + \omega^{1 - \sigma_g} \gamma_g^{\sigma_g})^{(\varphi - \sigma_g)/(1 - \sigma_g)}} \\ &\quad - \left(\frac{\mu}{1 - \mu} \right)^\varphi = 0. \end{aligned} \quad (21)$$

From the analysis in the previous subsection we know that the expression in square brackets is equal to A_s/A_g . The other terms in the second line are identical to those in (10), but their underlying functions are different, which becomes apparent in the third line.

The exogenous variables are h , γ_g , γ_s and Z_s/Z_g . As before, without loss of generality I set $\mu = 1/2$ and h evolves exactly according to the data. Given estimates for these parameters one can back out the parameters according to the previous specification. I pick a specification for the technological parameters that maintains constant growth rates,

$$\begin{aligned} Z_s/Z_g &= \exp \{z_0 + z_1 t + \varepsilon_t^z\} \\ \gamma_i &= \exp \{\gamma_{0,i} + \gamma_{1,i} t + \varepsilon_t^i\}, \quad i \in \{g, s\}, \end{aligned}$$

where ε_t^i are i.i.d. normal with zero mean and variance v_i^2 , $i \in \{z, g, s\}$. 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

³³See the **Appendix** for complete details on the derivation.

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 $Z_i = A_i (1 + \beta_i^{\rho_i})^{1/\rho_i}$.³⁴ However, both β_i and γ_i maintain constant growth rates and one can obtain the growth rate of one given the growth rate of the other, as will be demonstrated below.³⁵ Thus, the estimation procedure should not mechanically yield the exact same results.

The optimization procedure chooses $\tilde{\theta} = \{\sigma_s, \sigma_g, \gamma_{0,s}, \gamma_{1,s}, \gamma_{0,g}, \gamma_{1,g}, z_0, z_1, \varphi, v_s, v_g, v_z\}$ to minimize the same objective function

$$\tilde{\Psi} = \left[\ln \hat{\mathbf{x}}(\tilde{\theta}, \mathbf{h}, \mathbf{z}_r) - \ln \mathbf{x} \right]' \left[\ln \hat{\mathbf{x}}(\tilde{\theta}, \mathbf{h}, \mathbf{z}_r) - \ln \mathbf{x} \right].$$

As before, I implicitly use the weighting matrix $W = \text{diag}(xx')$. Results with no weighting scheme ($W = I$) are very similar. The estimation uses the same $R = 500$ draws of $\mathbf{z}_r$ standard normal shocks used in the previous estimation.

The estimates are reported in **Table 2**. The average value of the objective function is $\tilde{\Psi} = 2.08$. This is larger than $\Psi = 0.97$ in the main results reported in **Table 1**. The previous results provide a better fit. The estimates of the elasticities are on the same order of magnitude as before. One can back out the biases in technological change in the factor augmenting sense: $\tilde{\beta}_{1,i} = \gamma_{1,i}\sigma_i/(\sigma_i - 1)$. These are $\tilde{\beta}_{1,g} = 0.024$, which is very similar to what was estimated above, and $\tilde{\beta}_{1,s} = -0.17$, but is significantly larger in absolute value. This last result is due to the fact that the EoS in services is closer to one.

The bias in technological change in services is once again towards the less skilled workers. But since this specification has an inferior fit, I prefer the more reasonable estimate of $\beta_{1,s} = -0.07$. We also have falling relative productivity in services in the Hicks neutral sense, which is consistent with the fall in average labor productivity estimated above.

Thus, the main result of a low elasticity and bias towards the less skilled workers in services is upheld in this specification, despite the fact that it provides an inferior fit. It is reassuring that we get this result despite a different specification of the dynamics.

³⁴Alternatively, given constant growth rates for γ_i and Z_s/Z_g , the growth rate of A_s/A_g would not be constant.

³⁵See **Appendix** for more details on the static equivalence and dynamic differences between the two versions of the model.

7 Supporting evidence for trends in average productivity

The estimation results are that high school graduates (equivalents) in services are increasing their productivity faster than college graduates (equivalents)—and that the opposite is happening in the goods sector. In addition, high school graduates (equivalents) have increased their productivity in services faster than in goods.

The first part might be counter intuitive and is different from previous findings. And as Krugman (2000a) argues, technological explanations for the increase in the skill premium are too much of a "deus ex machina". Can these results be supported by evidence that is external to the analysis above? Could this shed some light on the mechanism that gives rise to these results? Methodologically, this is an interesting and important thing to do because it adds validity to the estimation results.

In this section I pour some content into the productivity indices, using occupational task requirements from the Dictionary of Occupational Titles (DOT). I show that changes in the occupational mix of high school equivalents and college equivalents in services are consistent with faster productivity growth for high school equivalents versus college equivalents in services. Changes in occupational mixes in the goods sector are consistent with faster productivity growth for college equivalents.³⁶

I proceed as follows. First I describe how the occupational mix affects productivity. Then I link variation over different types of occupational tasks to changes in productivity. Finally, I construct DOT task indices per sector and education level, and then show that these indices have changed in a way that is consistent with the productivity estimates.

7.1 Occupational composition and productivity

In this subsection I unpack the A and B productivity indices from the model into their occupational composition. This will allow me to relate them to the DOT task indices, that

³⁶U.S. Department of Labor (1999) (Text Table 4, pp. 47) reports that 40% of skill upgrading *within industries* between 1989 and 1997 is due to changes in the occupational mix, where the rest is attributed to skill upgrading within occupations. But whereas changes in the occupational mix actually hurt skill upgrading in the goods sector (*minus* 20%), in the service sector it contributed 54% and in some cases much more, as in F.I.R.E, where changes in the occupational mix contributed 82% of skill upgrading within that industry. The study also reports large differences in how the distribution of occupations has changed within the goods and services sectors (Table 2-1, pp. 64). For example, whereas the service sector decreased its share of managers and clerical occupations, and increased its share of professionals, the goods sector increased production occupations and decreased the share of professionals.

are defined per occupation.

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 annual hours worked by individual n and let b_n denote her efficiency units. Then we can write

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

where λ_n is the share of hours worked by individual n , H is the sum of hours worked by skilled workers and B is their average productivity

$$\begin{aligned} H &= \sum_n hrs_n \\ B &= \sum_n \frac{hrs_n}{H} b_n = \sum_n \lambda_n b_n. \end{aligned}$$

Note that the summation is over the relevant group of individuals.

Each individual n works in an occupation o . Therefore, we can write

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

where $n \in \langle o \rangle$ means that n has occupation o and o_n denotes n 's occupation. Assume that all individuals in this class and sector with occupation o have the same productivity. This means that $b_{o_n} = b_o$. Then we can write

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

where $\lambda_o = \sum_{n \in \langle o \rangle} \lambda_n$ is the share of hours worked in occupation o .³⁷ So

$$BH = \left(\sum_o \lambda_o^H b_o \right) H \tag{22}$$

³⁷The expression $B = \sum_o \lambda_o b_o$ implicitly 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.

and repeating the same manipulations for AL , we have

$$AL = \left(\sum_o \lambda_o^L a_o \right) L, \quad (23)$$

where I added superscripts to λ to differentiate the distributions of occupations for L and H . Recall that in the model there are two sectors, so (22) and (23) will also be indexed by sector. I do not require $a_o = b_o$ for the same occupation o .

We now have a way to relate occupational composition to average productivity: changes in λ_o^L and λ_o^H affect A and B productivity.³⁸ In what follows I will also take into account changes in a_o and b_o .

7.2 Occupation productivity and tasks: a conceptual framework

Autor, Levy, and Murnane (2003) make the case that computers are complementary to tasks that are non-routine and can substitute tasks that are routine. In a nutshell, their idea is that 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).³⁹ The following specification conceptualizes this. I build on the ideas of Autor, Levy, and Murnane (2003), but my approach differs from theirs in one important way. While they use tasks requirements as inputs in production, I use them to characterize occupations.

Suppose that output per hour worked (productivity) in some occupation is given by

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

where R_o is routine task requirement, N_o is non-routine task requirement and C is computer capital. The important features of this specification is that N_o and R_o are not perfect substitutes and that R_o is more substitutable by C than N_o is.⁴⁰ Notice that R_o and N_o are indexed by occupation o , which reflects my concept of task requirements as characterizing

³⁸Kambourov and Manovskii (2004) argue that individual occupational productivity shocks can explain wage inequality within observationally equivalent groups by causing occupation switching. My analysis differs as it takes a long-run point of view on occupational composition using average occupational productivities.

³⁹Bresnahan, Brynjolfsson, and Hitt (1999) and Bresnahan (1997) discuss how information technology affects the workplace and provide a similar conceptual explanation.

⁴⁰Another 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 the simplest one.

(defining) occupations.⁴¹

Now suppose that technological change induces computerization and use of information technology.⁴² A fall in the price of computing power will induce more use of computer inputs. This makes all occupations more productive over time since

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

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

$$\frac{\partial^2 a_o}{\partial C \partial N_o} = \delta (1 - \delta) \frac{N_o^{\delta-1}}{(R_o + C)^\delta} > 0, \quad (24)$$

and smaller for occupations that are more routine task intensive

$$\frac{\partial^2 a_o}{\partial C \partial R_o} = -\delta (1 - \delta) \frac{N_o^\delta}{(R_o + C)^{\delta+1}} < 0. \quad (25)$$

Therefore, computerization increases the *relative* productivity of occupations that have higher non-routine task requirements and lower non-routine task requirements.

