Wage Inequality in the U.S.: Capital-Skill Complementarity Vs. Skill-Biased Technological Change

Marta Ruiz-Arranz*
Harvard University

This draft: January 2003

Abstract

This paper provides a rigorous analysis of the sources of changes in the U.S. skill premium between 1965-1999. Over this period, the relative wages of skilled workers have increased significantly despite the substantial growth in their relative supply. I present new empirical estimates of the impact of technology and various measures of capital in the demand for skilled labor, based on a translog production model with four (and five) factors and separate trends for the factor biases of technical change. I find that capital-skill complementarity accounts for at most 40 percent of the rise in the skill premium, with factor nonneutral technological change and other unobservable factors accounting for most of the variation in the skill premium. Furthermore, the contribution of capital is decreasing over time while the technology effect is accelerating. I show that only a small fraction of equipment capital, information technology, is complementary to skilled labor. In fact, equipment excluding IT has narrowed the skilled wage gap. I also find that skill-biased technological change takes the form of rising skilled labor efficiency and declining unskilled labor efficiency, with the latter becoming increasingly important over time. In addition, IT-using innovations are found to drive the skill premium down, which suggests that the total effect of IT is smaller than the one predicted by changing quantities alone. Finally, I find that the data reject less flexible specifications in favor of the translog model.

*Department of Economics, Harvard University, Cambridge, MA 02138. Email: arranz@fas.harvard.edu. I am indebted to Francesco Caselli and Dale Jorgenson for their invaluable advice and support. A special thanks to Jon Samuels for his encouragement and help with the data. I also thank Daron Acemoglu, Alberto Alesina, Chris Foote, Fabia Gumbau, Larry Katz, and seminar participants at Harvard University and the EEA 2002 conference for helpful comments. Financial support from the McArthur Foundation and the Fundación Ramón Areces is gratefully acknowledged.

1 Introduction

Over the past 35 years, the share of workers with college education has nearly tripled in the U.S. Despite this strong upward trend in the relative supply of more-educated workers, there has been a substantial increase in the college/high school wage differential. These changes provide evidence of considerable shifts in the relative demand for more-educated workers. This paper develops a framework to analyze the sources of variation in the relative demand for skilled labor and applies it to time series data from the U.S. over the period 1965-1999. Specifically, I present new empirical estimates of the impact of factor nonneutral technological change and different types of capital on the rise in the skill premium, defined as the relative wage of skilled to unskilled labor. The framework I develop allows me to disentangle and separately quantify the effects of skill-biased technical change and capital-skill complementarity, as driving forces behind increased wage inequality. Although these two forces, to be formally defined later, have not explicitly been distinguished in previously literature, their different nature and evolution over time prove that the distinction is important.

Katz and Murphy (1992) propose a simple demand and supply framework to understand changes in the wage structure. They find that fluctuations in the growth of the relative supply of college workers combined with steady demand growth for these workers do fairly well in capturing observed movements in the skill premium over the period 1963-1987. A regression of the log of the college wage premium on the log quantity of college to high school graduates and a time trend delivers an R-squared of about 50 percent and implies an annual growth rate in the demand for skilled labor of 3.3 percent[1]. The quantification of the sources behind the increased demand for skill labor is beyond the scope of their paper. However, the authors associate this trend with nonneutral technological change, changes in prices of nonlabor input or steady shifts in industrial composition. In the literature, rapid growth in the demand for skilled labor is usually linked to the computer revolution, the new economy, and the diffusion of new technologies, which are likely to favor skilled workers and to displace less educated workers. Along these lines, the existence of a computer wage premium, as well as positive cross-industry correlations of capital intensity and indicators of new technologies with worker skills, provide evidence of both skill-biased technological change and capital-skill complementarity[2].

Revival of this literature at the macro level is due to Krusell et al (2000), who find that with

[1] Bound and Johnson (1992) also report the importance of a trend component. They conclude that observable variables can account for a very small fraction of the increased wage inequality, and that much of the variation in the skill premium is attributed to a residual trend -skill-biased technological change- that has shifted the demand for skilled labor.

[2] Krueger (1993), Berman et al (1994), Doms et al (1997), Autor et al (1998). For theoretical analysis of the skill-biased technological change hypothesis see Greenwood and Yorukoglu (1997), Galor and Tsiddon (1997), Acemoglu (1998), and Caselli (1999).

capital-skill complementarity[3], changes in observed inputs alone can account for most of the historical variation in the skill premium. According to the authors, the positive time trend in Katz and Murphy is capturing a large increase in the stock of equipment, which is complementary to skilled labor.

A simple regression analysis encompasses these two views and raises new interesting questions. Table 1 presents estimates of OLS regressions of the log of the college wage premium on a time trend and various measures of capital[4]. It is worth describing these results since they constitute the main motivation of this paper. Column 1 displays estimates of the Katz and Murphy specification applied to my data between 1965 and 1999. The estimates are consistent with the ones found by the authors, and suggest that the relative demand for college workers has been growing at an annual rate of 2 percent. The fit of this regression is considerably higher given the longer time period -the adjusted R-squared is 0.85 compared to 0.52 in Katz and Murphy. Column 2 shows a regression that replaces the time trend with the log ratio of equipment capital. Besides being significant and suggesting capital-skill complementarity effects, this term can account for a similar fraction of the variance in the skill premium as the time trend in Katz and Murphy. This result is hardly surprising given the high correlation between capital and a time trend. However, this effect disappears -it actually changes sign[5]- as soon as equipment and the time trend are entered simultaneously in the regression. Contrary to the finding by Krusell et al, this result suggests that the time trend in the Katz and Murphy model is not serving as a proxy for omitted capital-skill complementarity effects. The negative coefficient on equipment casts doubt on the hypothesis that links the increase in equipment capital to the rise in the skilled wage gap. It also motivates the first question this paper addresses: what fraction of the increased skill premium is accounted for by changes in capital, and what fraction is accounted for by technical change and other unobserved factors, proxied by a time trend in the regression? In other words, is it latent skill-biased technological change or capital-skill complementarity, or a combination of both, that has increased the skill premium?

A second set of questions arises when one analyzes the various components of capital in detail. The distinct evolution of a small subset of the stock of equipment, information technology (IT), with respect to the rest of equipment suggests the possibility of differentiating these two components in the regression analysis. On average, IT makes up for 17 percent of the total value of equipment[6]. The stock of IT has been growing at about five times the rate of equipment non IT over the period 1965-1999. Furthermore, the price of IT has decreased at an average rate of 3.6 percent per year, while the price of equipment non IT increased about 4 percent per year (see Figures 2.1-2.4).

With IT equipment, as opposed to total equipment, the implications of the simple regression

[3] The concept of capital-skill complementarity is formalized by Griliches (1969) in terms of Allens elasticities of substitution (Allen, 1938). Complementarity exists when increasing the amount of one factor raises the marginal benefit of another factor. This would suggest that complementary factors will tend to be used together in production.

[4] Table 2 contains OLS regressions, using prices of capital instead of quantities. The implications are similar.

[5] The negative coefficient on equipment capital is not statistically significant at 10 percent significant level.

[6] The share of IT in total equipment has grown from less than 9 percent in 1965 to 25 percent in 1999.

exercise change completely (see columns 4 and 5 of Table 1). In this case, the coefficient on IT is robust (positive and significant) to the inclusion of a time trend and the time trend is not significantly different from zero. IT-skill complementarity can account for most of the variation in the skill premium, with or without technical change (i.e. the time trend) in the model. In contrast, the regression with equipment excluding IT (EQnonIT) shows a positive and significant time trend and a negative relationship between the relative earnings of college workers and this measure of equipment, implying substitutability between the two inputs.

Columns 10 and 11 in Table 1 reinforce this finding. When IT and EQnonIT enter simultaneously in the regression, IT is found to drive the college premium up, whereas EQnonIT is found to have a negative and significant impact on the wages of more-educated workers. In addition, the fact that the time trend remains statistically significant when included along with these two measures of equipment suggests a potential separate role for biased technology and for each type of capital.

To summarize, a simple regression exercise shows that Katz and Murphy's time trend is not explained by equipment-skill complementarity, as argued by Krusell et al. In fact, the growth of the largest component of equipment has tended to narrow the skilled wage gap. However, a small but growing subset of the stock of equipment, IT capital, does show a close association with changes in the relative wages of skilled labor.

The questions this paper addresses are motivated by the regression results presented above. These results call for: first, a more rigorous analysis of the capital-skill complementarity hypothesis versus the skilled-biased technological change explanation of the increase in the skilled-wage gap. I set about trying to quantify what observable variables (measures of capital), as opposed to technical change and other unobservable factors, can explain about the rise in the skill premium. The second objective of this paper is to analyze the pattern of substitution among factors of production in order to identify which type of capital is complementary to skilled labor and can therefore be held responsible for the rise in inequality. The evidence presented above reveals how differently the two components of equipment interact with skilled labor input in production, and reinforces the need to treat them as differentiated factors. This paper constitutes the first attempt to examine substitutability/complementarity between IT and labor inputs. Finally, an explanation based on skill-biased technological change requires a definition and measurement of the factor biases of technical change, which is accomplished in this paper in a rather innovative way.

I develop a framework to disentangle the effects of skill-biased technological change and capital-skill complementarity and apply it to time series data from the U.S. over the period 1965-1999. Capital-skill complementarity is defined as in Griliches (1969). For comparative purposes, I sometimes use an alternative definition, by which there is X-skill complementarity if increases in type X capital -triggered by the decline of its price- induce a higher demand for skilled labor and raise the skill premium. Similarly, to the extent that technology increases the demand for skilled labor and their relative wage, I claim there is skill-biased technological change. This definition of skill-biased technological change is broad in that not only changes in the efficiency of skilled and unskilled workers may induce a response in the relative demand and price of skilled labor. Improvements in the technologies associated with capital inputs have also the potential to influence labor inputs and their prices.

To provide a complete model of the changes in the wage structure, I estimate a translog production function with four (and five) inputs and separate trends for the factor biases of technical change. I distinguish between two types of labor -skilled and unskilled workers- and two (or) three types of capital[7]. The estimated parameters of this model give a complete description of the pattern of substitution among inputs and of the nature of technical change. An important feature of this framework is that technology is allowed to enter in a non-neutral way. Hence, technical change might affect the absolute efficiency of the various inputs differently over time. This constitutes an improvement upon other models, which are only able to provide results regarding input technologies in relative terms.

The choice of the production function framework is crucial. More widely used production functions, such as CES and Cobb Douglas, are not appropriate for the research questions this paper addresses. These specifications are constrained in three significant ways: First, the elasticities of substitution must be the same between all inputs[8], which rules out *a priori* the hypothesis I test in this paper, mainly that skilled labor is more complementarity to capital than unskilled labor. Second, the elasticities of substitution are bounded to be positive to maintain the quasi-concavity of the production function. In other words, all inputs are assumed to be substitutes, which excludes absolute complementarity. Finally, the elasticities are constant over time. The translog specification overcomes all these limitations[9]. Translog elasticities of substitution vary over time, which helps to understand the historical variation of the skill premium. Both substitutability and complementarity between inputs are allowed. All elasticities describing the patterns of substitution among the factors are parameters to be estimated in the structural model and are therefore not constrained to be the same, which allows for tests of capital-skill complementarity.

In addition, this framework separately identifies the impact of each individual factor of production and each of the input biases of technical change on the growth of the skill premium. By aggregating these contributions, the growth of the skill premium is expressed as a function of four components. First, the *relative supply effect*, which involves the growth of the supplies of skilled and unskilled labor. Second, the *complementarity effect*, which, depends on the growth of IT capital relative to that of non IT capital. Third, a technology component involving the skilled and unskilled labor biases of technical change, which I call the *relative skilled labor technology effect*.

[7]In the four input model, I distinguish between IT capital and the rest of capital. In the five input model I distinguih between IT, equipment non IT, and structures capital.

[8]In the Cobb-Douglas case, all the elasticities of substitution among inputs are equal to one. Uzawa (1962) and MacFadden (1963) have shown that elasticities of substitution among all inputs must be the same in a CES function.

[9]See Christensen, Jorgenson and Lau (1971, 1973)

And finally, the *relative IT capital technology effect* that depends of the biases of the two types of capital. In the five input model, the quantities and the biases of technical change of three -as opposed to two- differentiated capital factors (IT, equipment non IT, and structures) contribute to the growth of the skill premium.

The results of this study show that:

- Capital-skill complementarity can account for at most 40 percent of the increase in the skill premium, with factor noneutral technological change and other unobservable factors accounting for most of the rise in the premium. Changes in the wage structure cannot therefore be explained by changes in observed inputs alone.

- Capital-skill complementarity takes the form of IT-skill complementarity and, to a lesser extent, structures-skill complementarity. On the other hand, growth in equipment excluding IT has narrowed the skilled-wage gap. The reason being that the two components of equipment have behaved very differently over this period, combined with the fact that they interact with skilled labor and unskilled labor in different ways in the production function.

- Skilled-biased technological change takes the form of declining unskilled labor efficiency and rising efficiency of skilled labor. Since 1980, innovations biased in an unskilled labor saving direction have become increasingly important.

- IT-biased technological change has narrowed the skilled wage gap, counteracting the IT-skill complementarity effect. Therefore, the overall contribution of IT capital to the growth in the skill premium is smaller than the one predicted by changing physical quantities alone.

- The contribution of IT capital-skill complementarity to the growth in the skill premium has decreased since 1980 because IT is found to be less and less complementary to skilled labor over time. On the other hand, I find evidence of acceleration in the pace of skill-biased technological change.

- Finally, I perform separability tests and find that the data reject less flexible specification in favor of the translog approach to modelling aggregate production.

The rest of the paper is outlined as follows. In section 2, I present the production function framework within which wage inequality is analyzed. In Section 3, I provide a description of the data used in the quantitative analysis and empirical trends of these data. Results follow in Section 4, and I conclude in Section 5.

2 Capital-Skill Complementarity and Skill-Biased Technological Change in a Multi-Input Production Function Framework

The analysis of wage inequality at the aggregate level is usually addressed within a production function framework. In this section I review the aggregate production functions used in previous related literature and highlight their limitations to address the questions this paper aims at evaluating. I then outline the translog production possibility frontier approach to modelling aggregate output and discuss the suitability of this framework. Capital-skill complementarity and skill-biased technological change are next defined in terms of the parameters of the translog model.

2.1 Analysis of Wage Inequality in a Production Function Framework

Using aggregate data between 1963 and 1987, Katz and Murphy estimate a supply and demand model specifying the log of the skill premium as a function of a linear trend and the log of the relative supply of skilled workers and find

$$\ln \frac{p_s}{p_u} = c - 0.71 \ln \frac{L_s}{L_u} + 0.033\ t \tag{1}$$

where $\frac{p_s}{p_u}$ is the college wage premium, $\frac{L_s}{L_u}$ is the relative supply of college equivalent workers, and t is a time trend. This implies that the labor market in the period 63-87 is characterized by an elasticity of substitution between skilled workers and unskilled workers of about $\sigma = \frac{1}{0.71} \approx 1.4$, and an annual growth rate in the demand for skills of 3.3 percent. Their results indicate that observed fluctuations in the rate of growth of the relative supply of college graduates combined with smooth trend demand growth in favor of more-educated workers can largely explain fluctuations in the college/high schools differential over the period.