It follows from (24) and (25) that if high school graduates work in occupations that have a relatively low non-routine task intensity and relatively high routine task intensity, then computerization will still increase their productivity, but slower than for college graduates. This would capture skill biased technological change. 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 further increase their *average* productivity. And if the reallocation is large enough in that direction, then the total increase in productivity can be even larger than the increase in productivity that college graduates experience.

My hypothesis is that in services λ_o^L in (23) has shifted towards non-routine task intensive and out of routine task intensive occupations faster than λ_o^H in (22), and that this has not occurred in the goods sector.

⁴¹If two occupations have different names, or titles, but identical task contents, then for the purpose of this exercise, they are the same occupation. In principle, δ could have also varied by occupation, but this is not important for what follows.

⁴²See Autor, Katz, and Krueger (1998). Krueger (1993) shows that workers who use computers more earn more.

Testing this hypothesis requires a mapping from occupations to tasks. This is given by the DOT, to which I turn next. Changes in average task requirements reflect changes in the distribution over occupations. An *increase* in average *non-routine tasks* reflects a shift towards computer complementary occupations, which, according to the conceptual framework, leads to faster productivity growth. A *decrease* in average *routine tasks* reflects a shift away from computer substitutable occupations, which, according to the conceptual framework, also leads to faster productivity growth.

7.3 Construction of DOT task indices

Five 1977-DOT task requirements by occupation (373) and gender (2) were obtained from David Autor.⁴³ The occupations are classified according to the 1990 Census system. The task requirements capture routine and non-routine tasks, which can be either manual or cognitive, as shown in **Table 3**.

The task requirements and their meanings are as follows: *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. Notice that *MATH* and *PLAN* are separate categories. Table B provides more details and examples for the task requirements and **Table C** reports summary statistics. The task measures vary over the [0,10] interval. 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 2001.⁴⁴

After matching the task requirements into the CPS sample, I aggregate tasks in every year into industry-education-gender cells. For each *TASK* I calculate the weighted average by industry-education-gender

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

where n denotes a particular individual, i is industry, g is gender and $e \in \{11, 12, 14, 16\}$ is education. 11 means less than 12 years of schooling, 12 means 12 years, 14 means 13-15

⁴³I am greatfull to David Autor for sharing this data with me.

⁴⁴Although a consistent occupation classification is used for the entire sample, it does not perform well for separate sectors outside of the 1967-2001 sample. For complete documentation see the Appendix.

years and 16 means 16 years or more. $n \in \langle ieg \rangle$ means that individual n is a member of the $\langle ieg \rangle$ cell. λ are CPS weights and hrs are annual hours. When doing this, also store

$$\begin{aligned}\lambda_{ieg} &= \sum_{n \in \langle ieg \rangle} \lambda_n \\ hrs_{ieg} &= \sum_{n \in \langle ieg \rangle} hrs_n.\end{aligned}$$

There are 1066 non-empty $\langle ieg \rangle$ cells in 1967, which constitute a grid over the task values. I construct the empirical distribution of $TASK_{ieg}$ in 1967. Denote this distribution by F . For each value of $TASK_{ieg}$ in the following years I find its position in the 1967 distribution, $F(TASK_{ieg})$. The task index used in the analysis is the average percentile in the 1967 distribution by sector and education level

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

where $i \in \langle s \rangle$ means that industry i is in sector $s \in \{goods, services\}$, and education, e , is defined above.⁴⁵ Finally, in order to compare changes in all the task indices for each education-sector group, normalize each task index to one in 1967 by dividing the index in all years by the value in 1967. Thus, $TASK_{se}$ is equal to one in 1967. I construct indices for high school and college equivalents using a similar procedure as for their labor supply.⁴⁶

Using the F -values, rather than the actual task values has two benefits. First, it makes the task indices comparable in magnitude, since they are all in percentiles. Second, it assigns smaller weight to extreme changes in $TASK_{ieg}$ values, especially in ranges that are less dense in 1967. The results are qualitatively the same if I just use weighted averages instead of using the 1967 distribution.

7.4 The evolution of task indices

The evolution of the five task indices for high school equivalents and college equivalents in services and goods sectors support the findings of the estimation. Before presenting the graphic evidence, I summarize the evolution of the five task indices as follows.

⁴⁵Spitz-Oener (2006) reports the evolution of similar task indices by education level in the German economy, but not in different sectors. She finds that the evolution of these indices is similar to what is observed in the U.S. economy by Autor, Levy, and Murnane (2003).

⁴⁶See the Appendix for more details on the construction.

1. *In the services sector* high school equivalents are increasing their non-routine tasks, which, according to the conceptual framework, accelerates their productivity growth. For college equivalents it is flat. High school equivalents are decreasing their routine tasks. College equivalents are actually increasing their routine cognitive tasks substantially, which slows down their productivity growth.
2. *In the goods sector* high school equivalents are increasing slightly their non-routine cognitive tasks and decreasing slightly their non-routine manual tasks. For college equivalents these are flat. High school equivalents are decreasing their routine tasks, but the decrease in routine tasks for college equivalents is even larger.

The occupational mix of high school equivalents in services has shifted towards non-routine tasks and away from routine tasks. But in order for this to imply relative productivity gains relative to college equivalents, it must happen to a greater extent than for college equivalents. In order to gauge how large the differences are, define

$$\Delta TASK_s = \frac{TASK_{s,HS}}{TASK_{s,COL}} - 1,$$

which measures the relative task intensity of high school versus college equivalents for each task, in services and goods sectors, $s \in \{goods, services\}$. Since all $TASK_{se}$ indices are equal to one in 1967, $\Delta TASK_s$ is equal to zero in 1967.

Figure 9 plots all five $\Delta TASK_s$ separately for goods and services. Both panels in the figure have the same scale. Three things immediately stand out. First, the changes in $\Delta TASK_s$ are much larger in services than in the goods sector. Second, ΔDEX and $\Delta STAND$ move in opposite directions in services and goods. Thirdly, $\Delta MATH$ increases substantially in services, but hardly in the goods sector.

Table 4 summarizes the differences in $\Delta TASK_s$ from 1967 to 2001 in percent points. In services, routine manual task intensity (ΔDEX) and routine cognitive task intensity ($\Delta STAND$) have substantially decreased for high school versus college equivalents. These actually increased in the goods sector. In services, analytical non-routine cognitive task intensity ($\Delta MATH$) has significantly increased for high school versus college equivalents, while it hardly changed in goods. Non-routine interactive task intensity ($\Delta PLAN$) for high school versus college equivalents has increased somewhat in both sectors. Finally. In

services non-routine manual task intensity ($\Delta COORD$) has substantially increased for high school versus college equivalents. In the goods sector it slightly decreased.

These changes point in the same direction. In services, high school equivalents have dramatically shifted out of occupations that are relatively more computer substitutable, and into occupations that are relatively more computer complementary. This tends to increase their productivity. Since college equivalents have not reallocated in that pattern, productivity growth for high school equivalents might well be faster than for college equivalents. We do not observe this pattern in the goods sector, which is consistent with faster productivity growth for college equivalents.

Recall that in the main estimation results we had $a_1 = 0.02$, i.e. unskilled workers have increased their productivity in services faster than in goods. The evolution of the occupational mixes is consistent with this. In particular, high school equivalents in services has shifted towards non-routine analytical intensive occupations much more than in the goods sector. In order to gauge this change, define

$$\Delta MATH_{HS} = \frac{MATH_{s,HS}}{MATH_{g,HS}} - 1.$$

$\Delta MATH_{HS}$ increased by 20 percent points from 1967 to 2001. The other four task intensities have remained roughly the same for high school graduates in services and goods sectors in relative terms.

8 Conclusions

Taking into account the sectoral composition of the economy changes our conclusions on the nature of technological change and the way it affects the relative wage of college graduates. Directly exploiting the general equilibrium restrictions and optimality conditions of the model reveals that technological change has been biased in opposite directions in the services and goods sectors. Whereas in the goods sector college graduates have been increasing their average productivity faster than high school graduates, the opposite is found in the services sector.

The overall effect of both biases in technological change in the two sectors drives 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 productive 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, which become relatively more productive. Overall, relative demand for unskilled workers falls, commensurate with a decline in their relative wage. Convolution of these two effects leads us to infer SBTC at the aggregate level. The sector bias in technological change does not play a prominent role in explaining the relative role demand for college versus high school graduates.

Faster average productivity growth of high school graduates in services can be explained by a shift in the mix of occupations which they practice. Many routine tasks have been replaced by computers, e.g. filing. In services, unskilled workers have moved out of routine task intensive occupations, e.g. bank tellers, and into occupations that are more complementary with computers, e.g. in call centers. I argue that this shift is strong enough to explain how their average productivity growth outpaced the average productivity growth of college graduates in services. By contrast, in the goods sector unskilled workers have not shifted into computer complementary occupations. This is consistent with a decline in their relative productivity.

The model's estimates raise concerns for aggregate explanations for the increase in the college premium that rely on an aggregate elasticity of substitution between skilled and unskilled labor greater than one, e.g. Acemoglu (1998) and Thoenig and Verdier (2003). However, the trends in 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 characterizing occupations.

Much is left to be explained in future work. A quantitative structural analysis that takes into account education levels and the DOT tasks explicitly in production might be a first step towards a better understanding of the nature of occupational productivity and how it affects wage inequality over time. This might lead to a new theory for endogenous, induced technical change. One way to use the insights from such an exercise is to devise better educational policies.

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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, <http://www.unicon.com>, 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, including their estimate of the aggregate elasticity of substitution. In particular, I replicate their famous estimate of equation 19, which fits the following regression $\log(\omega_t) = c - (1/\sigma) \log(h_t) + \delta \cdot t$, where ω is the relative wage of college graduates versus high school graduates, and h is their relative supply.

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 $\min\{\text{age} - \text{years of schooling} - 7\}$, 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 we 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

$$hrs_{ct} = \frac{\sum_{n \in \langle c \rangle} \lambda_{nt} hrs_{nt}}{\sum_n \lambda_{nt} hrs_{nt}}, \quad (26)$$

where $t = 1963, 1964 \dots 2005$ is time in 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, which is calculated using data obtained from the 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

$$w_{ct} = \frac{\sum_{n \in \langle c \rangle} w_{nt} \lambda_{nt} hrs_{nt}}{\sum_n \lambda_{nt} hrs_{nt}}, \quad (27)$$

where $t = 1963, 1964 \dots 2005$ is time in 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 survey 1975. For those years weeks are imputed by calculating the average number of weeks within those bracket by gender.

Top coding. Until survey 1995, top coded wages were 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 set top code are grouped by sex, race, and worker status (full time full year/other). A mean income value is calculated within these groups and assigned to these individuals. Therefore, the largest values observed for these variables are greater than the topcode values.

Industry and occupation re-classifications. Over the 1963-2006 there have been a few industry and occupation re-classifications, the most substantial of which was in CPS 2003. This results in a 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 $M(i, j)$ 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 j_{1990} according to the Census 1990 system. The original matrix actually gives the information in the opposite direction (i.e. from j_{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 uses 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 Katz and Murphy (1992), except for the relative price of services.

As noted above, there are 64 cells in every year. I use a fixed weight to construct aggregated wage series

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

where hrs_{ct} is described above in (26). Using this fixed weights vector (this is KM's N vector) to calculate wages for more aggregate groups has the benefit of keeping the composition of the labor force fixed at some average level, so the results are not driven by changes in composition of large groups.

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

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

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

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

The regression embodies the assumption that high school dropouts and people with some college education are linear combinations of high school and college graduates in terms of their productivity. 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 A**. I collapse the merged count sample and wage sample into 8 cells by education level and sector in every year

$$w_{est} = \frac{\sum_{c \in \langle es \rangle} w_{ct} \overline{hrs_c}}{\sum_{c \in \langle es \rangle} \overline{hrs_c}} \quad \text{and} \quad hrs_{est} = \sum_{c \in \langle es \rangle} hrs_{ct},$$

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. $c \in \langle es \rangle$ 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. Then 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. 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). The industries roughly correspond to the industrial classification of the CPS which is described in the top

panel of **Table A**. 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 Aggregate pseudo elasticity

By totally differentiating (10) with respect to ω and h , one can gauge the aggregate EoS. By the implicit function theorem,

$$\frac{d\omega}{dh} = -\frac{\Phi_h}{\Phi_\omega}$$

and the pseudo aggregate EoS is given by

$$\tilde{\sigma} = -\frac{d \ln(h)}{d \ln(\omega)} = -\frac{dh/h}{d\omega/\omega} = \frac{\omega \Phi_\omega}{h \Phi_h}.$$

To ease notation, let

$$a = \left(\frac{A_s}{A_g} \right)^{1-\varphi}, \quad m = \left(\frac{\mu}{1-\mu} \right)^\varphi, \quad \eta_s = \frac{\varphi - \sigma_s}{1 - \sigma_s}, \quad \eta_g = \frac{\varphi - \sigma_g}{1 - \sigma_g}.$$

Derivation of $\omega \Phi_\omega$

$$\begin{aligned} \Phi_\omega &= a \frac{\sigma_g h_g \omega^{-1} (h_s - h) + \sigma_s h_s \omega^{-1} (h - h_g)}{(h_s - h)^2} \frac{(1 + \omega h_s)^{\eta_s}}{(1 + \omega h_g)^{\eta_g}} \\ &\quad + a \left(\frac{h - h_g}{h_s - h} \right) \frac{\eta_s (1 - \sigma_s) h_s (1 + \omega h_g)^{\eta_g - 1} + \eta_g (\sigma_g - 1) h_g (1 + \omega h_s)^{\eta_s - 1}}{(1 + \omega h_g)^{2\eta_g}} \\ &= a \left[\frac{\sigma_g h_g \omega^{-1}}{h - h_g} + \frac{\sigma_s h_s \omega^{-1}}{h_s - h} \right] \left(\frac{h - h_g}{h_s - h} \right) \frac{(1 + \omega h_s)^{\eta_s}}{(1 + \omega h_g)^{\eta_g}} \\ &\quad + a \left(\frac{h - h_g}{h_s - h} \right) \frac{(1 + \omega h_s)^{\eta_s}}{(1 + \omega h_g)^{\eta_g}} \left[\frac{\eta_s (1 - \sigma_s) h_s}{1 + \omega h_s} + \frac{\eta_g (\sigma_g - 1) h_g}{1 + \omega h_g} \right] \\ &= m \left[\frac{\sigma_g h_g \omega^{-1}}{h - h_g} + \frac{\sigma_s h_s \omega^{-1}}{h_s - h} + \frac{(\varphi - \sigma_s) h_s}{1 + \omega h_s} + \frac{(\sigma_g - \varphi) h_g}{1 + \omega h_g} \right]. \end{aligned}$$

So that

$$\omega \Phi_\omega = m \left[\frac{\sigma_g h_g}{h - h_g} + \frac{\sigma_s h_s}{h_s - h} + \frac{(\varphi - \sigma_s) \omega h_s}{1 + \omega h_s} + \frac{(\sigma_g - \varphi) \omega h_g}{1 + \omega h_g} \right].$$

Given our assumptions on $h_i, h_s > h > h_g$, we have $\omega\Phi_\omega > 0$. Proof: rewrite $\omega\Phi_\omega$ as follows

$$\omega\Phi_\omega = m \left[\sigma_g \frac{h_g + \omega h_g h}{(h - h_g)(1 + \omega h_g)} + \sigma_s \frac{h_s + \omega h_s h}{(h_s - h)(1 + \omega h_s)} + \varphi \frac{\omega(h_s - h_g)}{(1 + \omega h_s)(1 + \omega h_g)} \right].$$

All the terms in the brackets are positive.

Derivation of $h\Phi_h$

$$\begin{aligned} \Phi_h &= a \frac{(h_s - h) + (h - h_g)(1 + \omega h_s)^{\eta_s}}{(h_s - h)^2 (1 + \omega h_g)^{\eta_g}} \\ &= a \left(\frac{h - h_g}{h_s - h} \right) \frac{(1 + \omega h_s)^{\eta_s}}{(1 + \omega h_g)^{\eta_g}} \left[\frac{1}{h - h_g} + \frac{1}{h_s - h} \right] \\ &= m \left[\frac{(h_s - h_g)}{(h - h_g)(h_s - h)} \right]. \end{aligned}$$

So that

$$h\Phi_h = m \left[\frac{(h_s - h_g)h}{(h - h_g)(h_s - h)} \right].$$

Given our assumptions $h_s > h > h_g$, we have $h\Phi_h > 0$. Recall that h_i are functions of ω and β_i .

Aggregate pseudo EoS

$$\begin{aligned} \tilde{\sigma} &= \frac{\omega\Phi_\omega}{h\Phi_h} = \frac{m \left[\frac{\sigma_g h_g}{h - h_g} + \frac{\sigma_s h_s}{h_s - h} + \frac{(\varphi - \sigma_s)\omega h_s}{1 + \omega h_s} + \frac{(\sigma_g - \varphi)\omega h_g}{1 + \omega h_g} \right]}{m \left[\frac{(h_s - h_g)h}{(h - h_g)(h_s - h)} \right]} \\ &= \sigma_g \left[\frac{h_g(1 + \omega h)(h_s - h)}{h(1 + \omega h_g)(h_s - h_g)} \right] + \sigma_s \left[\frac{h_s(1 + \omega h)(h - h_g)}{h(1 + \omega h_s)(h_s - h_g)} \right] + \varphi \left[\frac{\omega(h - h_g)(h_s - h)}{h(1 + \omega h_g)(1 + \omega h_s)} \right] \end{aligned}$$

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 α_s 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 $Z_i [(1 - \alpha_i) L_i^{\rho_i} + \alpha_i H_i^{\rho_i}]^{1/\rho_i} \geq I$, where $I \in \{G, S\}$. This yields the following unit

cost functions

$$c_g = \frac{1}{Z_g} \left[(1 - \alpha_g)^{\sigma_g} w_L^{1-\sigma_g} + \alpha_g^{\sigma_g} w_H^{1-\sigma_g} \right]^{\frac{1}{1-\sigma_g}} \quad (28)$$

$$c_s = \frac{1}{Z_s} \left[(1 - \alpha_s)^{\sigma_s} w_L^{1-\sigma_s} + \alpha_s^{\sigma_s} w_H^{1-\sigma_s} \right]^{\frac{1}{1-\sigma_s}}, \quad (29)$$

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

$$h_g = \omega^{-\sigma_g} \gamma_g^{\sigma_g} \quad (30)$$

$$h_s = \omega^{-\sigma_s} \gamma_s^{\sigma_s}, \quad (31)$$

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 productivity of skilled workers.