Acemoglu (2000) fits Katz and Murphy's analysis into a model of production, and derives their specification from the first order conditions of a profit maximizing economy with the following production function

$$Y = [(A_u L_u)^\rho + (A_s L_s)^\rho]^{1/\rho} \tag{2}$$

where A_u and A_s are labor augmenting factors reflecting the impacts of technical change. The skill bias of the technical change is determined by the relative growth rates in A_s and A_u.

Combining first order conditions he obtains

$$\begin{aligned} \ln \frac{p_s}{p_u} &= \frac{\sigma - 1}{\sigma} \ln \frac{A_s}{A_u} - \frac{1}{\sigma} \ln \frac{L_s}{L_u} \qquad \sigma = \frac{1}{1-\rho} \\ \ln \frac{A_s}{A_u} &= \gamma_0 + \gamma_1 t \end{aligned} \tag{3}$$

Therefore, one could interpret the time trend in the Katz and Murphy model as the relative efficiency of skilled labor to unskilled labor. This model is fairly restrictive because it excludes capital as a factor of production and thus ignores capital-skill complementarity as a source of changes in the skill premium. Even though capital-skill complementarity might be implicitly contained in the demand shifter term, represented by a time trend in Katz and Murphy, the model does not account for this effect in an explicit way, and its impact cannot be distinguished from the effect of other demand factors, such as latent skill-biased technological change.

Krusell et al discusses the extent to which the trend term in the Katz and Murphy model may be serving as a proxy for omitted capital-skill complementarity effects. In order to allow for these effects, they estimate a four-factor production function with two types of capital (equipment and structures) and two types of labor (skilled and unskilled). They assume the production function is Cobb-Douglas over capital structures, K_s, and a CES function of the three remaining inputs, K_e, L_u, L_s (equipment capital, unskilled and skilled labor).

$$Y = K_s^{\alpha}\left[\mu L_u^{\sigma} + (1-\mu)\left(\lambda K_e^{\rho} + (1-\lambda)L_s^{\rho}\right)^{\sigma/\rho}\right]^{\frac{1-\alpha}{\sigma}} \tag{4}$$

where μ and λ are parameters that govern income shares, and σ, ρ govern the substitution elasticities.

According to the authors, the elasticity of substitution between equipment (or skilled labor) and unskilled labor is $\frac{1}{1-\sigma}$ and the elasticity between equipment and skilled labor is $\frac{1}{1-\rho}$. Capital equipment-skill complementarity requires therefore that $\sigma > \rho$, -i.e. the elasticity of substitution between unskilled labor and equipment is higher than the elasticity of substitution between skilled labor and equipment- so that an increase in the capital stock increases the marginal product of skilled labor more than the marginal product of unskilled labor, increasing thus the skill premium.

However, neither the above nesting of K_e, L_u, L_s is CES in general nor the expressions found by the authors correspond to the elasticities of substitution[10]. The Allen elasticity of substitution (Allen, 1938) between unskilled labor and skilled labor and that between unskilled labor and equipment are indeed constant and equal to $\frac{1}{1-\sigma}$. However, the Allen elasticity of substitution between skilled labor and equipment is $\frac{1}{1-\sigma} + \frac{Y}{p_s L_s + p_e K_e}\left[\frac{1}{1-\rho} - \frac{1}{1-\sigma}\right]$, where p_s is the skilled wage and p_e is the rental price of equipment capital. This elasticity is not constant unless $\sigma = \rho$. But this case is not interesting, since it does not allow for capital-skill complementarity effects. Adopting another definition of the elasticity of substitution[11], the *direct elasticity of substitution*, Krusell et al' specification does not deliver constant elasticities for all inputs either.

[10] I am grateful to Francesco Caselli for pointing this out to me.

[11] There are different schools of thought on the appropriate measure for the elasticity of substitution between two inputs in the context of a multiple-input function. The simplest measure is the direct elasticity of substitution, which assumes that the other factors quantities in the production function are fixed and thus can be ignored. The most popular measure of the elasticity of substitution in general application is perhaps the Allen elasticity of substitution (also known as the partial elasticity of substitution). This measure does not have a straightforward interpretation, except in its relation to the input demand elasticities. However, capita-skill complementarity can be formalized in

As mentioned in the introduction, a CES specification would not serve the purpose of testing for capital-skill complementarity. Uzawa (1962) and McFadden (1963) show that in a CES production function with more than two inputs, the elasticities of substitution among all inputs must be essentially the same.

Because elasticities of substitution are not constant, the statement that $\sigma > \rho$ implies capital-skill complementarity is not strictly correct. However, under an alternative definition in which there is capital-skill complementarity if the skill premium increases when the capital stock increases, then the statement is appropriate.

The authors find that $\sigma > \rho$ and that observable variables alone can account for most of the variance of the skill premium over the past thirty years, implying that the time trend in Katz and Murphy is capturing these capital-skill complementarity effects. However, the simple regression exercise I described in the introduction showed that the time trend in Katz and Murphy is not explained by equipment-skill complementarity. This result motivates the development of a new framework that enables to account for -and disentangle- both capital-skill complementarity effects and skill-biased technological change in order to shed new light on the sources of changes in the skill premium.

On top of the debate that relates capital-skill complementarity to observable variables (measures of capital) and skill-biased technological change to unobservables, which provides an empirical reason to distinguish these two concepts, there is also a theoretical reason to do so. From a production theory viewpoint, capital-skill complementarity refers to the shape (curvature) of the isoquants and to the ease with which some inputs can be substituted for others in production. On the other hand, skill-biased technological change provides information about non-parallel shifts of the isoquants, hence about the way technology affects the relative efficiency of the inputs. These two concepts must, consequently, be distinguished both for theoretical and empirical reasons. In addition, this differentiation has implications for policy and economic growth.

The representation of production used in this paper, which allows to separately identify these two effects, is given by the translog production function. In the translog approach all elasticities are parameters to be estimated, which provides a more complete description of the pattern of substitution among factors. With four inputs, for instance, there are a total of six elasticities to be estimated (excluding the own-price elasticities). The translog production function allows for both substitutability and complementarity between inputs. In addition, translog substitution elasticities vary over time, which helps to understand the historical variation of the skill premium. In addition, the translog specification I employ incorporates separate trends for the factor biases of technical change. From them, the nature of technical change is determined and the hypothesis of skill-biased

terms of Allen elasticities of substitution in a way consistent with Hicks' original idea of factor substitution (Griliches, 1969). A third measure is the Morishima elasticity of substitution. Blackorby and Rusell (1989) argue this is the most sensible generalization of the Hicks elasticity of substitution. Thompson (1997) introduces the bilateral elasticity and shows that its performance in applications is better than the Morishima elasticity.

technological change tested.

2.2 The Translog Production Function

The translog production function can be envisaged as a second-order Taylor's series approximation in logarithms to an arbitrary production function (Christensen Jorgenson, Lau, 1971,1973). In this study I opt for the dual representation of aggregate production under constant returns to scale, which is a price function, giving the logarithm of the price of output as a quadratic function of the logarithms of the input prices and the level of technology[12]

$$\ln P = \alpha_0 + \boldsymbol{\alpha}_p' \ln p + \alpha_t t + \frac{1}{2} \ln p' B_{pp} \ln p + \ln p' \boldsymbol{\beta}_{pt}\ t + \frac{1}{2}\beta_{tt}\ t^2 \tag{5}$$

where P is the price of output, p is a vector of input prices, and t is the level of technology[13]. The matrix B_{pp} provides a description of the nature of substitution among inputs and is used to evaluate and quantify the capital-skill complementarity hypothesis. The vector $\boldsymbol{\beta}_{pt}$ characterizes the nature of technical change and is used to analyze the skill-biased technological change hypothesis.

To generate an econometric model of production that allows me to estimate the parameters of interest, the price function is differentiated with respect to input prices and equilibrium conditions under competitive markets are applied. A system of simultaneous equations is obtained, determining the value shares as functions of the input prices and technology, which is estimated jointly with the price function[14]

$$v = \frac{\partial \ln P}{\partial \ln p} = \boldsymbol{\alpha}_p + B_{pp} \ln p + \boldsymbol{\beta}_{pt}\ t \tag{6}$$

where v is the vector of input shares.

The parameters estimated from these equations are defined as follows:

- **Share Elasticities**: give the response of the value shares of all inputs to proportional changes in the input prices. If a share elasticity is positive (negative), the corresponding value share increases (decreases) with the input price. If I specialize to the case of one output and four inputs (say, skilled labor,s; unskilled labor, u; IT capital, i; and non IT capital,n) the share

[12] The dual formulation of production theory under constant returns to scale is due to Samuelson (1954).

[13] Technology is modeled as a time trend in this framework. Work in progress analyzes alternative representations of technology.

[14] One could estimate the translog cost function directly, but gains in efficiency can be realized by estimating the value shares too.

elasticities are given by

$$B_{pp} = \frac{\partial v}{\partial \ln p} = \frac{\partial^2 \ln P}{\partial \ln p^2} = \begin{pmatrix} \beta_{ss} & \beta_{su} & \beta_{si} & \beta_{sn} \\ \beta_{us} & \beta_{uu} & \beta_{ui} & \beta_{un} \\ \beta_{is} & \beta_{iu} & \beta_{ii} & \beta_{in} \\ \beta_{ns} & \beta_{nu} & \beta_{ni} & \beta_{nn} \end{pmatrix} \tag{7}$$

- **Allen partial elasticities of substitution:**

$$\begin{aligned} \sigma_{jk} &= \frac{\beta_{jk} + v_j v_k}{v_j v_k} \qquad j,k = s,u,i,n, \text{ but } j \neq k \\ \sigma_{jj} &= \frac{\beta_{jj} + v_j^2 - v_j}{v_j^2} \qquad j = s,u,i,n \end{aligned} \tag{8}$$

Positive σ_{jk}'s indicate that factor inputs j and k are substitutes, negative that factors are complements. These elasticities are not constrained to be constant but may vary with the value shares. Allen elasticities of substitution are often criticized for adding no information to that contained in the related (constant-output) price elasticities of demand for factors of production, expressed as

$$\varepsilon_{jk} = \frac{\partial \ln q_j}{\partial \ln p_k} = \frac{p_k}{q_j}\frac{\partial q_j}{\partial p_k} = v_k \sigma_{jk}$$

However, capital-skill complementarity can be formalized in terms of Allen elasticities in a way that is consistent with Hicks factor substitution. Griliches (1969) shows that for the capital-skill complementarity hypothesis not to be rejected, the estimated Allen elasticity between skilled labor and capital must be greater than that between unskilled labor and capital[15].

- **Biases of technical change**: are obtained by differentiating the logarithm of the price function twice with respect to the logarithm of input prices and the level of technology

$$\boldsymbol{\beta}_{pt} = \frac{\partial v}{\partial t} = \frac{\partial^2 \ln P}{\partial \ln p \partial t} = \begin{pmatrix} \beta_{st} \\ \beta_{ut} \\ \beta_{it} \\ \beta_{nt} \end{pmatrix} \tag{9}$$

[15] A necessary condition for IT capital-skill complementarity is that

$$\frac{\partial \ln\left(\frac{L_s}{L_u}\right)}{\partial \ln\left(\frac{p_i}{p_s}\right)} = \varepsilon_{si} - \varepsilon_{ui} = v_i(\sigma_{si} - \sigma_{ui}) < 0$$

That is, $\sigma_{si} - \sigma_{ui} < 0$.

If a bias of technical change is positive (negative), the corresponding value share increases (decreases) with a change in the level of technology and technical change is said to be input-using (input-saving). The effects of each of the input technologies on the evolution of the skill premium will be specified as functions of these biases of technical change. The extent of skill-biased technological change is also quantified from these parameters.

The economic theory of production implies restrictions on all these parameters. A detailed explanation of these restrictions can be found in the Appendix II, as well as how I deal with the concavity constraints in the estimation of the econometric model.

2.3 Decomposition of the Growth in the Skill Premium

The estimated parameters are next used to derive the growth rate of the skill premium predicted by the model, and the contribution of each factor and nonneutral technological change to this growth. A straightforward application of Shepherd's lemma allows for a decomposition of the growth of the skill premium into four main components[16]:

1. **Relative supply effect**: describes the impact of the growth in the supplies of skilled and unskilled workers on the growth of the skill premium.

2. **Complementarity effect**: depends on the growth rate of the stock of IT relative to that of non-IT and on the way these two types of capital interact with skilled and unskilled labor in production.

3. **Relative skilled labor technology effect**: involves the efficiency parameters of the two types of labor.

4. **Relative IT capital technology effect**: involves the two capital biases of technical change.

By Shepherd's lemma

$$q = \frac{\partial(P * Q)}{\partial p} = \frac{\partial P}{\partial p}Q + \frac{\partial Q}{\partial p}P = \frac{\partial \ln P}{\partial \ln p}\frac{P}{p}Q = v\frac{PQ}{p} \tag{10}$$

where q is the vector of input quantities, p is the vector of input prices, v is the vector of input shares, P is the price of output, and Q is the quantity of output. Therefore, the skill premium is expressed as

$$\frac{p_s}{p_u} = \frac{v_s}{v_u}\frac{q_u}{q_s} \tag{11}$$

[16] Appendix IV describes how the estimated parameters are used to decompose the growth of the relative share of skilled to unskilled labo into different components.

Taking logarithms to $p = \frac{vPQ}{q}$ and differentiating with respect to time, I obtain

$$g_p = g_v - g_q + g_{PQ} \tag{12}$$

where g_x denotes the growth rate of vector x.

The first term of the above expression can be written as

$$g_v = \frac{\partial \ln \left(\boldsymbol{\alpha}_p + B_{pp} \ln p + \boldsymbol{\beta}_{pt}\ t \right)}{\partial t} = \Lambda \left(B_{pp} g_p + \boldsymbol{\beta}_{pt} \right) \tag{13}$$

where Λ is a diagonal matrix whose (j,j) element is $\frac{1}{v_j}$.

I can then rewrite g_p as[17]

$$g_p = \left(\Lambda B_{pp} - I \right)^{-1} \left(g_q - \Lambda \boldsymbol{\beta}_{pt} - g_{PQ} \right) \tag{14}$$

If $g_p = (g_{p_s}, g_{p_u}, g_{p_i}, g_{p_n})$ is the vector of growth rates of input prices for skilled labor, unskilled labor, IT capital, and non-IT capital, I can express the growth of the skill premium, $(g_{p_s} - g_{p_u})$ as a function of four components

$$g_{p_s} - g_{p_u} = (\phi_1 g_{q_s} + \phi_2 g_{q_u}) + (\phi_3 g_{q_i} + \phi_4 g_{q_n}) + (\psi_1 \beta_{st} + \psi_2 \beta_{ut}) + (\psi_3 \beta_{it} + \psi_4 \beta_{nt}) \tag{15}$$

where ϕ_k is the element $(1,k)$ minus the element $(2,k)$ in matrix $\left(\Lambda B_{pp} - I \right)^{-1}$, and ψ_k is the element $(1,k)$ minus the element $(2,k)$ in matrix $-\left(\Lambda B_{pp} - I \right)^{-1} \Lambda$, for $k = 1, 2, ..4$. Note that the above expression is for any given time period. Thus, ϕ_k and ψ_k vary over time, and can be either positive or negative[18].