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 (28)-(29) to get

$$c_g = \frac{w_L}{Z_g (1 - \alpha_g)^{\frac{\sigma_g}{\sigma_g-1}}} [1 + \omega h_g]^{\frac{1}{1-\sigma_g}} = 1$$

$$c_s = \frac{w_L}{Z_s (1 - \alpha_s)^{\frac{\sigma_s}{\sigma_s-1}}} [1 + \omega h_s]^{\frac{1}{1-\sigma_s}} = p.$$

Take the ratio and use (30) and (31) to get the relative price of services

$$p = \frac{Z_g (1 - \alpha_g)^{\frac{\sigma_g}{\sigma_g-1}} [1 + \omega h_s]^{\frac{1}{1-\sigma_s}}}{Z_s (1 - \alpha_s)^{\frac{\sigma_s}{\sigma_s-1}} [1 + \omega h_g]^{\frac{1}{1-\sigma_g}}}. \quad (32)$$

Unit factor requirements were obtained by taking the derivative of the unit cost functions with respect to the wage. By using (30)-(31) we can write them as follows

$$L_i^1 = \frac{1}{Z_i (1 - \alpha_i)^{\frac{\sigma_i}{\sigma_i-1}}} [1 + \omega h_i]^{\frac{\sigma_i}{1-\sigma_i}}$$

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

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

$$\begin{aligned} L &= SL_s^1 + GL_g^1 = S \frac{1}{Z_s (1 - \alpha_s)^{\frac{\sigma_s}{\sigma_s - 1}}} [1 + \omega h_s]^{\frac{\sigma_s}{1 - \sigma_s}} + G \frac{1}{Z_g (1 - \alpha_g)^{\frac{\sigma_g}{\sigma_g - 1}}} [1 + \omega h_g]^{\frac{\sigma_g}{1 - \sigma_g}} \\ H &= SH_s^1 + GH_g^1 = S \frac{1}{Z_s \alpha_s^{\frac{\sigma_s}{\sigma_s - 1}}} \left[1 + (\omega h_s)^{-1} \right]^{\frac{\sigma_s}{1 - \sigma_s}} + G \frac{1}{Z_g \alpha_g^{\frac{\sigma_g}{\sigma_g - 1}}} \left[1 + (\omega h_g)^{-1} \right]^{\frac{\sigma_g}{1 - \sigma_g}} \end{aligned} \quad (33)$$

By manipulating (33)-(34) we obtain the following expression for relative output

$$\frac{S}{G} = \frac{Z_s (1 - \alpha_s)^{\frac{\sigma_s}{\sigma_s - 1}}}{Z_g (1 - \alpha_g)^{\frac{\sigma_g}{\sigma_g - 1}}} \left(\frac{h - h_g}{h_s - h} \right) \frac{(1 + \omega h_g)^{\frac{\sigma_g}{1 - \sigma_g}}}{(1 + \omega h_s)^{\frac{\sigma_s}{1 - \sigma_s}}}, \quad (35)$$

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

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

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

Using this together with (35) and (30)-(31) we get

$$\begin{aligned} &\Phi(\omega, h, \gamma_g, \gamma_s, Z_s/Z_g) \\ &= \left[\frac{Z_s (1 - \alpha_s)^{\frac{\sigma_s}{\sigma_s - 1}}}{Z_g (1 - \alpha_g)^{\frac{\sigma_g}{\sigma_g - 1}}} \right]^{(1 - \varphi)} \left(\frac{h - h_g}{h_s - h} \right) \frac{(1 + \omega h_s)^{(\varphi - \sigma_s)/(1 - \sigma_s)}}{(1 + \omega h_g)^{(\varphi - \sigma_g)/(1 - \sigma_g)}} - \left(\frac{\mu}{1 - \mu} \right)^{\varphi} \\ &= \left[\frac{Z_s (1 - \alpha_s)^{\frac{\sigma_s}{\sigma_s - 1}}}{Z_g (1 - \alpha_g)^{\frac{\sigma_g}{\sigma_g - 1}}} \right]^{(1 - \varphi)} \left(\frac{h - \omega^{-\sigma_g} \gamma_g^{\sigma_g}}{\omega^{-\sigma_s} \gamma_s^{\sigma_s} - h} \right) \frac{(1 + \omega^{1 - \sigma_s} \gamma_s^{\sigma_s})^{(\varphi - \sigma_s)/(1 - \sigma_s)}}{(1 + \omega^{1 - \sigma_g} \gamma_g^{\sigma_g})^{(\varphi - \sigma_g)/(1 - \sigma_g)}} \\ &\quad - \left(\frac{\mu}{1 - \mu} \right)^{\varphi} = 0. \end{aligned} \quad (36)$$

Note that the only differences between (36) 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

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

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

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

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 ,

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

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 $\gamma_i = \exp\{\gamma_{0,i} + \gamma_{1,i} t\}$, versus $A_s/A_g = \exp\{a_0 + a_1 t\}$ and $\beta_i = \exp\{\beta_{0,i} + \beta_{1,i} t\}$, $i \in \{g, s\}$. There is an equivalent representation of β_i in terms of γ_i and vice versa. Since $\beta = \gamma^{1/\rho}$, we have $\beta_i = (\exp\{\gamma_{0,i} + \gamma_{1,i} t\})^{1/\rho} = \exp\{(\gamma_{0,i}/\rho) + (\gamma_{1,i}/\rho) t\}$, 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 $Z_i = A_i (1 + \beta_i^\rho)^{1/\rho_i}$. 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 $A_i = Z_i (1 + \gamma_i)^{-1/\rho_i}$.

F Construction of DOT task indices: 1967-2001

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 requirements from the Dictionary of Occupational Titles (DOT).

Consistent occupation classification. I re-classify the occupations in the CPS to a consistent occupation classification according to the 1990 Census system. This is done using Stata code obtained from Peter Meyer, which is based on Meyer and Osborne (2005). After some testing, I slightly modified the code to capture a few additional occupations which were originally missed.

Although the consistent occupation classification is used for the entire sample, it does not perform well outside of the 1967-2001 sample. 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 requirements. Five 1977-DOT task requirements by occupation (373) and gender (2) were obtained from David Autor. The occupations are classified using the same consistent system mentioned above, with very minor modifications.

After merging, each individual in the sample has five task requirements: *DEX* (finger dexterity), *COORD* (eye hand foot coordination), *STAND* (set limits, tolerances and standards), *MATH* (math aptitude) and *PLAN* (direction, control and planning). **Table B** provides more details and examples for the task requirements. 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 potentially vary over the $[0, 10]$ interval. In **Table C** I report summary statistics for the original 746 observations on each task.

Originally, there were 3886 1977-DOT occupations, which were assigned to 411 1970 Census occupations. This was done using the April 1971 CPS, for which experts from the National Academy of Sciences assigned DOT occupations. The task measures 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.

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

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

$$F(TASK_{ieg}) = F_r \text{ if } TASK_r \leq TASK_{ieg} < TASK_{r+1}.$$

I do not interpolate between values because it is computationally taxing (in Stata) and really redundant because the grid for 1967 is very fine (there are 1066 points). Not interpolating introduces a very slight downward bias in the indices for all years after 1967, but this does not affect how the index evolves after 1968.

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.

Implementation: college and high school equivalents. In practice, we 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 (23), except that here a_o^e is indexed by education level. This reflects the assumption that two individuals with different education levels but working in the same occupation have different occupational productivity. Now, 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 productivities are in the same denomination, a_o^{12} , we can drop the superscript, while remembering that these are high school equivalent productivities. 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 productivity 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 productivity 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

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

The equivalence weights ensure that the weighted average is consistent with the quantities that entered the empirical analysis.

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 productivity of one class to 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

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

where $\tilde{\epsilon}_{11}^{12}$ 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 productivities.

Table 1: Estimates

	Services	Goods	Demand
Elasticities of substitution	$\sigma(s)$	$\sigma(g)$	φ
	0.625	6.88	0.013
	(0.01)	(0.3)	(0.019)
	Productivity parameters		
	Services	Goods	
Bias in technological change	$\beta(1,s)$	$\beta(1,g)$	$a(1)$
	-0.07	0.02	0.02
	(0.002)	(0.001)	(0.0015)
Initial value	$\beta(0,s)$	$\beta(0,g)$	$a(0)$
	1.77	-0.133	2.1
	(0.04)	(0.025)	(0.0275)
Standard deviation of technological shocks	$v(s)$	$v(g)$	$v(a)$
	0.01	0.008	0.008
	(0.015)	(0.01)	(0.01)
Fit (sum squared deviations)	0.97		

Notes: Reported numbers are average estimates of 500 simulations. Each simulation uses a different random draw of error terms. For each draw the model was estimated by simulated method of moments. Standard errors in parentheses are calculated using the estimates of 500 simulations. The technological parameters are for the relative productivity of skilled versus unskilled labor in services $\beta(s,t)=\exp\{\beta(0,s)+\beta(1,s)t+e(s,t)\}$, in the goods sector $\beta(g,t)=\exp\{\beta(0,g)+\beta(1,g)t+e(g,t)\}$, and for the relative productivity of unskilled in services versus unskilled in the goods sector $A_s/A_g=\exp\{a(0)+a(1)t+e(a,t)\}$. $v(i)$ are the estimated standard deviations of $e(i)$, for $i=s, g$ or a .

Table 2: Estimates of Auxiliary Model

	Services	Goods	Demand
Elasticities of substitution	$\sigma(s)$ 0.83 (0.1)	$\sigma(g)$ 5.9 (0.66)	φ 0.1 (0.22)
	Productivity parameters		
	Services	Goods	
Rate of change	$\gamma(1,s)$ 0.035 (0.002)	$\gamma(1,g)$ 0.02 (0.002)	$z(1)$ -0.022 (0.001)
Initial value	$\gamma(0,s)$ -0.759 (0.05)	$\gamma(0,g)$ -0.218 (0.062)	$z(0)$ 1.06 (0.4)
Standard deviation of technological shocks	$v(s)$ 0.016 (0.02)	$v(g)$ 0.0016 (0.0026)	$v(z)$ 0.001 (0.014)
Fit (sum squared deviations)	2.08		
Implied bias in technological change	$\beta(1,s)$ -0.171	$\beta(1,g)$ 0.024	

Notes: Reported numbers are average estimates of 500 simulations. Each simulation uses a different random draw of error terms. For each draw the model was estimated by simulated method of moments. Standard errors in parentheses are calculated using the estimates of 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 $\gamma(s,t)=\exp\{\gamma(0,s)+\gamma(1,s)t+e(s,t)\}$, in the goods sector $\gamma(g,t)=\exp\{\gamma(0,g)+\gamma(1,g)t+e(g,t)\}$, and for the relative Hicks-neutral productivity in services versus the goods sector $Zs/Zg=\exp\{z(0)+z(1)t+e(z,t)\}$. $v(i)$ are the estimated standard deviations of $e(i)$, for $i = s, g$ or z . 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 .

Table 3: DOT Task Requirements

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

Notes: Task requirements 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 4: Changes in Relative DOT Task Requirements: 1967-2001

	Services	Goods
<i>FINGDEX</i>	-14	5
<i>STAND</i>	-45	13
<i>COORD</i>	19	-2
<i>MATH</i>	15	0.7
<i>PLAN</i>	7	5

Notes: The table reports percent changes from 1967 to 2001 of $\Delta TASK$, which is the relative task intensity of high-school versus college equivalents for each *TASK*. Task requirements are from the Dictionary of Occupational Titles. *FINGDEX*: Finger-dexterity, *COORD*: eye-hand-foot coordination, *STAND*: set limits, tolerances and standards, *MATH*: math aptitude, *PLAN*: direction, control and planning.

Appendix Table A: Goods and Services Industries

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

Appendix Table B: DOT Task Definitions and Examples

Variable	DOT task definition	Interpretation	Example tasks from <i>Handbook of Analyzing Jobs</i>
<i>MATH</i> (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.
<i>PLAN</i> (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.
<i>STAND</i> (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.
<i>FINGDEX</i> (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.
<i>COORD</i> (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.

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

Appendix Table C: DOT Tasks Summary Statistics

A. Sample Statistics

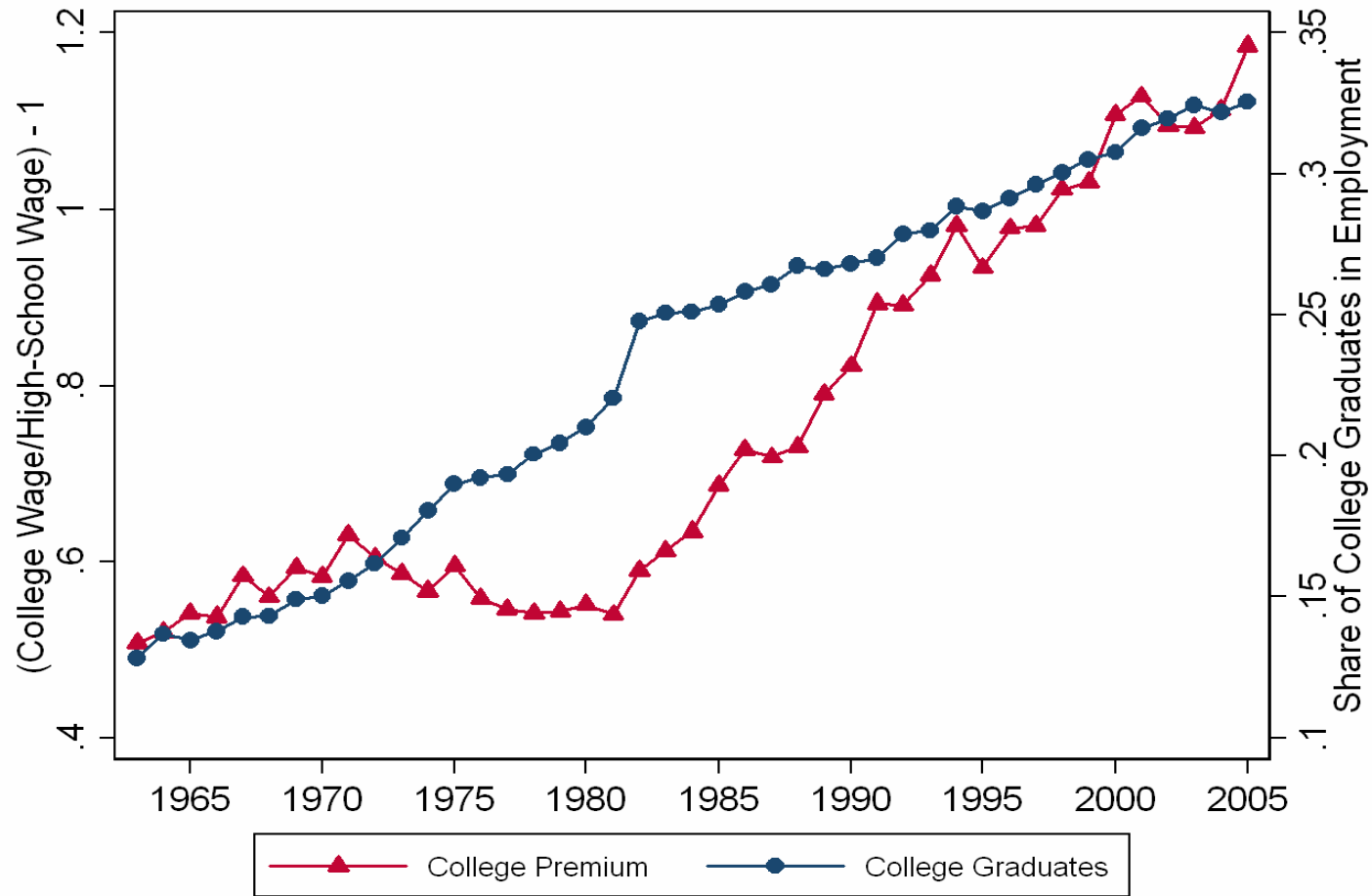
	Median	Mean	S.D.	Min	Max
FINGDEX	3.8	3.9	1.3	0	9
COORD	0.77	1.2	1.4	0	10
STAND	5.8	5.1	3.8	0	10
MATH	3.5	3.8	2.3	0	10
PLAN	0.5	2.3	3.2	0	10

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

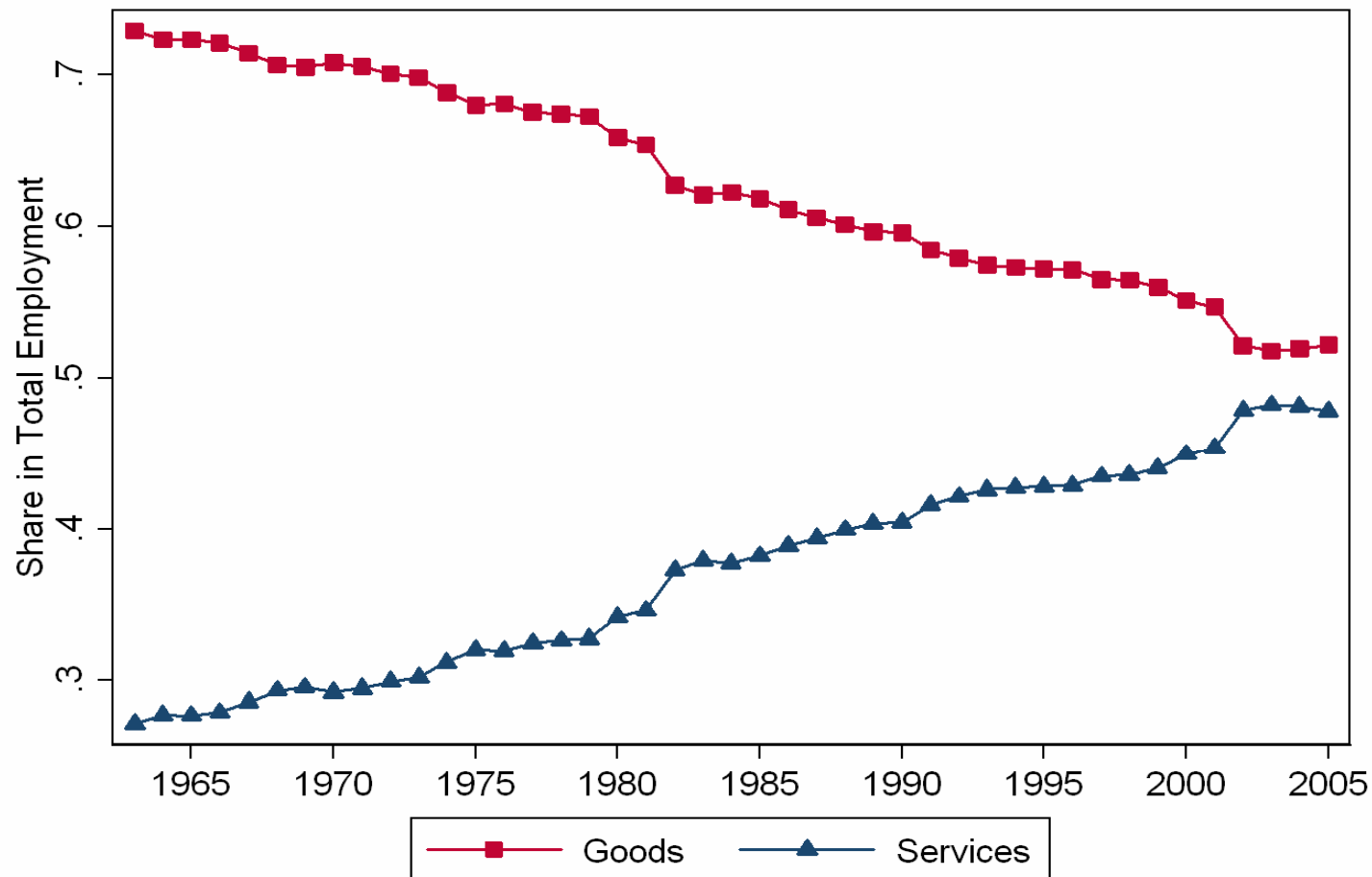
Notes: Statistics are calculated for 746 observations by occupation and gender. * denotes 5% statistical significance level.