The first component, $(\phi_1 g_{q_s} + \phi_2 g_{q_u})$, affects the growth rate of the skill premium through the growth in the supplies of skilled and unskilled labor. This is the *relative supply effect*. Production theory requires own price elasticities must be negative. Therefore, at any given time period, ϕ_1 is expected to be negative and ϕ_2 is expected to be positive. Given the strong upward trend in the relative abundance of skilled workers relative to unskilled workers, I expect the entire term to affect negatively the growth of the skill premium.

The second component, $(\phi_3 g_{q_i} + \phi_4 g_{q_n})$, *the complementarity effect*, depends on the growth of IT capital relative to that of non-IT capital and on the nature of substitution between the two types of capital and the two types of labor. The sign of ϕ_3 depends, essentially, on two substitution elasticities: that between skilled labor and IT, and that between unskilled labor and IT. Suppose, as I actually find, that IT and skilled labor are complements, while IT and unskilled labor are substitutes. Then ϕ_3 would be positive, since increases in IT generate a higher demand for skilled labor and a lower demand for unskilled labor, which would drive the skill premium up.

[17] Alternatively: $g_p = \left(B_{pp} - V \right)^{-1} \left(V \left(g_q - g_{PQ} \right) - \boldsymbol{\beta}_{pt} \right)$
where V is a diagonal matrix whose (j,j) element is v_j

[18] Also note that $\psi_k = -\frac{1}{v_k} \phi_k$.

The third term in equation 15, $(\psi_1\beta_{st} + \psi_2\beta_{ut})$, is the *relative skill technology effect.* Essentially, a positive skilled labor bias of technical change and a negative unskilled labor bias lead to increases in the skilled wage gap. The last term, the *relative IT technology effect*, $(\psi_3\beta_{it} + \psi_4\beta_{nt})$, depends on the capital biases of technical change, as well as on the patterns of substitution. I sometimes summarize these two last terms in a single *technology effect*.

3 Data and Empirical Trends

The objective of this section is to describe the data used in this study and to illustrate the major trends since 1965. The data consist of annual U.S. time series of capital and labor between 1965 and 1999.

I distinguish between two types of labor: skilled and unskilled. I define skilled labor as those workers with at least college degree (minimum 16 years of education). These data are drawn from the Annual Demographic March Files of Current Population Survey (CPS)[19]. Labor input is a quality adjusted measure of total labor hours. The methodology used to construct the labor input and price series is based on Jorgenson, Gollop, and Fraumeni (1987). However, they do not use the annual data from the CPS to estimate the matrix of demographic groups, but use it to create smaller matrices, which are used to interpolate and extrapolate demographic information given in the Decennial Censuses of Population. Furthermore, my definition of demographic groups is different, as well as the treatment of some special features of the data, such as top-code income and imputed incomes. A detailed explanation of my methodology can be found in Appendix I.

Figure 1.1 shows the evolution of the skill premium. The features of this series are: moderate increase during the 1960s, decline over the 1970s, and sharp increase since 1980. The skilled wage gap increase about 20 percent in the period between 1965 and 1999 despite the growth of over a hundred percent in the relative abundance of skilled labor (see Figure 1.2). Figure 1.3 also shows a strong upward trend in the relative share of skilled labor to unskilled labor.

Output and capital data are taken from Jorgenson (2001). The output data are based on the 1999 benchmark version of the National Income and Product Accounts (NIPA), published by the Bureau of Economic Analysis (BEA). Real output is measured in chained 1996 dollars, and its price is the corresponding implicit deflator. The concept of output used is the one developed by Christensen and Jorgenson (1969)[20]. The capital estimates begin with investment data from the BEA, then capital stocks by asset are computed using the perpetual inventory method, and finally they are aggregated using rental prices as weights. Rental prices are calculated using the

[19] CPS data are taken from Unicon Research Corporation (www.unicon.com). I refer readers to Appendix I for information about Unicon.

[20] In contrast with the standard NIPA definitions, consumers' durable goods are treated symmetrically with investment goods. Thus, the stock of consumer durables is included in the flow of capital services and spending on consumer durables is included in investment rather than consumption spending.

Jorgenson user-cost formula, which incorporates asset-specific rates of return, depreciation rates, and revaluation terms. This is particularly important for IT assets, which have high depreciation rates, high marginal products, and therefore should receive a higher capital service price. The difference between the growth in capital stock and the growth in capital services is the growth in capital quality, which represents substitution toward assets with higher marginal products (see Jorgenson and Stiroh, 2000). Also of importance is the incorporation of constant-quality investment price indices, which is done by the BEA for computers and office equipment, the prepackaged part of software[21], and the switchgear part of communications equipment, and enters into the cost of capital through the asset-specific revaluation term. For a more detailed explanation about the construction of the capital data, and in particular, the hedonic quality-adjusted measures of information technology equipment see Jorgenson (2001).

I distinguish between different types of capital too. The sum of information technology equipment (IT), equipment non IT (EqnonIT), and structures adds up to total capital. Information technology is defined to include three main categories: computers and peripheral equipment, software, and communications equipment. There are significant differences in the evolution of the prices and quantities of the various components of capital. Structures grew at an average rate of 2.7 percent per year between 1965 and 1999 whereas total equipment increased twice as much. Within equipment, the IT component has been growing at an average rate of 15.2 percent per year, about five times the rate of the non IT component. These time series and their growth rates are displayed in Figures 2.1 and 2.2. Regarding prices, the differences are even more noteworthy (see Figures 2.3 and 2.4). Since 1965 the price of IT equipment has decreased in absolute terms at an average rate of about 3.6 percent per year. Meanwhile, the price of structures and the price of equipment non IT increased over 4 percent. In contrast to the growth rates in the prices of structures and equipment non IT, which were approximately the same before and after 1980, the decline in the price of IT accelerated after 1980, its growth rate went from -0.9 percent to -5.47 percent.

Also interesting is the evolution of the ratio of skilled labor to capital, displayed in Figure 3.1. A substantial decline in the ratio of skilled labor to IT capital is observed. Mild increase in this ratio with other types of capital. Figure 3.2. presents the ratio of the price of skilled labor to the price of capital. This ratio has increased consistently over the entire period for capital IT. The rise in the series for structures and equipment non IT is considerably smaller.

The series of the shares of income earned by skilled labor, unskilled labor, IT, EQnonIT, and structures are presented in Figure 3.3. The skilled labor share of income has grown at an average rate of 2.4 percent per year, while the unskilled labor share decreased almost one percent per year. Between 1965 and 1999, the IT share increased over 4 percent per year, while the equipment non IT share has been roughly constant, and the structures share declined slightly.

[21] Prices of own account and custom software are not quality adjusted.

4 Empirical Results

This section presents the estimates of the translog price function for the benchmark model and quantify the implications of changes in various factors for the behavior of the skill premium over the last thirty five years. Results for an extended model, which differs from the benchmark model in the number of inputs and the treatment of capital, are also discussed. I then explain briefly how the growth of the factors of production and technology have influenced the evolution of the relative share of skilled labor. Finally, separability tests of the validity of restrictions on the forms of the production and price functions are performed.

4.1 Estimates of the translog function. IT Model

The benchmark model, the IT Model, describes aggregate output as a function of four inputs - skilled and unskilled labor, IT capital, and non-IT capital- and separate trends for the factor biases of technical change.

Four equations, corresponding to three of the value shares derived in section 2 and the translog price function, are estimated jointly using iterative three stage least squares on time series data. A more detailed explanation of the econometric strategy, as well as information on the instruments used in this analysis and the test of their validity, can be found in Appendix III. Table 3 contains the estimates of this model. The complete model consists of 15 free parameters: three elements of the vector $\{\alpha_p\}$, which represent the estimates of the input value shares in the base year (1996); three biases of technical change in the vector $\left\{\boldsymbol{\beta}_{pt}\right\}$; six share elasticities in the matrix $\{B_{pp}\}$; and the scalars α_o, α_t, and β_{tt}, which complete the description of technology. The remaining 6 parameters in $\{\alpha_p\}, \left\{\boldsymbol{\beta}_{pt}\right\}$, and $\{B_{pp}\}$, as well as the Allen partial elasticities of substitution, are obtained as functions of these free parameters.

The estimated biases of technical change (panel B, Table 3) reveal the non Hicks neutral nature of technical change, which has indeed affected the efficiency of the various inputs differently[22]. Innovation in the U.S. economy over 1965-99 has been strongly biased in an unskilled labor saving direction. The estimate of the annual rate of unskilled labor saving technological change is 0.6 percent. Over the same period, technological change has favored the use of skilled labor and the two types of capital. The positive trend of the skilled labor bias of technology and the negative trend of the unskilled labor bias of technology represent one of the sources of the increases in the skill premium. The total effect of technical change on the skill premium depends also on the capital biases of technical change and the way the two types of capital interact with labor.

The pattern of factor substitution over time is given by the Allen partial elasticities of substitution (AES), which are calculated from the share elasticities and the input shares. AES's and their

[22] A test of Hicks neutrality that sets all the biases of technical change equal to zero is rejected at 1 percent significance level.

corresponding confidence intervals are plotted in Figure 4. The average values of these elasticities are displayed in panel D of Table 3.

The labor market between 1965 and 1999 has been governed by an elasticity between skilled and unskilled labor of 2, which is consistent with other micro and macro estimates in the literature. This panel reveals how differently IT capital and non IT capital interact with skilled labor in the production function. Only IT capital is found to be complementary to skilled labor; their average AES is -2.1, while that between skilled labor and non IT is 0.7. Griliches's hypothesis to test IT-skill complementarity is $Ho : \sigma_{si} = \sigma_{ui}$ against $Ha : \sigma_{si} < \sigma_{ui}$. The null hypothesis is clearly rejected at 1 percent significance level in favor of IT-skill complementarity.

Also noteworthy is that unskilled labor is more substitutable to IT than to non IT capital. These values suggest that the large increase in the stock of IT, triggered by its price decline, (see figures 2-3) has come along with a large demand for its complementary labor input (skilled workers) and a reduction in the demand for its substitutable labor input (unskilled workers). Both effects result in a higher skill premium. The effect of changes in non IT capital on the skill premium is ambiguous since non IT capital is substitutable to both types of labor. The analysis of the contribution of each input to the growth in the skill premium, performed in the next section, will shed new light on the total impact of non IT capital on the evolution of the relative wages of skilled workers.

An interesting feature of Figure 4 is that IT-skill complementarity was larger during the late 60s and 70s than in the period that experienced the largest growth in the skilled wage gap, as well as the largest growth in IT capital. Despite being negative for the whole period, the AES between skilled labor and IT has increased over time, implying that these two inputs are becoming less and less complements in production. This result suggests that the impact of the so-called new economy and the boom of Internet and the start-ups on wage inequality has been smaller than the initial diffusion of computerization and basic communication capital in the 70s. It also suggests that the role of IT capital in accounting for the rise in wage inequality is expected to decrease further. One way to explain this phenomenon is that complementarity of IT to skilled labor has become less stringent as more people, not only skilled workers, have learned how to use IT more effectively. In other words, new machines have become more and more accessible or more user-friendly so that also the unskilled can handle them. Also noteworthy is the evolution of, σ_{un}, the elasticity between unskilled workers and non IT, which is decreasing over time and approaching zero. This suggests that current changes in the price of non IT capital are not having as large an impact on the demand for unskilled labor. Next section discusses the implications of non constant elasticities of substitution on the behavior of the skill premium over time.

4.2 Contribution of Various Factors to the Growth in the Skill Premium. IT Model

To see how well the model does in predicting the behavior of the skill premium and the input shares, Figure 5.1-5.3 show the series in the estimated model and in the data. I find that the estimated model does fairly well at capturing the changes of these variables. The R-squared corresponding to the estimated system of equation are: 0.98 for the skilled labor share equation, 0.98 for the unskilled labor equation, 0.95 for the IT share equation, and 0.90 for the price equation.

The estimates of the IT model are plugged into equation 15 to quantify what fraction of the variation of the skill premium is accounted for by changes in each of the factor supplies and each of the input biases of technical change. The first component in equation 15 relates to how changes in the supply of skilled and unskilled workers affect the skill premium. The complementarity effect (second component) results from adding the contribution of the two capital inputs to the growth in the skill premium. Similarly, the sum of the labor (capital) technology components represents the relative skill (IT) technology effect. Finally, I group all technology terms into a single technology component, which is also the effect due to unobservable variables, as opposed to the effect due to observable quantities represented by the relative supply and complementarity effects. The total contribution of each of these factor to the growth in the skill premium is presented in Table 4 below

Table 4: Total Contribution of Various Factors to the Growth in the Skill Premium IT Model

Observables				**Unobservables**			
Rel Supply Effect		Complementarity Effect		Technology Effect			
-80		41		58			
				Rel Sk Technology		Rel IT Technology	
				80		-22	
Sk Labor	Usk Labor	IT	Non IT	Sk Tech	Usk Tech	IT Tech	Non IT Tech
-124	44	50	-9	37	43	-24	2

Note: the figures represent cumulative percentage terms.

The sum of bottom and upper lines add up to 19 (total increase in the estimated skill premium)

Overall, the relative supply effect has driven the skill premium down about 80 percent while the complementarity and technology effects have driven the premium up 41 and 58 percent respectively over the period 1965-1999. The sum of these three effects results in an increase in the estimated skill premium of about 19 percent. In other words, controlling for the evolution of the relative supply of skilled labor, capital-skill complementarity accounts for 41.4 (41/99) percent of the rise in inequality and factor nonneutral technological change for 58.6 percent. Therefore, observables variables alone cannot account for most of the variation in the skill premium, as suggested by

Krusell et al. In fact, capital-skill complementary together with the relative supply effect, which constitute the effect due to observable variables, is negative. Thus, if only the quantities of labor and capital had changed, keeping the level of technology fixed, the skill premium would have been lower in 1999 than what it was in 1965.

Capital-skill complementarity takes the form of IT-skill complementarity. Growth in IT, triggered by its price decline, has a positive impact of 50 percent. The effect of non IT, which was ambiguous from the direct observation of the Allen elasticities of substitution, has resulted in a negative impact on the skill premium because increases in the price of non IT has substituted skilled labor more intensively than unskilled labor.