Figure 1: College Premium and Relative Supply of College Graduates



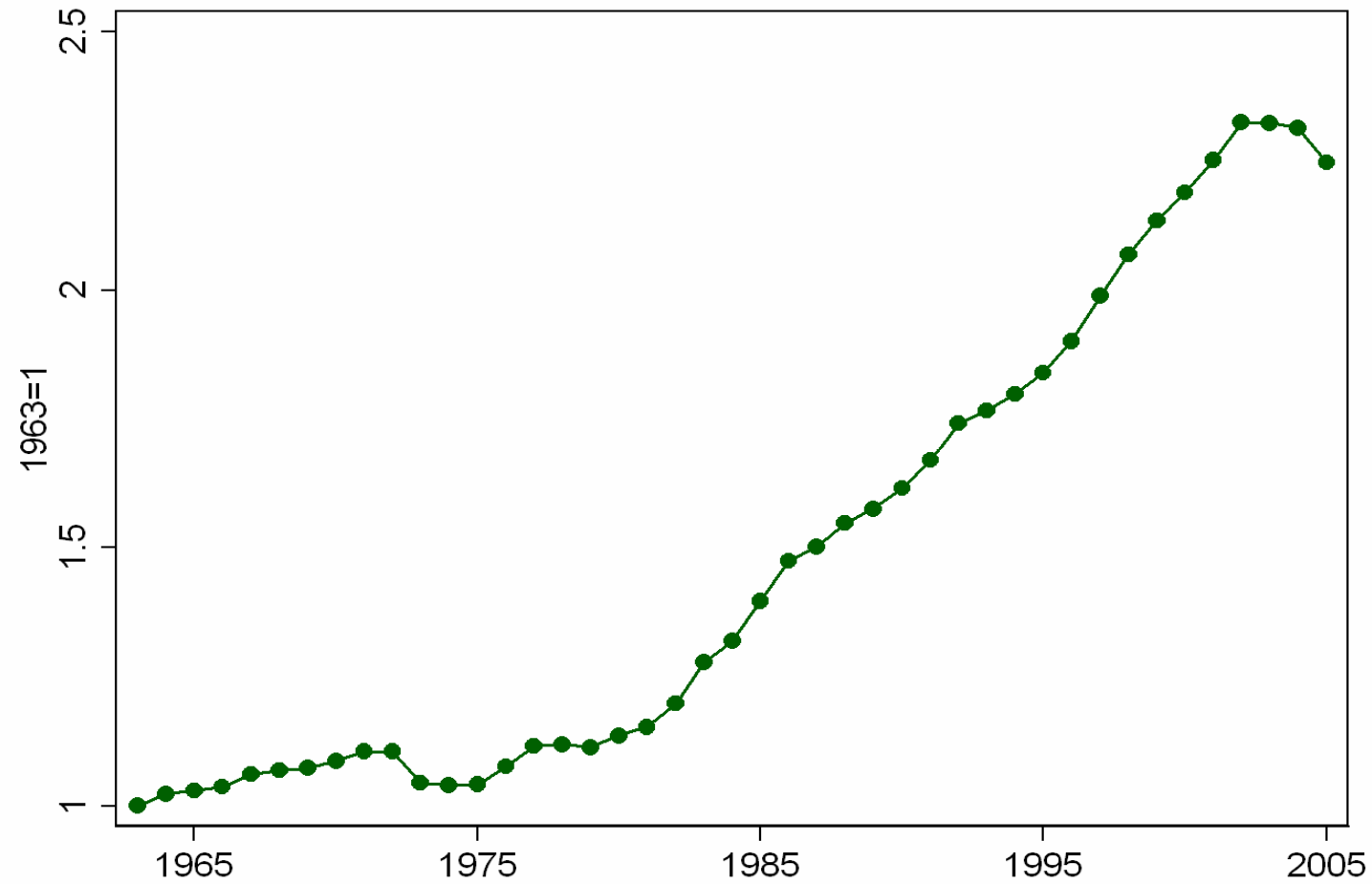
Notes: The College Premium is equal to the ratio of the average weekly wage of college graduates to average weekly wage of high-school graduates, minus one. College graduates are reported as their percent of the labor force. Source: March CPS 1964-2006.

Figure 2: Employment Shift Towards Skill-Intensive Services



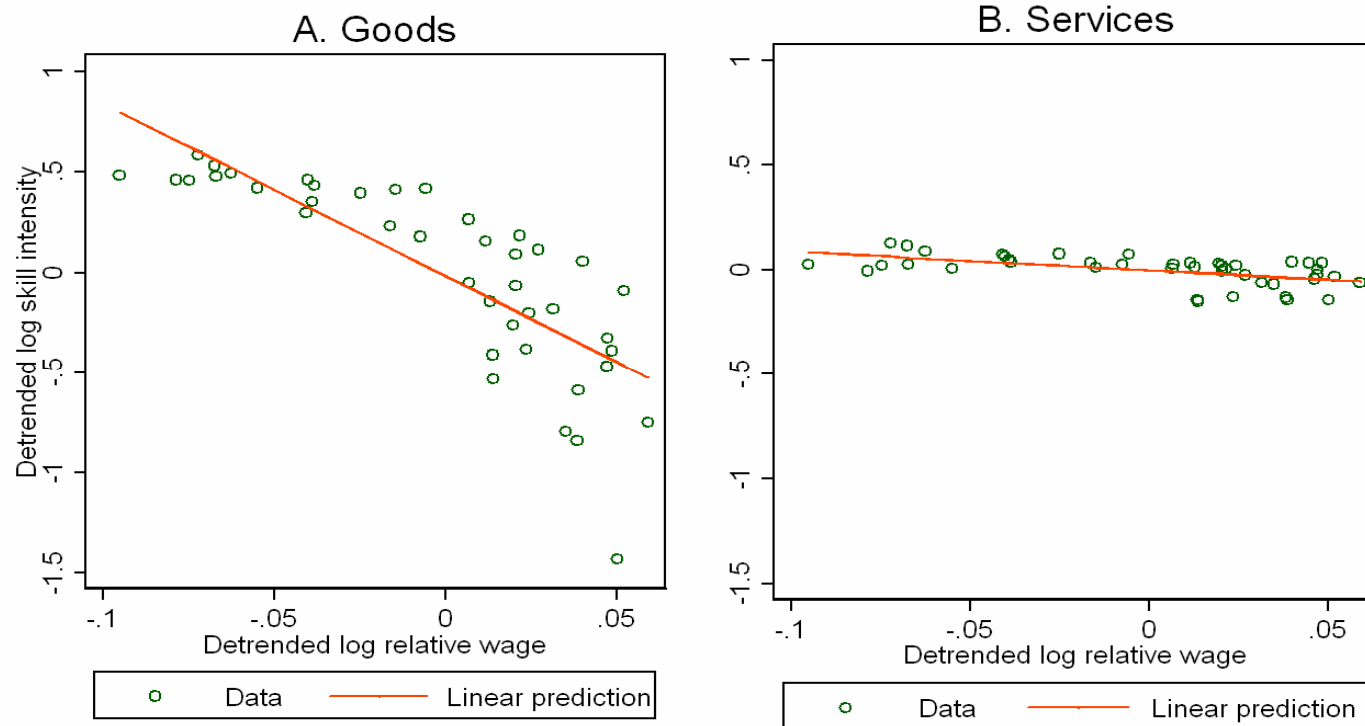
Notes: Employment is measured in annual hours times CPS weights as a fraction of total private sector employment. Sectors are defined in **Table A**. The breaks in the series in 1981-1982 and in 2001-2002 are due to industry reclassifications in the CPS. For the 2001-2002 break a reallocation procedure 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.