The estimates in table 4 suggest that the rise in the skill premium cannot be understood without accounting for technical change. Indeed, changing input efficiencies have significantly influenced the skilled wage gap. The implications of skilled labor using and unskilled labor saving innovations translate into a strong upward pressure on the skill premium, which I call the relative skilled labor technology effect. On the other hand, the IT bias of technology has driven the premium down by 24 percent. With IT-skill complementarity, IT-using technical change reduces the growth in the skill premium[23]. The reason for this effect works through understanding the induced effect of technical change on IT capital prices and the mechanism behind capital-skill complementarity. Innovations increase the need for new capital, reflected by the positive IT bias of technical change. In turn, the induced rise in the marginal return to IT causes a decrease in the demand for its complementary factor -skilled labor- diminishing therefore the skill premium.

There are therefore two effects related to IT that have operated in opposite directions. On one hand, more intensive use of IT capital, triggered by declines of IT prices, has created a greater demand for the labor input complementing this factor, skilled labor, increasing consequently the skilled wage differential. On the other hand, IT-using technical change tends to increase both the demand and the price of IT, resulting in a decrease in the demand for skilled labor. The total impact on the skill premium depends on the relative strength of these two effects. Overall, capital-skill complementarity has dominated. However, ignoring the effect associated to IT-biased technical change would over-estimate the effect of IT investment. This results reinforces the importance played by technical change and calls for precaution when forecasting the implications of further IT capital deepening in the economy.

Previous literature has recognized the role of skill-biased technological change but has usually ignored the role of IT-biased technological change, which influences the skill premium in the opposite direction. The mechanism behind capital-skill complementarity has often been misunderstood too. In this model, increased demand for skilled labor is induced by declines in the relative price of IT capital (which in turn induces a higher supply of IT).

[23] A positive IT bias of technical chnage ($\frac{\partial w_{\mathsf{i}}}{\partial t} > 0$), a negative IT share elasticity with respect to skilled labor ($\frac{\partial w_{\mathsf{i}}}{\partial \ln p_{\mathsf{s}}} < 0$), and a positive IT share elasticity with respect to unskilled labor ($\frac{\partial w_{\mathsf{i}}}{\partial \ln p_{\mathsf{u}}} > 0$) translate into a negative effect of technical change on the skill premium ($\frac{\partial \ln p_{\mathsf{s}}}{\partial t} < 0$ and $\frac{\partial \ln p_{\mathsf{u}}}{\partial t} > 0$).

Another way of summarizing the total impact of the various inputs in the growth of the skill premium, in addition to the already mentioned dichotomy of observables versus unobservables, is to distinguish between total contribution of labor and total contribution of capital, accounting for both the behavior of physical quantities and their corresponding efficiencies. The conclusion of this exercise is that labor cannot explain much of the rise in the skill premium. This is so because the negative supply effect has offset completely the positive relative skill technology effect. On the other hand, total capital, involving a positive complementary effect and a negative relative technology effect, could account for most of the total 19 percent rise. Note that this refers to the total cumulative impact as of 1999. At any given point in time within the sample period, the relative contributions of total capital and total labor are different.

Although table 4 is possibly the best summary of the results in this paper, the plots in Figure 6 are more informative in that they represent the evolution of the contributing effects over time. Panels 1-4 involve each of the 4 terms in equation 15 while panels 5 and 6 correspond to more aggregated effects. All series are in logs and they have been normalized to be 0 in 1965. Therefore, increments along the Y-axis should be read as percentage changes. Starting at the origin, the skill premium should have a value of about 0.2 at the end of the sample period. Bearing this in mind I can assess the separate impact of each of these effects over time and compare their relative contribution. These series show cumulative growth rates, therefore an increasing (decreasing) trend translate into a positive (negative) effect on the skill premium growth. The curvature of the series tells whether the effect is getting stronger or weaker over time. For instance, an increasing but flattening curve means that the factor has contributed to increase the skill premium, but its impact is getting smaller over time.

Figure 6.1 shows the relative supply effect decomposed into its two components. As expected, increased supply of skilled labor has had a negative impact on the skill premium over the whole period while the unskilled labor effect is increasing over time. Growth in the supply of more educated workers was more rapid in the 70s than in the last decades. This is reflected in the shape of the series, which is steeper during the 70s than later on. The complementarity effect and its two components are displayed in Figure 6.2. The IT effect is increasing over the entire period, but it does so at decreasing rates. This implies that IT-skill complementarity is having a positive impact on the skill premium, but this effect is becoming less important over time. As mentioned earlier, this is the result of the increasing substitution elasticity between skilled labor and IT. Since the mid 70s, non IT capital is having a negative effect on the skill premium, which is accelerating over time. The combination of these two effects result in a positive but decreasing contribution of total capital on the growth of the skill premium till the late 80s. Since then the total contribution of capital has turned negative.

Figure 6.3 shows the large impact of the technologies associated to labor inputs on the growth of the skill premium. Technical change biased in favor of skilled labor and against unskilled labor have contributed to the overall growth of the premium in similar proportions. These findings are consistent with the hypothesis that new technologies favor skilled workers, make them more efficient, and replace tasks previously performed by the less educated. However, I observe an acceleration of the effect due to the negative trend of the unskilled labor bias of technology, while the effect due to the skilled labor using innovations is losing strength starting in the 80s.

Labor and capital technologies work in opposite direction in what refers to their impact on the skill premium (see panel 4). The relative IT capital technology effect is totally driven by IT technology, which has contributed to decrease the skill premium in a way that was stronger at the beginning of the sample period than in the last decade. The non IT bias of technical change can be disregarded as a source of changes in the skill premium. Figure 6.5 combines the two relative technologies effects into a single technology series. If technology alone had changed between 1965 to 1999, the skill premium would have increased about 58 percent, as opposed to the actual increase of about 20 percent. Furthermore, the impact of technology seems to have accelerated over time. The last panel illustrates the total role of capital in accounting for changes in the skill premium. As mentioned before, the overall effect of capital is smaller than the predicted by capital-skill complementarity only, since the effect of capital technology has worked in the opposite direction. However, both effects are turning milder over time.

While in Figure 6 the contribution of each factor is analyzed independently, in panel 1 of Figure 7, I aggregate them into three main effects: relative supply, complementarity, and technology, and plot them together along with the estimated skill premium. The sum of the three effects add up to the skilled wage premium. Figure 7.2 further aggregates the various effects into what can be accounted for by observables and what can be accounted for by unobservables. As implied by this figure, none of them alone is enough to explain the total variation of the skill premium during the last 35 years.

To summarize, controlling for the evolution of the relative supply of skilled labor, capita-skill complementarity accounts for 41.4 percent of the increased skill premium while technological change accounts for the remaining 58.6 percent. Furthermore, the contribution of capital is decreasing over time while the effect of technology is growing. If only observable quantities had changed, while keeping technology constant, the skill premium would have been about half the value in 1965, which cast doubt on Krusell et al result. The analysis of more disaggregated effects reveal that capital-skill complementarity takes the form of IT-skill complementarity, and that the contribution of technical change consists of two main components: relative skilled labor technology and relative IT technology, that have worked in opposite directions.

4.3 Five Input Model

I now discuss the results obtained from the estimation of the five input model. This model differs from the benchmark model in the number of capital factors. The five input model splits total capital into IT capital, equipment excluding IT, and structures. Estimates of the translog price function, which are contained in Table 5, are consistent with the results of both the IT model and the regression analysis and provide more detailed information about the non IT capital component. The interpretation of the Allen partial elasticities of substitution in panel D is that skilled labor is complementary to IT capital, and to a smaller degree, to structures, while it is substitutable to equipment non IT. In contrast, unskilled labor and all types of capital are substitutes. A summary table of these relationships is given by table 6 below

Table 6: Summary of the Substitution Patterns Between Labor and Capital Inputs

	Skilled Labor		Unskilled Labor	
IT	complements	−	substitutes	+
Structures	complements	↓	substitutes	↓
EQnonIT	substitutes	+	substitutes	−

The arrows indicate the direction of the intensity of the interaction. Unskilled labor is thus more substitutable with IT and much less substitutable with equipment non IT.

Table 7 summarizes the total contribution of each input and the input biases of technology in the growth in the skill premium and Figures 8.1-8.6 present the evolution of these contributions -and more aggregated effects- over time.

Table 7: Total Contribution of Various Factors to the Growth in the Skill Premium. Five Input Model

Observables					Unobservables				
Rel Supply Effect		Complementarity Effect			Technology Effect				
-73		31			61				
					Rel Sk Technology		Rel IT Technology		
					82		-21		
Sk Labor	Usk Labor	IT	EQnonIT	STR	Sk Tech	Usk Tech	IT Tech	EQnIT Tech	STR Tech
-115	42	49	-30	12	41	41	-26	6	-1

Note: the figures represent cumulative percentage terms.

The sum of bottom and upper lines add up to 19 (total increase in the skill premium)

Tables 6 and 7 show two noteworthy results, which were implied by the regression analysis and by the descriptive features of the data. First, the two component of equipment interact very differently with the labor inputs in production. This combined with the fact that their prices and stocks have behaved very differently over time have resulted in opposite effects on the growth of the skill premium. While IT has driven the skill premium up, equipment excluding IT has narrowed the skilled wage gap. The total effect of equipment on the skill premium is positive but small. Second, structures capital has had a positive, though small, effect on the rise of inequality, both through mild complementarity to skilled labor and through substitutability to unskilled labor. Complementarity between skilled labor and structures might be driven by certain sectors, such as government and finance, insurance and real state (FIRE), which employ high proportions of skilled labor and invest heavily in structures capital[24]. Figure 8.1 shows how the three components of capital has affected the evolution of the skill premium over time. This figure is analogous to Figure 6.2 for the benchmark model but disaggregates the non-IT series into its two contributing factors: equipment non IT and structures.

In conclusion, the extended model is consistent with the findings of the benchmark model in that capital-skill complementarity accounts for much less of the variation of the skill premium than technological change[25]. It also confirms the role of the individual biases of technical change. In addition, it highlights the importance of treating the three components of capital as differentiated factors, since their patterns of substitution with the labor inputs and their impact on the growth of the skill premium are very different.

4.4 Decomposition of the Growth in the Relative Share of Skilled Labor

The relative share of skilled to unskilled labor grew over 100 percent between 1965-1999. As I did for the skill premium, I identify and quantify the factors that contributed to this growth. Details follow in Appendix IV. The decomposition of the estimated relative share into three main effects: relative supply of skilled labor, complementarity, and technology is displayed in Figure 9.1. The implications are similar to the ones found with the decomposition of the predicted skill premium. Finally, figure 9.2 aggregates the contributions into two aggregate effects: one due to observable variables (supply and complementarity) and another due to unobservables (technology). I conclude that none of them alone is able to account for the whole increase in the relative share of skilled labor.

4.5 Groupwise Separability Tests

As already mentioned, a great advantage of the translog specification is its flexibility by not imposing any *a priori* relation among factors of production. This section evaluates the use of more

[24]Over the period 1965-1999, the share of structures capital in the value of total capital is 87 and 80 percent for Government and FIRE respectively, compared to an average share of 50 percent for the whole economy. The share of skilled labor in total labor in these sectors is close to 45 percent while it is 32 percent for the whole economy. Government and FIRE account for approximately 23 percent of aggregate value added and 33 percent of aggregate labor services.

[25]In the benchmark model, capital-skill complementarity is found to account for 41 percent of the rise in the premium. The five input model predicts a smaller contribution, 34 percent. The true estimate should lie withing this range. However, the better fit of the benchmark model suggests that a 40 percent impact is possibly the best estimate of this contribution.

restrictive functional forms and performs tests of these restrictions. I consider restrictions on the patterns of substitution implied by groupwise separability -also called nesting of inputs within a function . A price function F is separable in the K input prices (p_1,p_2,...,p_K) if the price function can be represented in the form $P = F(G(p_1,p_2,...,p_K), p_{K+1},..., p_J,t)$, where the function G is independent of the $J-K$ input prices ($p_{K+1}, p_{K+2},...,p_J$), and the level of technology t. Different separability assumptions are tested in Table 8. I employ tests statistics based on the Wald statistic: $W = n{\cdot}\text{trace}\left[\widehat{\Sigma}_{\Omega}^{-1}\left(\widehat{\Sigma}_{\omega} - \widehat{\Sigma}_{\Omega}\right)\right]$, where $\widehat{\Sigma}_{\omega}$ is the restricted estimator of the variance-covariance matrix and $\widehat{\Sigma}_{\Omega}$ is the unrestricted estimator. Under the null hypothesis this test statistic is distributed, asymptotically, as a chi-squared with number of degrees of freedom equal to the number of restrictions to be tested.

Among others, the data reject separability of skilled labor and equipment from the other inputs, and technology -i.e. the nesting. $P = F(G(p_s,p_e), p_u, p_n, t)$-. This result suggests that Krusell et al specification, which assumes separability of equipment and skilled labor from unskilled labor, is clearly too restrictive. Furthermore, their specification imposes that the elasticity of substitution between skilled and unskilled labor must be equal to that between unskilled labor and equipment. They also assume that the elasticities between structures and the rest of factors is equal to one. The estimation of a model[26], which differentiates between equipment and structures the same way the authors do, shows how restrictive these assumptions might be when the estimates are allowed to be estimated freely.

5 Conclusions

Empirical work, both at the micro and macro levels, is inconclusive as regards whether the spectacular development of information technology equipment (IT) accounts for the large increase in wage inequality experienced in the U.S. since 1980. This paper searched for the effects of IT and other capital investments in macro statistics and attempted to disentangle such effects from non-neutral technological change. The different nature and evolution over time of the two phenomena at work -capital-skill complementarity and skill-biased technological change- proved that the distinction is important in explaining wage inequality. I developed a framework based on a translog production function with four (and five) inputs and separate trends for the factor biases of technical change, and applied it to time series data from the U.S. over the period 1965-1999. I found that skilled labor-using innovations and the acceleration in the decline of unskilled labor efficiency constitute the main forces behind increased wage inequality. This might suggest that better education and training for unskilled workers would be a successful policy to reduce educational inequalities.

Complementarity between IT and skilled labor also explains a significant fraction of the variation in the skill premium, but this effect is decreasing over time. This result suggests that, as time goes

[26]Not presented. Available upon request.

by, machines become more and more accessible or more user-friendly so that also the unskilled can handle them. That is, the compementarity between IT and skilled labor becomes less stringent as more people, not only skilled workers, learn how to use IT more effectively. I also showed that investments in non IT equipment and IT-using technology have worked in the direction of closing the skilled wage gap. Thus, capital accumulation accounts for at most 40 percent of the rise in inequality, while technology and other unobserved factors are responsible for the remaining 60 percent.

It is worth noting that one channel through which IT, and more generally capital, could affect inequality is through 'spillovers' or 'externalities'. This channel refers to effects beyond those directly related to the size of the capital stock in the economy. For example, investment in new capital might come along with a re-organization of labor in production and other organizational innovations, which are likely to further influence wage inequality[27]. These spillover effects will not be captured by the capital component in equation 15, but by the unobservable (technology) component. In this sense, the role of IT is underestimated (and that of technology overestimated) under this production function framework. I could have been overestimating the contribution of skill-biased technological change through still another channel: the parametrization of technology as an exponential time trend. Work in progress analyzes the robustness of the results to alternative non-parametric representations of technology.