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



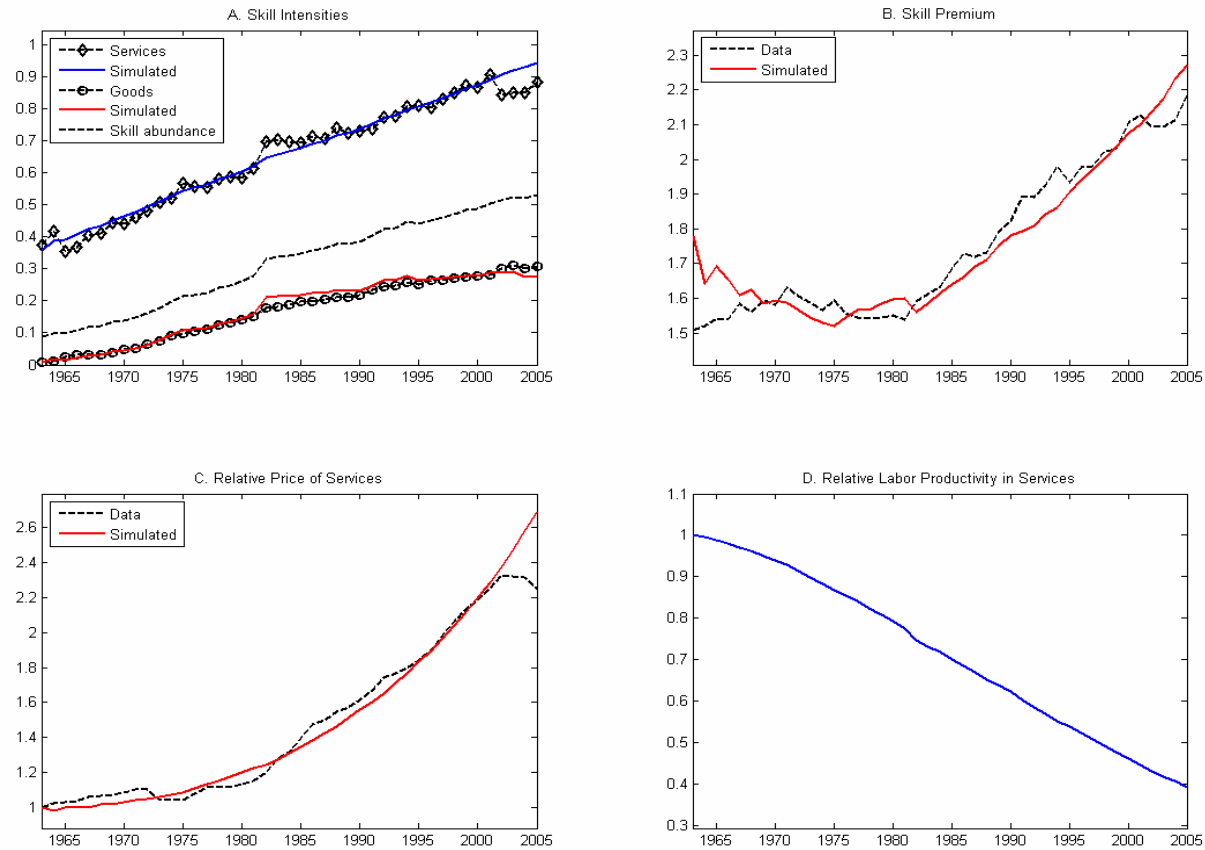
Notes: The price for the skill-intensive and goods sectors in each year is a weighted average of chain-type prices of industries that fall in that sector, where the weights are value added. The relative price of services versus goods is their ratio, which is normalized to one in 1963. Sectors are defined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

Figure 4: Relative Wage and Skill Intensity



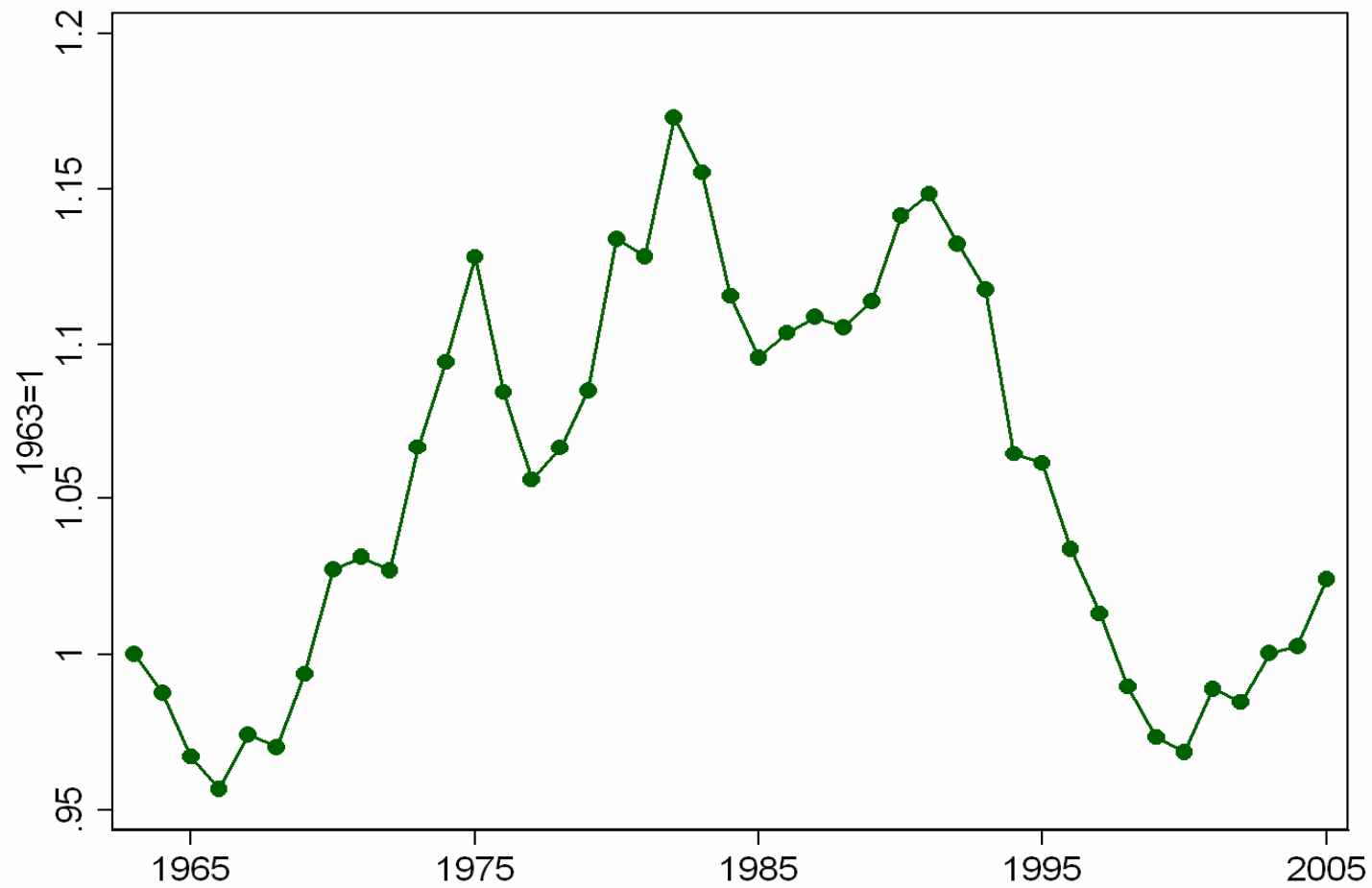
Notes: The relative wage is for college graduates versus high-school graduates in the entire economy. Skill intensities are the ratio of college to high-school equivalents in the goods and services sectors. Sectors are defined in **Table A**. All detrended series are residuals from a regression of the 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