The results regarding IT-skill complementarity and IT-biased technical progress have important implications for the effects of further capital deepening in the economy and for economic growth. To investigate these implications by analyzing the impact of IT-skill complementarity and IT-biased technological change on IT-producing sectors compared to IT-using sectors appears a fruitful area for future research. Other interesting questions about the role of IT cannot be addressed within the scope of the production-frontier model. For example, the analysis pointed out the important role of falling IT prices in the economy, but it takes these changes as given. Clearly, an important direction for future research is an analysis of why IT prices have been falling so drastically over time and whether it is reasonable to model these changes as exogenous. Furthermore, understanding the effects of the factor bias of technical change can also help explain wage inequality across countries[28]. As Acemoglu (2000) points out, over the past decades wage inequality has grown substantially in the U.S., U.K. and Canada, with little or no change in European countries. At the same time, the share of capital has increased rapidly in the European economies while remaining constant in the Anglo-Saxon countries. This differential behavior might be the result of differences in the nature of technical change and capital-skill complementarities across these economies.

[27] Ichniowski and Shaw (2000) study working practices in steel mills and conclude that IT use is complementary with changes in human resource management (HRM) practices. Overall, it is the combined effects of IT use and innovative organizational practices that shape the demand for unskilled workers.

[28] See Tenreyro (2000) for an analysis of the linkage between inequality and technological progress across countries.

References

[1] Acemoglu, D. (1998), "Why Do New Technologies Complement Skills? Directed Technical Change and Wage Inequality", *Quarterly Journal of Economics, 113.*

[2] Acemoglu, D. (2000), "Labor- and Capital-Augmenting Technical Change", *NBER Working Paper 7544.*

[3] Acemoglu, D. (2000), "Technical Change, Inequality and the Labor Market", *NBER Working Paper 7800.*

[4] Allen, R. G. D. (1938), *Mathematical Analysis for Economists,* London: Macmillan.

[5] Autor, D., A. Krueger, and L. Katz (1998), "Computing Wage Inequality: Have Computers Changed the Labor Market?", *Quarterly Journal of Economics*, CXIII.

[6] Becker, G.(1964) *Human Capital.* Chicago: The University of Chicago Press.

[7] Berman, E,. J. Bound, and Z. Griliches (1994), "Changes in the Demand for Skilled Labor within U.S. Manufacturing Industries: Evidence from the Annual Survey of Manufactures, " *Quarterly Journal of Economics, 109.*

[8] Berman, E., J. Bound and S. Machin (1998), "Implications of Skilled-Biased Technological Change: International Evidence, " *Quarterly Journal of Economics, CXIII.*

[9] Blackorby, C. and R, Russell (1989), "Will the Real Elasticity of Substitution Please Stand Up? (A Comparison of the Allen/Uzawa and Morishima Elasticities)," *American Economic Review.*

[10] Borjas, G. and V. Ramey (1995),. "Foreign Competition, Market Power, and Wage Inequality",. *Quarterly Journal of Economics*, November 1995: 1075-1110.

[11] Bound, J., and G. Johnson (1992), "Changes in the Structure of Wages during the 1980's: An Evaluation of Alternative Explanations", *American Economic Review.*

[12] Bresnahan, T. F., E. Brynjolfsson, and L. M. Hitt (1999), "Information Technology, Workplace Organization and the Demand for Skilled-Labor: Firm-level Evidence." NBER Working Paper 7136.

[13] Caselli, F. (1999), "Technological Revolutions," *American Economic Review.*

[14] Caselli, F., and W.J. Coleman II (2000), "The World Technology Frontier," NBER Working Paper 7904.

[15] Caselli, F. and W. J. Coleman II (2000), "Cross Country Technology Diffusion: The Case of Computers." NBER Working Paper 8130.

[16] Christensen, L.R., and D.W. Jorgenson (1969) "The Measurement of U.S. real Capital Input, 1929-1967", *Review of Income and Wealth,* ser. 16, no.1 (March): 19-50.

[17] Christensen, L.R., D.W. Jorgenson, and L.J.Lau (1973) "Transcedental Logarithmic production Frontiers," *Review of Economics and Statistics* 55, no. 1 (February): 28-45

[18] DiNardo J., N. Fortin, and T. Lemieux.(1996) "Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semi-Parametric Approach", *Econometrica*, Vol.64(5) 1001-1044.

[19] Galor O. and D. Tsiddon (1997), "Technological Progress, Mobility, and Economic Growth." *American Economic Review,* June 1997, 87(3), pp. 363-82.

[20] Galor, O. and O. Maov (2000), "Ability Biased Technological Transition, Wage Inequality and Economic Growth," *Quarterly Journal of Economics,* 115.

[21] Goldin, C. and L. Katz (1998), "The Origins of Technology-Skill Complementarity," *Quarterly Journal of Economics,* 113.

[22] Goldin, C. and L. Katz (1999), "The Returns to Skill in the United States across the Twentieth Century*," NBER Working Paper 7126.*

[23] Greenwood, J. Z. Hercowtiz and P. Krusell (1997), "Long-Run Implications of Investment-Specific Technological Change," *American Economic Review.*

[24] Greenwood, J.Z., and M. Yorukoglu (1997), "1974." *Carnegie-Rochester Conference Series on Public Policy,* June 1997, 46, pp. 49-95.

[25] Grilliches, Z. (1969), "Capital-Skill Complementarity," *Review of Economics and Statistics* 51.

[26] Ho M.S., and D. W. Jorgenson (1999), "The Quality of the U.S Work Force, 1948-95," manuscript Harvard University.

[27] Hornstein, Y. and P. Krusell (1996), "Can Technology Improvements cause Productivity Slowdowns?," NBER *Macroeconomic Annual,* vol.11.

[28] Jorgenson D.W., L.J. Lau (1974). "The Duality of Technology and Economic Behavior," *Review of Economic Studies* 41(2), no. 126 (April): 181-200.

[29] Jorgenson D.W., F.M. Gollop, and B. M. Fraumeni (1987), *Productivity and U.S. Economic Growth.* Cambridge, MA: Harvard University Press.

[30] Jorgenson, D.W. (2000), *Econometrics,* Vol 1. The MIT Press.

[31] Jorgenson, D.W. and K. (2000), "Raising the Speed Limit: U.S. Economic Growth in the Information Age," *Brookings Papers on Economic Activity.*

[32] Jorgenson, D.W. (2001), "Information Technology and the U.S. Economy" *American Economic Review* 91, 1.

[33] Kalt, J. P. (1978), "Technological Change and Factor Substitution in the United States: 1926-1967," *International Economic Review.*

[34] Katz, L.and K.Murphy (1992), "Changes in Relative Wages: Supply and Demand Factors," *Quarterly Journal of Economics,* CVIIKatz, L.and D. Autor (1999), "Changes in the Wage Structure and Earnings Inequality" in O. Ashenfelter and D. Card, eds., *The Handbook of Labor Economics Volume III,* Amsterdam: Elsevier.

[35] Katz, L.and D. Autor (1999), "Changes in the Wage Structure and Earnings Inequality" in O. Ashenfelter and D. Card, eds., *The Handbook of Labor Economics Volume III,* Amsterdam: Elsevier.

[36] Krueger, A. (1993), "How Computers have Changed the Wage Structure: Evidence from Microdata, 1984-1989," Q*uarterly Journal of Economics,* CIIX.

[37] Krusell, P., L. Ohanian, V. Rios-Rull, and G. Violante (2000), "Capital-skill Complementarity and Inequality," *Econometrica 68, 5, 1029-1053.*

[38] McFadden, D. (1963), "Further Results on CES Production Functions", *Review of Economic Studies* 30.

[39] Mincer, J. (1991), "Human Capital, Technology, and the Wage Structure: What do Time Series Show?," *NBER Working Paper* 3581.

[40] Mincer, J. (2001), "Technology and the Labor Market," mimeo Columbia University.

[41] Tenreyro, Silvana (2000), "Technological Progress and Inequality," mimeo, Harvard University.

[42] Thompson, H. (1997), "Substitution Elasticities with Many Inputs," *Appl. Math. Lett.* Vol. 10, No. 3, pp123-127.

[43] Murphy, K. and F. Welch (1992), "The Structure of Wages," Q*uarterly Journal of Economics,* CVII.

[44] Uzawa, H (1962), "Production Functions with Constant Elasticities of Substitution, " *Review of Economic Studies 29, no.81: 291-299.*

[45] Wood, A. (1994), *North-South Trade, Employment and Inequality: Changing Fortunes in a Skill driven World,* Oxford, Claredon Press

Appendix I: Construction of the Labor Data

The source of the data are the CPS Annual Demographic March Files for the years 1964-2000.[29] I restrict attention to all people between 16 and 70 years old. The sample does not include individuals for whom the Census imputed wages due to the fact that the imputation procedures changed between the 1975 and 1976 March CPS surveys. Katz and Murphy includes these workers, but makes a correction to account for this change[30]. Adjustments for top coded earnings are also made, especially to correct for the big change in the topcode in 1995. I account for self-employed workers, but assume that their wage distribution is the same as that of the other workers.

The series for skilled and unskilled labor input and wages are constructed in two steps. In the first step, 88 demographic groups are constructed. In the second step, these groups are sorted into two categories: skilled labor and unskilled labor. The key variables are aggregated across groups to obtain category specific averages. In the second step there is some weighting that goes beyond the CPS weighting scheme needed for adjusting the sampling probability. In what follows, I describe how the groups are constructed, what criteria I use to sort the demographic groups into skilled and unskilled categories, and how the group variables are aggregated and weighted to construct the skilled and unskilled labor input and wage series.

For each record in the CPS, I record demographic characteristics, such as age, sex, and highest education attended, as well as the CPS weights. I also record current employment status, weeks worked last year, hours worked last week, and labor income earned last year.

All workers in the sample are grouped according to their demographic characteristics. The groups I consider are distinguished by the following[31];

- Age: there are 11 five-year groups
- Sex

[29] We used the CPS files from Unicon Research Corporation.Unicon addresses all of the deficiencies and difficulties related to the files provided by Census Bureau. Some of these problems are that variables change location and length over time, old variables are dropped and new ones added, codings change from time to time, as do the questions from which the variables are derived. Moreover, these changes in questionnaire content are often subtle. The values at which monetary variables are top-coded vary over time, often in ways not clearly spelled out in the documentation supplied with the surveys. The software provided by Unicon enables the user to locate relevant variables with relative ease, to produce data files by simply naming variables and years, to collect and view in compact form all coding and universe information for a variable across all survey years, and to ascertain easily the survey questions that led to the variable of interest. Moreover, the system provides some information that is not available in the written documentation available from the Census Bureau, and it offers uniformly recoded versions of selected variables.

[30] To adjust group average wages for changes in the imputation procedures, Katz multiplies the average wages in each cell for the years 1963-1975 by a time-invariant, cell-specific, adjustement factor. The adjustment factors were picked to impose the condition that the average percentage wage difference between the wages of all workers and those of workers without wage imputations were the same in the 1967-1975 and 1975-1988 periods. The author claims that, qualitatively, there is no difference between doing this adjustment and excluding workers with imputed wages.

[31] We define demograhic categories as in Krusell et al (2000). Katz and Murphy (1992) consider, instead, 40 single-year potential experience categories, where experience is defined as min(age-years of schooling-7,age-17). Therefore, they divide the data into 320 distinct labor groups.

- Education: the education status is grouped as follows:

1. $E_i \leq 11$: no high school diploma
2. $E_i = 12$: high school graduate
3. $12 < E_i \leq 15$: some college
4. $E_i > 15$: college graduate and more

Each worker is assigned to one of the resulting 88 groups defined by age, sex, and education. For the computation of the group labor input, I must take into account the labor input of those workers who reported zero hours worked last week[32]. I have made this correction by assuming that their weekly supply of hours is equal to that of the average worker with nonzero hours worked belonging to their same group. I have made an analogous correction for those who reported zero total earnings.

The methodology to aggregate groups into skilled and unskilled categories is described in Ho and Jorgenson (1999) and Jorgenson, Gollop and Fraumeni (1987), However, they do not aggregate over skilled and unskilled categories, but over other demographic groups. As opposed to Katz and Murphy, this methodology is based on an index number approach and does not use a fixed-weight aggregation scheme. The main feature of this methodology is that it combines hours for workers with different characteristics, using hourly wage rates as weights, into a constant quality index of labor input. These indices incorporate characteristics of individual workers such as age, sex, and education. A constant quality index of labor input is a superior than hours of work as a measure of labor input because it captures substitution among different types of labor by weighting the components by their marginal products.

Skilled labor input, L_S, is a translog function of its individual components, so that the growth rate of skilled labor input is a weighted average of the growth rates of its components

$$\Delta \ln L_{S,t} = \sum_{j \in S} \nu_{j,t} \Delta \ln L_{j,t}$$

The weights are given by the average shares of the components in the value of skilled labor compensation

$$\nu_{j,t} = \frac{p_{j,t} L_{j,t}}{\sum_{j \in S} p_{j,t} L_{j,t}}$$

where p_j for $j \in S$ is the set of prices of all types of skilled labor input.

The corresponding price index of labor input, P_S, is the ratio of the value of skilled labor compensation to the skilled labor input index.

$$P_{S,t} = \frac{\sum_{j \in S} p_{j,t} L_{j,t}}{L_{S,t}}$$

[32] This can happen although they worked for a positive number of weeks: the week before the survey they were unemployed or, if they had a job, they were not at work.

I assume that labor input is proportional to hours worked.. Thus, I define the index of skilled labor quality, q_S, as

$$q_{S,t} = \frac{L_{S,t}}{H_{S,t}}$$

where H_S is the unweighted sum of hours worked by all types of skilled labor

$$H_{S,t} = \sum_{j \in S} H_{j,t}$$

Therefore, the growth rate of the skilled labor quality is given by the difference between weighted and unweighted growth in skilled labor hours. This reflects substitutions among heterogeneous types of labor with different characteristics and different marginal products.

$$\Delta \ln q_{S,t} = \sum_{j \in S} \nu_{j,t} \Delta \ln H_{j,t} - \Delta \ln H_{S,t}$$

Similar variables are defined for the unskilled group.

Appendix II: Constraints Implied by the Theory of Production

The constraints on the system of share equations implied by the theory of production are:

- Homogeneity. The value shares are homogenous of degree zero in the input prices. This implies that the parameters of the price function must satisfy the restrictions

$$\begin{aligned} B_{pp}\mathsf{i} &= 0 \\ \boldsymbol{\beta}'_{pt}\mathsf{i} &= 0 \end{aligned}$$

where i is a vector of ones.

- Product exhaustation. The sum of the value shares is equal to unity. In other words

$$\begin{aligned} \alpha'\mathsf{i} &= \mathsf{1} \\ B'_{pp}\mathsf{i} &= 0 \\ \boldsymbol{\beta}'_{pt}\mathsf{i} &= 0 \end{aligned}$$

- Symmetry. The matrix of share elasticities, biases of technical change, and deceleration of technical change must be symmetric, which implies

$$\begin{bmatrix} B_{pp} & \boldsymbol{\beta}_{pt} \\ \boldsymbol{\beta}'_{pt} & \beta_{tt} \end{bmatrix} = \begin{bmatrix} B_{pp} & \boldsymbol{\beta}_{pt} \\ \boldsymbol{\beta}'_{pt} & \beta_{tt} \end{bmatrix}'$$

- Nonnegativity. The value shares must be nonnegative. That is

$$\boldsymbol{\alpha}_p + B_{pp} \ln p + \boldsymbol{\beta}_{pt}\ t = 0$$

- Concavity. The matrix of share elasticities must be nonpositive definite.

Concavity Constraints

A complication that arises when estimating the model is that the aggregate production frontier should be concave. Most of the conditions implied by the theory of production translate easily on restrictions on the coefficients. However, concavity requires that the Hessian must be nonpositive definite, and imposing this turns out to be a little bit more complicate.

The translog price function is concave if $H = \left[\frac{\partial^2 P}{\partial p \partial p'}\right]$ is non-positive definite, i.e., $u'Hu \leq 0$ for all vectors u. In the log form of the price function I have

$$\begin{aligned}
\frac{\partial^2 \ln P}{\partial \ln p_j \partial \ln p_k} &= \frac{\partial}{\partial \ln p_k} \frac{p_j \partial P}{P \partial p_j} = -p_j \frac{\partial P}{\partial p_j} \frac{p_k \partial P}{P^2 \partial p_k} + \frac{p_j}{P} p_k \frac{\partial^2 P}{\partial p_j \partial p_k} \\
&= -v_j v_k + \frac{p_j p_k}{P} \frac{\partial^2 P}{\partial p_j \partial p_k}
\end{aligned}$$

and

$$\frac{\partial^2 \ln P}{\partial \ln p_j^2} = \frac{p_j}{P}\frac{\partial P}{\partial p_j} - \frac{p_j}{P^2}\left(\frac{\partial P}{\partial p_j}\right)^2 + \frac{p_j^2}{P}\frac{\partial^2 P}{\partial p_j^2} = v_j - v_j^2 + \frac{p_j^2}{P}\frac{\partial^2 P}{\partial p_j^2}$$

giving the following relation between the two Hessian matrices

$$\begin{aligned}
\frac{1}{P} NHN &= \begin{bmatrix} p_1 & & & \\ & p_2 & & \\ & & \ddots & \\ & & & p_n \end{bmatrix} \left[\frac{\partial^2 P}{\partial p \partial p'}\right] \begin{bmatrix} p_1 & & & \\ & p_2 & & \\ & & \ddots & \\ & & & p_n \end{bmatrix} \\
&= \left[\frac{\partial^2 \ln P}{\partial \ln p_j \partial \ln p_k}\right] + \begin{bmatrix} v_1 v_1 & \cdots & v_1 v_n \\ v_1 v_2 & & \vdots \\ \vdots & \ddots & \\ v_1 v_n & & v_n v_n \end{bmatrix} - \begin{bmatrix} v_1 & & \\ & \ddots & \\ & & v_n \end{bmatrix} \\
&= B_{pp} + vv' - V
\end{aligned}$$

If H is non-positive definite, then so is $\_B_{pp} + vv' - V$. A sufficient condition for this is that B_{pp} is non-positive definite. However, this is a very restrictive condition and I shall concentrate on the entire expression. The price function will be globally concave if $B_{pp} + vv' - V$ is non-positive definite for all values of v. This, however, is hard to satisfy with the data and I shall merely impose local concavity, that is, the matrix is to be non-positive definite for the realized values of v.

To implement this curvature restriction a Cholesky decomposition is done on both B_{pp} and $B_{pp}+vv'-V$ matrices. First I decompose the B_{pp} matrix for the case of four inputs

$$\begin{aligned}
B_{pp} &= \Lambda\Delta\Lambda \\
&= \begin{bmatrix} 1 & & & \\ \lambda_{12} & 1 & & \\ \vdots & & 1 & \\ \lambda_{14} & \cdots & \lambda_{34} & 1 \end{bmatrix} \begin{bmatrix} \delta_1 & & & \\ & \delta_2 & & \\ & & \delta_3 & \\ & & & \delta_4 \end{bmatrix} \begin{bmatrix} 1 & & & \\ \lambda_{12} & 1 & & \\ \vdots & & 1 & \\ \lambda_{14} & \cdots & \lambda_{34} & 1 \end{bmatrix} \\
&= \begin{bmatrix} \delta_1 & & & \\ \delta_1\lambda_{12} & \delta_1\lambda_{12}^2+\delta_2 & & \\ \delta_1\lambda_{13} & \delta_1\lambda_{12}\lambda_{13}+\delta_2\lambda_{23} & \ddots & \\ \delta_1\lambda_{14} & \delta_1\lambda_{12}\lambda_{14}+\delta_2\lambda_{24} & \cdots & \delta_1\lambda_{14}^2+\delta_2\lambda_{24}^2+\delta_3\lambda_{34}^2+\delta_4 \end{bmatrix}
\end{aligned}$$

The second matrix $B_{pp}+vv'-V$ is decomposed similarly

$$B_{pp}+vv'-V = LDL'$$

I use d_j and l_{jk} in place of δ_j and λ_{jk} for the first matrix. The following relations can then be derived for the second equation

$$\begin{aligned}
d_1 &= \beta_{11}+v_1^2-v_1 \\
l_{12} &= (\beta_{12}+v_1v_2)/d_1 \\
d_2 &= \beta_{22}+v_2^2-v_2-d_1l_{12}^2 \\
l_{13} &= (\beta_{13}+v_1v_3)/d_1 \\
l_{23} &= (\beta_{23}+v_2v_3-d_1l_{12}l_{13})/d_2 \\
d_3 &= \beta_{33}+v_3^2-v_3-d_1l_{13}^2-d_2l_{32}^2 \\
l_{14} &= (\beta_{14}+v_1v_4)/d_1 \\
l_{24} &= (\beta_{24}+v_2v_4-d_1l_{12}l_{14})/d_2 \\
l_{34} &= (\beta_{34}+v_3v_4-d_1l_{13}l_{14}-d_2l_{23}l_{24})/d_3 \\
d_4 &= \beta_{44}+v_4^2-v_4-d_1l_{14}^2-d_2l_{24}^2-d_3l_{34}^2
\end{aligned}$$

In the estimation of the model, B_{pp} (equivalently, Δ and Λ) is estimated. I can then calculate $\widehat{B}_{pp}+v_tv_t'-V_t$ and $L_t\ D_tL_t'$ for each t. The concavity conditions are imposed by "squeezing" the δ and $\lambda's$ so that the derived d_{jt} 's are negative in the sample period.

Appendix III: Econometric Strategy

To estimate the price function jointly with the share equations, it is necessary to specify a stochastic framework. I do this by adding a random disturbance term to each equation in the system and assume that the resulting vector is multivariate normally distributed with mean zero and constant covariance matrix.

Homogeneity of degree one of the price function implies that the value shares sum to unity and that these shares are homogeneous of degree zero in the input prices. This feature of the share equation system implies that estimation of the four share equations will be non-feasible, since the disturbance covariance matrix will be singular and non-diagonal. The most common procedure to handle this singularity problem is to drop an arbitrary equation. Some estimation procedures, such as iterated three-stage least squares are invariant to the choice of which three equations are directly estimated. I decide to drop the share equation for non-IT capital in the four input model, and for structures in the five input model.

At the level of an individual firm it may be reasonable to assume that the supply of inputs is perfectly elastic, and therefore that input prices can be taken as fixed. With aggregate data the price that determine demands and supplies cannot be treated as exogenous variables. Thus, the estimation procedure is iterated three-stage least squares. The I3SLS estimator is consistent and asymptotically efficient. The necessary condition for identification is that

$$\frac{1}{2}(J+3) < (J-1)\min(I, T-1)$$

where J is the number of inputs, and I is the number of instruments. The instruments used in the estimation include measures of tax rates, population, government demand, and lagged values of prices and wealth. The complete list of instruments, as well as Hausman tests, can be found in Table A1.

3SLS is equivalent to GMM with efficient weights. The model is estimated in two steps. In the first step, the model is estimated without imposing the concavity constraints, and using the identity matrix as the weighting matrix. The residuals from each equation are used to compute the covariance matrix of the system, which is then used in forming the weighting matrix $\widehat{\Sigma}^{-1}$ in the second stage. The second stage imposes the concavity constraints derived above. This stage is equivalent to finding the set of parameters that minimize the following quadratic form subject to the concavity constraints

$$J = (Y - X\Theta)' \left(\Sigma^{-1} \otimes \left(Z \left(Z'Z\right) Z'\right)\right) (Y - X\Theta)$$

where Y is a vector of stacked dependent variables, X is a block-diagonal matrix of the independent variables with the cross equation constraints imposed, Θ is the vector of parameters to be estimated, and Z is the matrix of instruments. Note that Θ include α_o, α_j, α_t, β_{jk} β_{jt}, and β_{tt} for $j = s, u, i, n$.

Hausman Test

I test the validity of the instruments contained in Table A1 performing some Hausman exogeneity tests. A Hausman test compares two sets of estimates of the same parameters using the same data: one obtained using an efficient estimation technique,$\widehat{\delta}^*$, (in this case, 3SLS assuming all the 15 instruments are exogenous), and another obtained by an estimation method, which is consistent but not efficient, $\widehat{\delta}$, (in this case, 3SLS excluding one of the potential instruments). The test statistic is $W = \left(\widehat{\delta}^* - \widehat{\delta}\right)' \left\{Est.Var\left[\widehat{\delta}\right] - Est.Var\left[\widehat{\delta}^*\right]\right\}^{-1} \left(\widehat{\delta}^* - \widehat{\delta}\right)$. This is the Wald statistic based on the difference of the two estimators and is distributed as a χ^2 with degrees of freedom equal to the number of observations minus the number of parameters estimated. The null hypothesis is that the 3SLS estimates using the fifteen instruments is more efficient that the estimates using all instruments but a given subset of them. The high p-values showed in Table A1 confirm the exogeneity of the instruments.

Appendix IV: Decomposition of the growth of the relative share of skilled labor

The decomposition of the growth rate of the relative share of skilled labor is performed similarly to the decomposition of the growth rate of the skill premium presented in the text. The vector of input shares, v, is given by

$$\begin{aligned} v &= \boldsymbol{\alpha}_p + B_{pp} \ln p + \boldsymbol{\beta}_{pt}\ t \\ &= \boldsymbol{\alpha}_p + B_{pp} \ln\left(\frac{vPQ}{q}\right) + \boldsymbol{\beta}_{pt}\ t \end{aligned}$$

Taking logs and differentiating with respect to time, we obtain

$$g_v = \Lambda \left(B_{pp}\left(g_v - g_q + g_{PQ}\right) + \boldsymbol{\beta}_{pt}\right)$$

where g_x is the growth rate of variable x, Λ is a diagonal matrix whose (j,j) element is $\frac{1}{v_j}$. Since $B_{pp}g_{PQ} = 0$, we can rewrite the above expression as

$$g_v = \left(B_{pp} - V\right)^{-1}\left(B_{pp}g_q - \boldsymbol{\beta}_{pt}\right)$$

where V is a diagonal matrix whose (j,j) element is v_j.

If $v = (v_s, v_u, v_i, v_n)$, the growth rate in the relative share of skilled labor can be written as

$$g_{v_s} - g_{v_u} = \left(\phi_1 g_{q_s} + \phi_2 g_{q_u}\right) + \left(\phi_3 g_{q_i} + \phi_4 g_{q_n}\right) + \left(\psi_1\beta_{st} + \psi_2\beta_{ut}\right) + \left(\psi_3\beta_{it} + \psi_4\beta_{nt}\right)$$

where ϕ_k is the element $(1,k)$ minus the element $(2,k)$ in the matrix $\left(B_{pp} - V\right)^{-1} B_{pp}$, and ψ_k is the element $(1,k)$ minus the element $(2,k)$ in the matrix $\left(B_{pp} - V\right)^{-1}$ for $k = 1, 2, ..4$. ϕ_k and ψ_k vary over time.

The first component, $\left(\phi_1 g_{q_s} + \phi_2 g_{q_u}\right)$, affects the growth rate of the relative share of skilled labor through the growth in the supplies of skilled and unskilled labor. This is the relative supply effect. The second component, $\left(\phi_3 g_{q_i} + \phi_4 g_{q_n}\right)$, the complementarity effect, depends on the growth of IT capital relative to that of non-IT capital. Finally, the last two components constitute the technology effect. The technology component involves: first, the relative efficiency of skilled labor, which is a function of the biases of technical change of skilled and unskilled labor, and, second, the relative efficiency of IT capital, which depends on the biases of technical change of IT capital, and non IT capital.

Table 1: The Effect of Capital and Technology on the Skill Premium

Dependent Variable is Log College Wage Premium

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Rel. Supply	**-0.574*** **	**-0.596*** **	**-0.551*** **	**-0.595*** **	**-0.595*** **	**-0.686*** **	**-0.364*** **	**-0.763*** **	**-0.3818*** **	**-0.406*** **	**-0.354*** **	**-0.416*** **	**-0.297*** **
	(0.043)	(0.053)	(0.047)	(0.039)	(0.040)	(0.087)	(0.055)	(0.081)	(0.083)	(0.042)	(0.036)	(0.050)	(0.046)
Trend	**0.021*** **		**0.031*** **		**0.002**		**0.040*** **		**0.036*** **		**0.018*** **		**0.022*** **
	(0.001)		(0.008)		(0.007)		(0.0041)		(0.005)		(0.004)		(0.004)
Log(EQ)		**0.362*** **	**-0.178**										
		(0.031)	(0.152)										
Log(IT)				**0.149*** **	**0.136*** **					**0.271*** **	**0.181*** **	**0.266*** **	**0.178*** **
				(0.009)	(0.049)					(0.021)	(0.027)	(0.024)	(0.026)
Log(EQnonIT)						**0.571*** **	**-0.602*** **			**-0.555*** **	**-0.708*** **	**-0.579*** **	**-0.643*** **
						(0.070)	(0.1263)			(0.093)	(0.084)	(0.113)	(0.087)
Log(STR)								**1.031*** **	**-0.812*** **			**0.075**	**-0.335***
								(0.106)	(0.308)			(0.200)	(0.177)
Adjusted-R2	0.85	0.79	0.85	0.88	0.88	0.65	0.91	0.73	0.87	0.94	0.96	0.94	0.96
DW	0.55	0.50	0.53	0.73	0.72	0.39	0.72	0.48	0.48	0.99	1.43	1.00	1.52

Note: This table presents the results of OLS regressions. EQ, IT EqnonIT, STR stand for equipment capital, information technology capital, equipment excluding information technology, and structures, respectively. Rel. Supply is the ratio of skilled to unskilled workers. Skilled labor is defined as requiring college completion. DW is the Durbin-Watson statistic for serial correlation.
Standard errors in parentheses. *** indicates statistical significance at 1% level, ** at 5% level, * at 10% level.