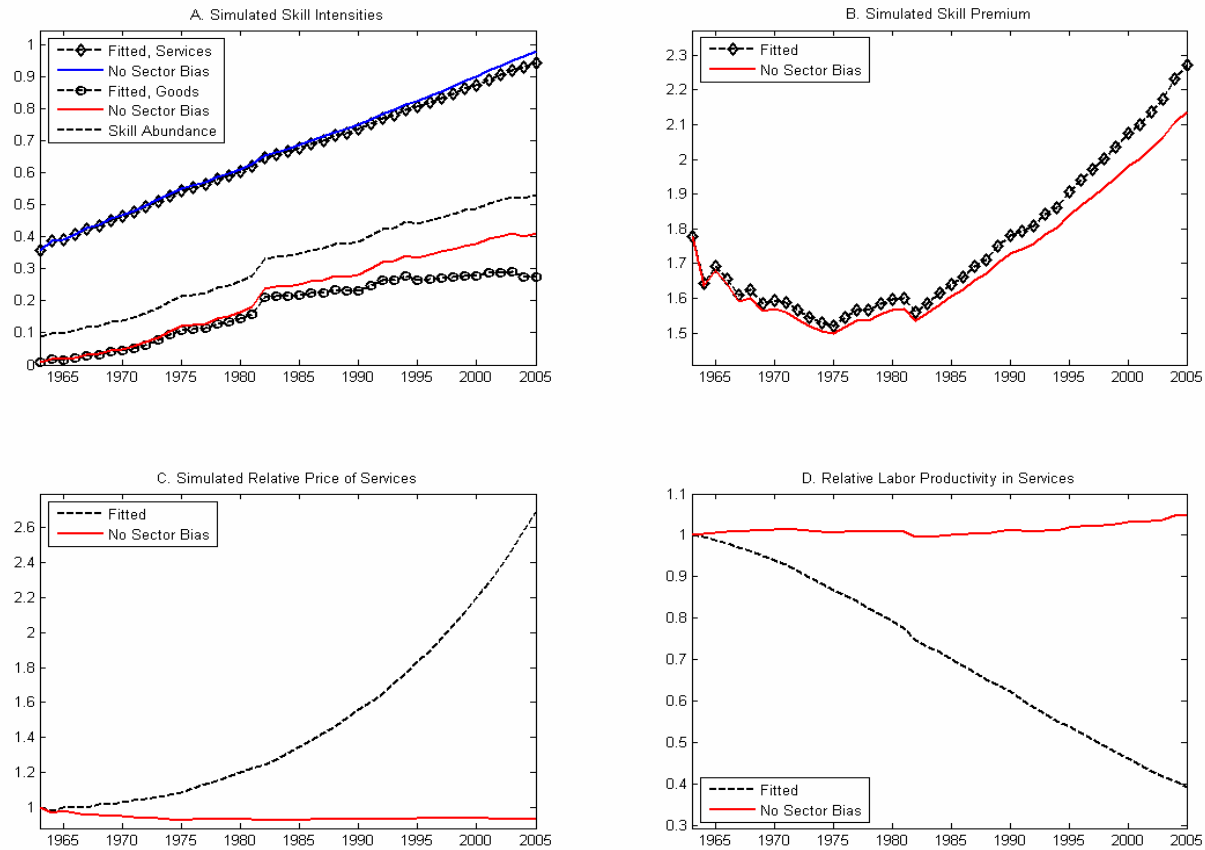
Notes: The figure shows the data that was used for the simulated method of moments estimation and the simulated series with the optimal parameters.

Figure 6: Relative Output of Services versus Goods



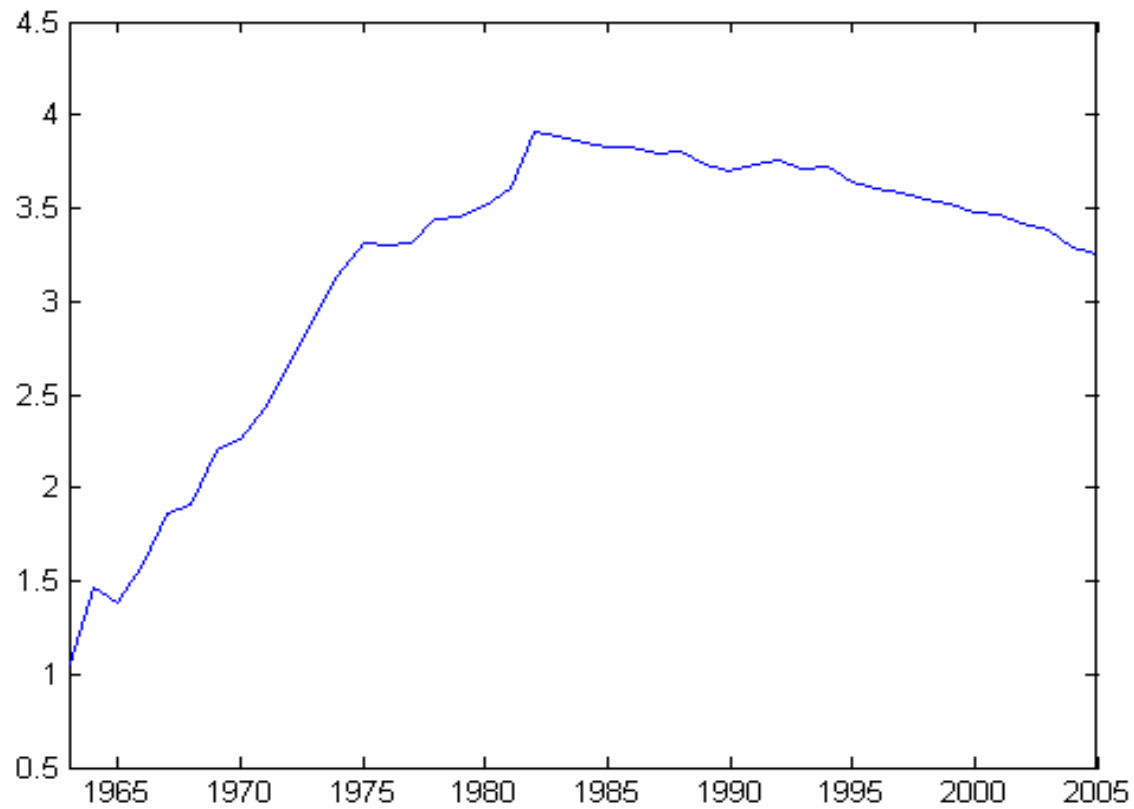
Notes: Relative output in skill-intensive services versus goods is calculated as the ratio of value-added in the service sector divided by value-added in the goods sector, further divided by the relative price of services, defined above in the text. The ratio is normalized to one in 1963. Sectors are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

Figure 7: Fixed Inter-Sector Productivity



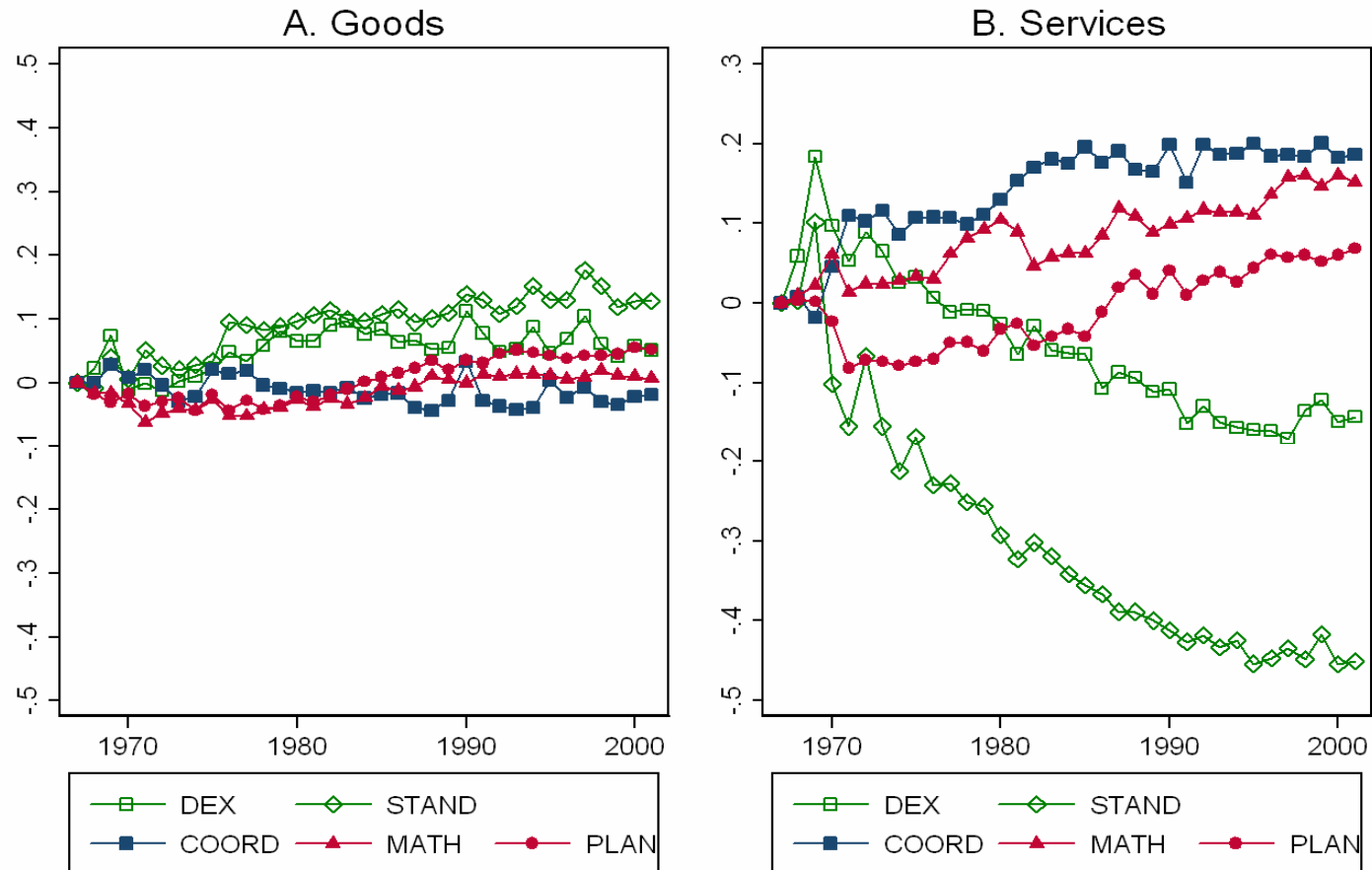
Notes: Fitted series are simulated using the estimated parameters from the estimation. No Sector Bias series are simulated while keeping the Hicks-neutral relative productivity of services versus goods fixed. In that case all other parameters are held at the estimated values.

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 calculated using the estimates of the model from **Table 1**.

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



Notes: Each task index is a weighted average of percentiles in the 1967 distribution, normalized to one in 1967. The relative task index is the ratio of the index for high-school to college equivalents, minus one, which normalizes it to zero in 1967. 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.