Table 2: The Effect of Capital Prices and Technology on the Skill Premium

Dependent Variable is College Wage Premium

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Rel.Supply)	**-0.574*****	**-0.232***	**-0.574*****	**-0.459*****	**-0.569*****	**-0.555*****	**-0.428*****	**-0.546*****
	(0.043)	(0.085)	(0.046)	(0.052)	(0.041)	(0.050)	(0.055)	(0.047)
Trend	**0.021*****		**0.021*****		**0.015*****	**0.021*****		**0.015*****
	(0.001)		(0.002)		(0.002)	(0.001)		(0.003)
Log(P_EQ/P_STR)		**-0.360****	**0.002**					
		(0.119)	(0.059)					
Log(P_IT/P_STR)				**-0.229*****	**-0.078*****		**-0.227*****	**-0.079****
				(0.023)	(0.031)		(0.021)	(0.033)
Log(P_EQNIT/P_STR)						**0.044**	**0.179****	**0.088**
						(0.061)	(0.077)	(0.060)
Adjusted R2	0.85	0.18	0.85	0.76	0.87	0.85	0.76	0.87

Note: This table presents the results of OLS regressions. P_EQ, P_IT P_EqnonIT, P_STR stand for price of equipment capital, information technology capital, equipment excluding information technology, and structures, respectively. Rel. Supply is the ratio of skilled to unskilled workers. Skilled labor is defined as requiring college completion.
Standard errors in parentheses. *** indicates statistical significance at 1% level, ** at 5% level, * at 10% level.

Table 3: Estimates of the Translog Price Function. IT Model

PANEL A: Intercept Parameters (α_j)

Skilled labor	Unskilled labor	IT capital	Non IT capital
0.250* **	**0.342*** **	**0.050*** **	**0.358*** **
(0.002)	(0.003)	(0.001)	(0.003)

PANEL B: Biases of technical change (β_{jt})

Skilled labor	Unskilled labor	IT capital	Non IT capital
0.0026* **	**-0.0066*** **	**0.0016*** **	**0.0023*** **
(0.0006)	(0.0005)	(0.0003)	(0.0006)

PANEL C: Share elasticities (β_{jk})

	Skilled labor	Unskilled labor	IT capital	Non It capital
Skilled labor	**-0.052*** **			
	(0.022)			
Unskilled labor	**0.092*** **	**0.021**		
	(0.017)	(0.017)		
IT capital	**-0.020*** **	**0.001**	**0.004**	
	(0.008)	(0.007)	(0.005)	
Non It capital	**-0.020**	**-0.114*** **	**0.015***	**0.120*** **
	(0.014)	(0.013)	(0.008)	(0.021)

PANEL D: Allen partial elasticities of substitution (σ_{jk})

	Skilled labor	Unskilled labor	IT capital	Non It capital
Skilled labor	**-5.211**			
Unskilled labor	**2.040**	**-1.180**		
IT capital	**-2.086**	**1.082**	**-27.053**	
Non IT capital	**0.694**	**0.208**	**2.433**	**-0.934**

Note: The table presents the results of 3SLS estimation of the system defined by the input share equations and the price function. Instruments and Hausman tests are presented in Table A1. The R2 corresponding to these equations are: 0.98 for the skilled labor share equation, 0.98 for the unskilled labor share equation, 0.95 for the IT share equation, and 0.90 for the price equation. The period of analysis is 1965-1999. Standard errors within parentheses. *** indicates statistical significance at 1% level, ** at 5 % level, * at 10% level. Allen partial elasticities of substitution in panel D represent mean values over the entire sample. The time series and their corresponding confidence intervals are showed in Figure 4. The remaining estimates of the system are: i) the negative of the rate of technical change in 1996, α_t =0.0024 with standard error of 0.001; ii) the deceleration of technical change, β_{tt} =0.0002 with standard error of 0.00009; iii) the intercept parameter of the price function, α_0 =0.008 with standard error of 0.008.

Table 5: Estimates of Translog Price Function. Five Input Model

PANEL A: Intercept Parameters (α_j)

Skilled labor	Unskilled labor	EQ non IT	IT	Structures
0.249* **	**0.342*** **	**0.169*** **	**0.050*** **	**0.191*** **
(0.003)	(0.003)	(0.003)	(0.001)	(0.004)

PANEL B: Biases of technical change (β_{jt})

Skilled labor	Unskilled labor	EQ non IT	IT	Structures
0.0032* **	**-0.0066*** **	**0.0013** **	**0.0017*** **	**0.0004**
(0.0007)	(0.0006)	(0.0007)	(0.0003)	(0.0008)

PANEL C: Share elasticities (β_{jk})

	Skilled labor	Unskilled labor	EQ non IT	IT	Structures
Skilled labor	**-0.074** **				
	(0.037)				
Unskilled labor	**0.111*** **	**0.010**			
	(0.029)	(0.026)			
EQ non IT	**0.018**	**-0.062** **	**0.031**		
	(0.032)	(0.026)	(0.036)		
IT	**-0.018** **	**0.003**	**0.005**	**0.006**	
	(0.009)	(0.008)	(0.009)	(0.004)	
Structures	**-0.038**	**-0.062*** **	**0.009**	**0.005**	**0.086*** **
	(0.024)	(0.022)	(0.028)	(0.009)	(0.029)

PANEL D: Allen partial elasticities of substitution (σ_{jk})

	Skilled labor	Unskilled labor	EQ non IT	IT	Structures
Skilled labor	**-5.755**				
Unskilled labor	**2.259**	**-1.239**			
EQ non IT	**1.592**	**0.062**	**-4.270**		
IT	**-1.765**	**1.203**	**1.951**	**-25.190**	
Structures	**-0.044**	**0.206**	**1.317**	**1.848**	**-1.896**

Note: The table presents the results of 3SLS estimation of the system defined by the input share equations and the price function. Instruments and Hausman tests are presented in Table 7. The R2 corresponding to these equations are: 0.98 for the skilled labor share equation, 0.98 for the unskilled labor share equation, 0.76 for the EqnonIT share equation, 0.95 for the IT share equation, and 0.92 for the price equation. Period of analysis is 1965-1999. Standard errors within parentheses. *** indicates statistical significance at 1% level, ** at 5 % level, * at 10% level. Allen partial elasticities of substitution in panel D represent mean values over the entire sample. The time series and their corresponding confidence intervals are available upon request. The remaining estimates of the system are: i) the negative of the rate of technical change in 1996, α_t =0.0023 with standard error of 0.001; ii) the deceleration of technical change, β_{tt} =0.0002 with standard error of 0.00009; iii) the intercept parameter of the price function, α_0 =0.008 with standard error of 0.008.

Table 8: Testing Groupwise Separability in Inputs

Wald statistics for translog price and production functions

	Degrees of freedom	Price	Production
{S,I} separable from {U,NI}	1	20.34	27.8
{U,I} separable from {S,NI}	1	16.92	29.67
{S,U} separable from {I,NI}	1	-0.87	10.68
{S,E} separable from {U,STR}	1	54.92	26.81
{U,E} separable from {S,STR}	1	24.07	-2.23
{S,U} separable from {E,STR}	1	1.88	-5.88

Critical values of Chi-Squared Distribution

Degrees of freedom	Level of significance 0.1	0.05	0.01
1	2.71	3.84	6.64

Note: S=skilled labor, U=unskilled labor, I=IT, NI=nonIT, E=equipment, STR=structures

Figure 1.1. The Skill Premium (normalized with 1996=1)

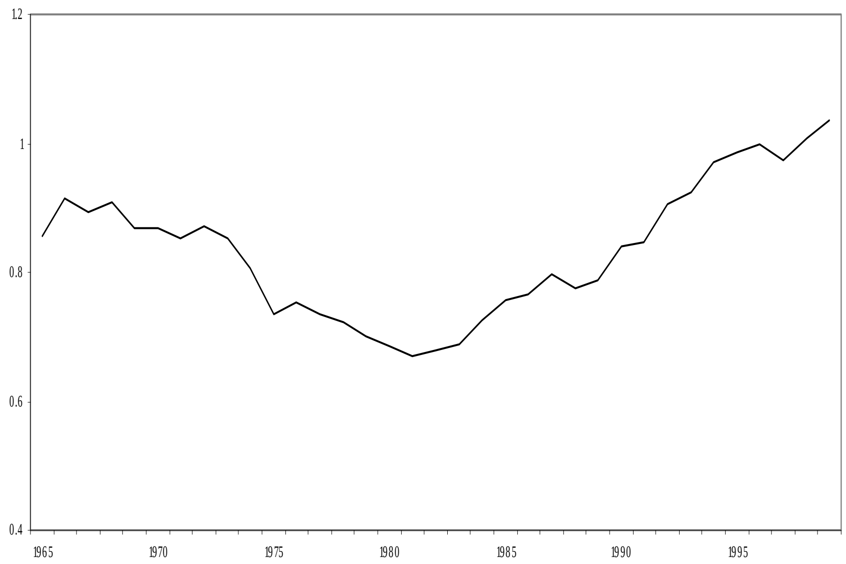


Figure 1.2. Relative Supply of Skilled to Unskilled Labor

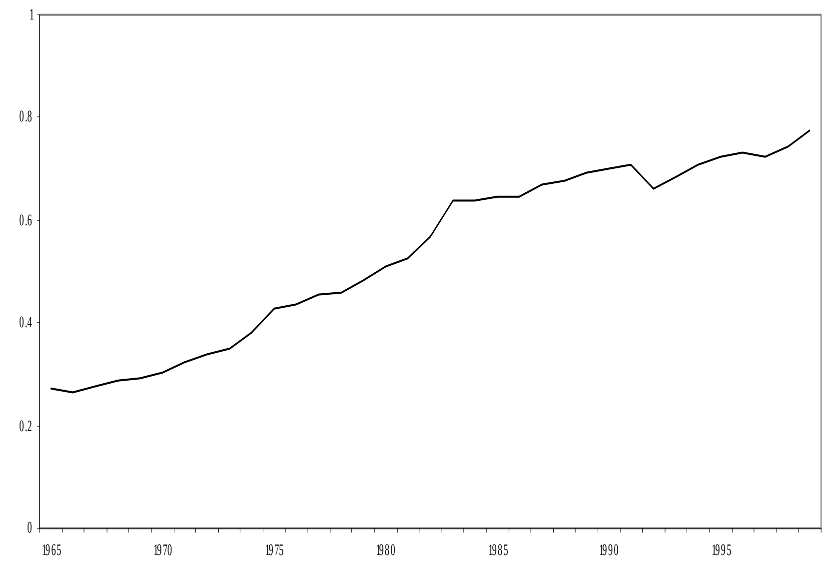
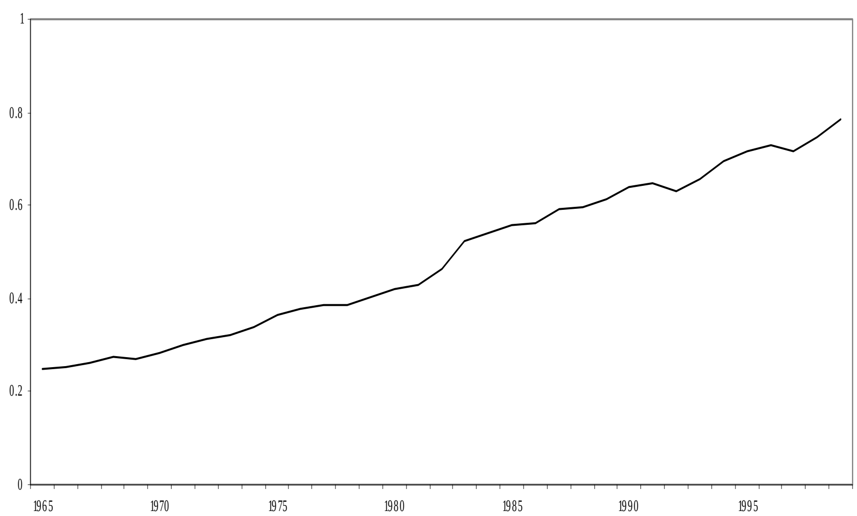


Figure 1.3. Relative Share of Skilled to Unskilled Labor



Note: Skilled labor is defined as requiring college completion or better. Workers with less than 16 years of education are defined as unskilled labor. Labor input is a quality adjusted measure of total labor hours. Data from March CPSs.

Figure 2.1. Capital Services (logs)

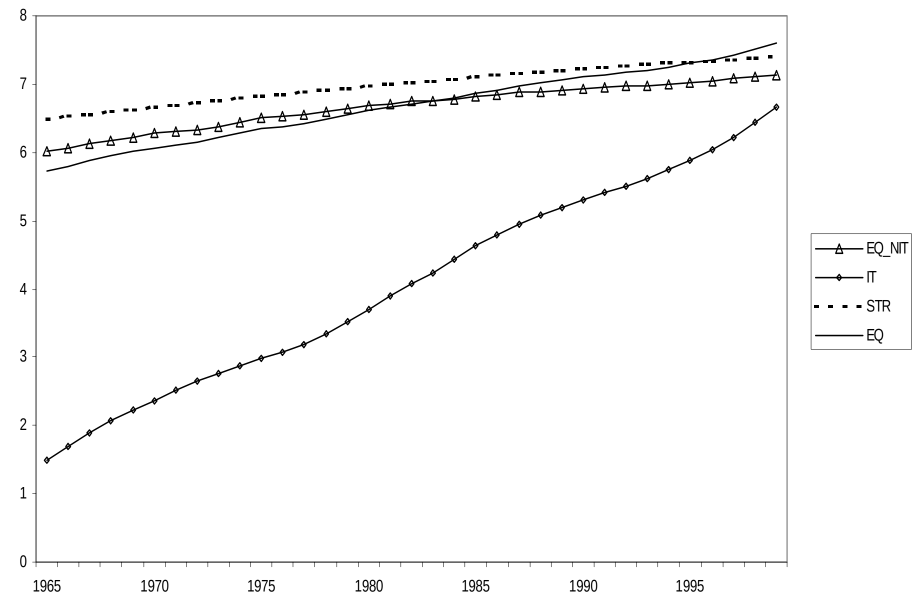


Figure 2.2. Growth Rates of Capital Services

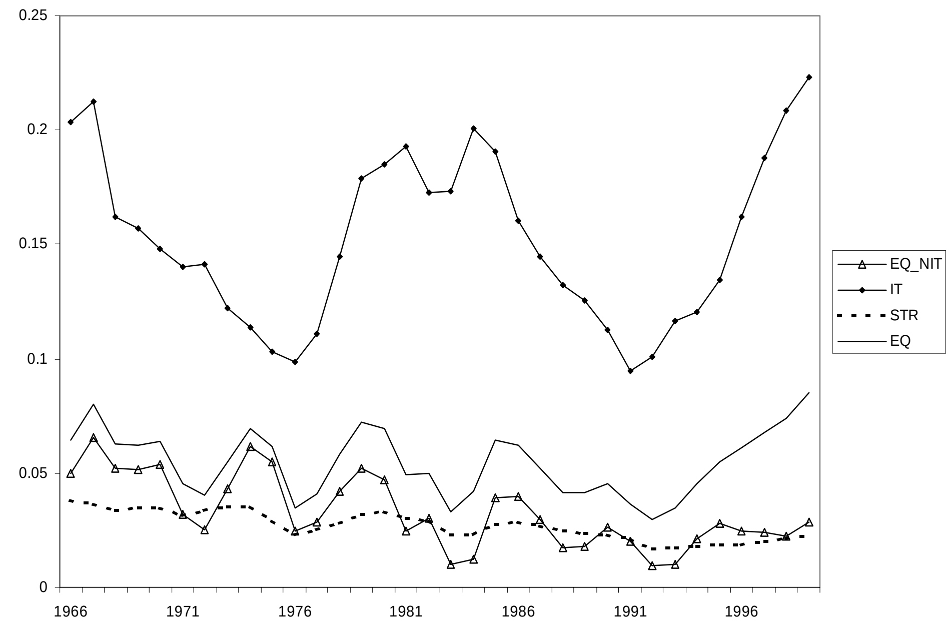


Figure 2.3. Price of Capital (logs, normalized with 1996=0)

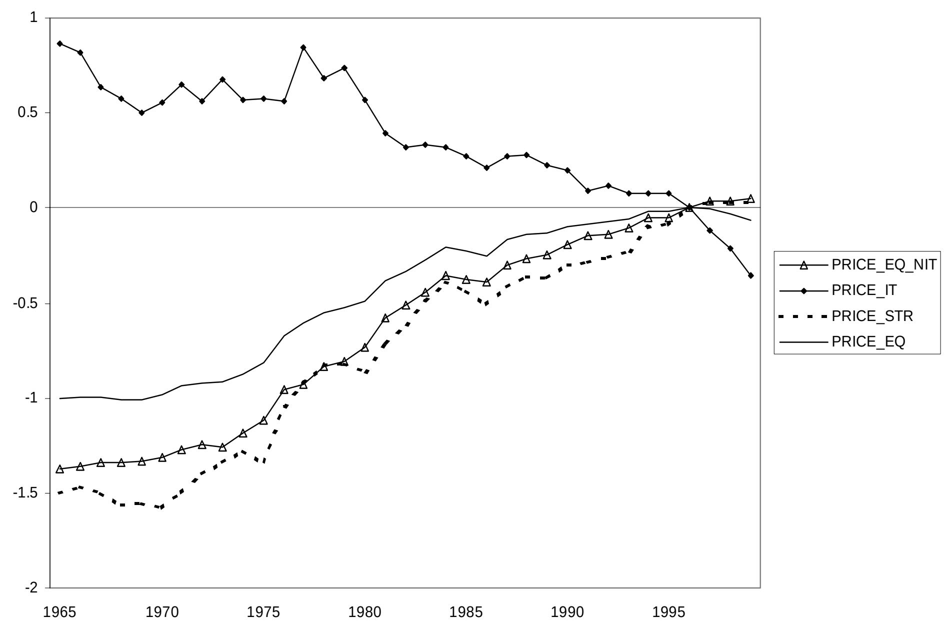


Figure 2.4. Growth Rates of Price of Capital

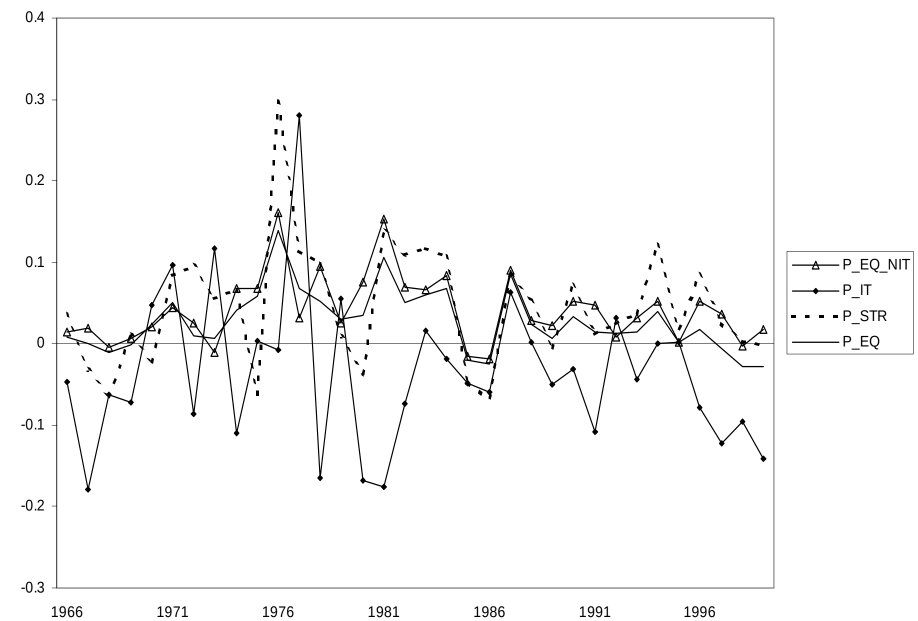


Figure 3.1. Skilled Labor to Capital (logs)

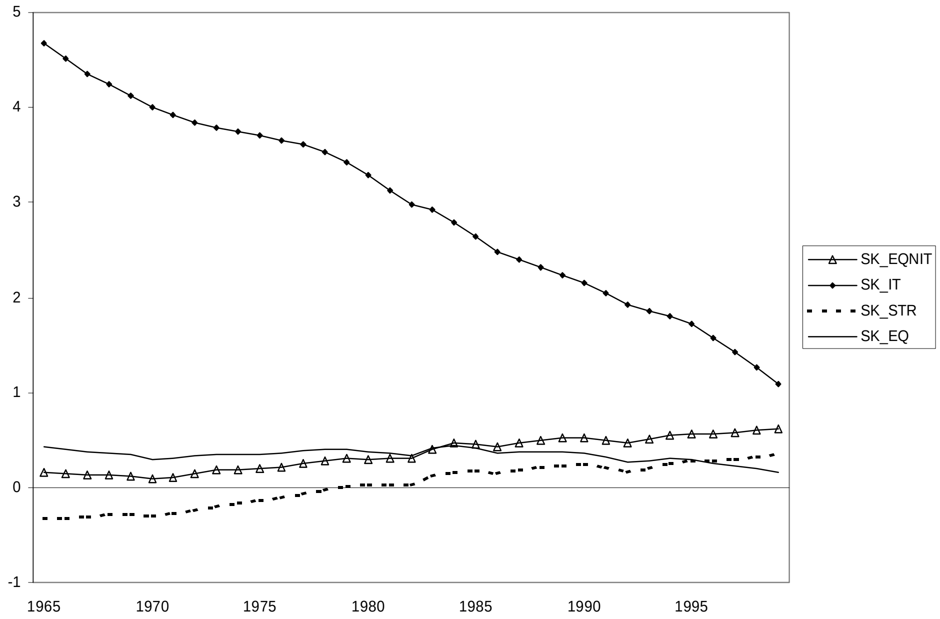


Figure 3.2. Relative Price of Skilled Labor to Capital (logs, normalized with 1996=0)

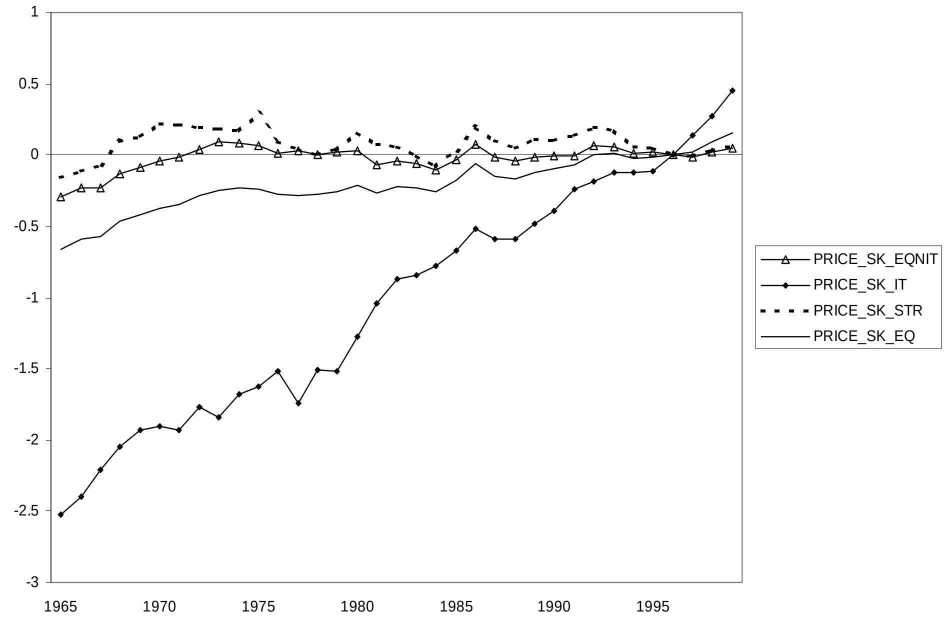
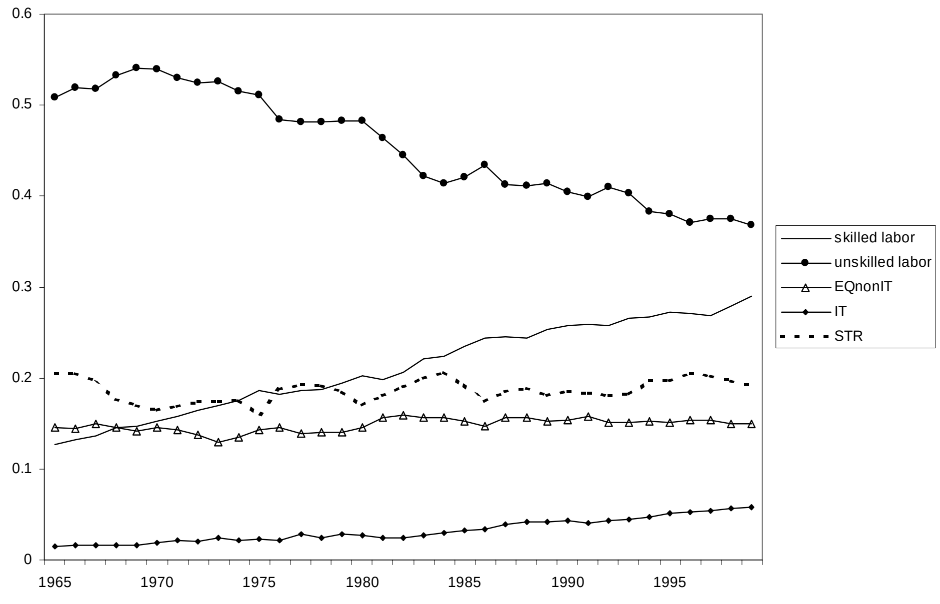


Figure 3.3. Evolution of the Shares



Note: Capital and output data, based on the National Income and Product Accounts published by the Bureau of Economic Analysis, are taken from Jorgenson (2001).

Figures 4.1-4.10: Allen Elasticity of Substitution and Standard Error Bands. IT Model

Figure 4.1: AES Skilled Labor

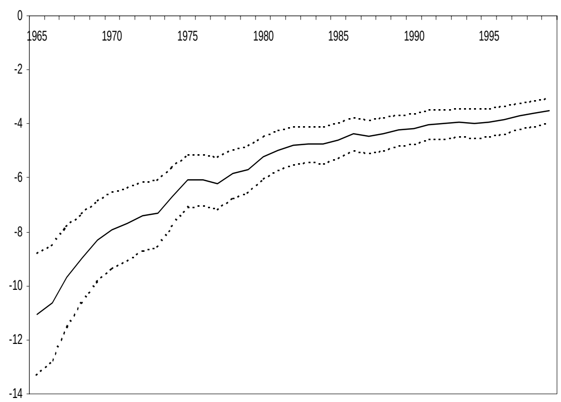


Figure 4.2: AES Skilled and Unskilled Labor

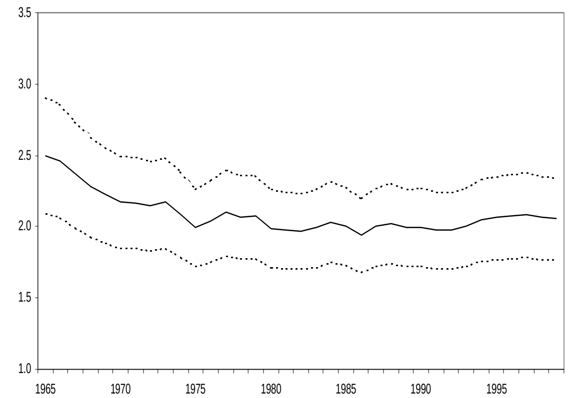


Figure 4.3: AES Skilled Labor and IT

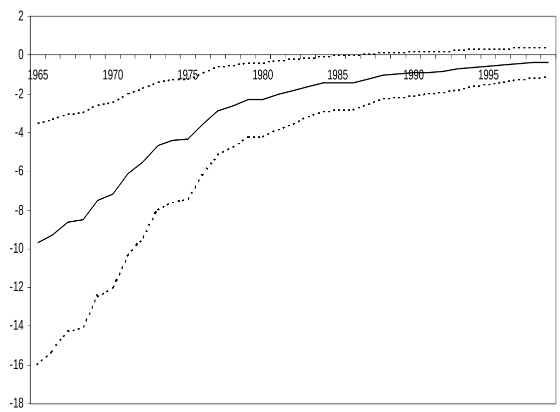


Figure 4.4: AES Skilled Labor and Non IT

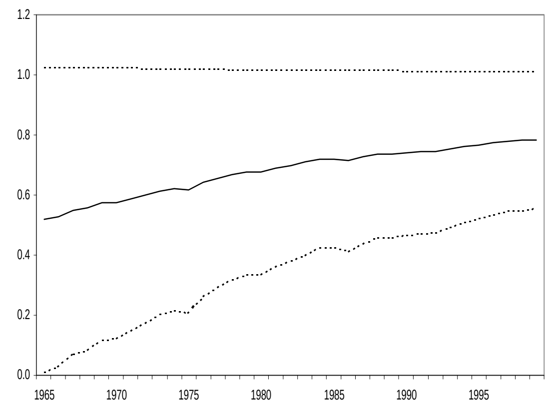


Figure 4.5: AES Unskilled Labor

Figure 4.6: AES Unskilled Labor and IT

Figures 4.1-4.10: continued

Figure 4.7: AES Unskilled Labor and Non IT

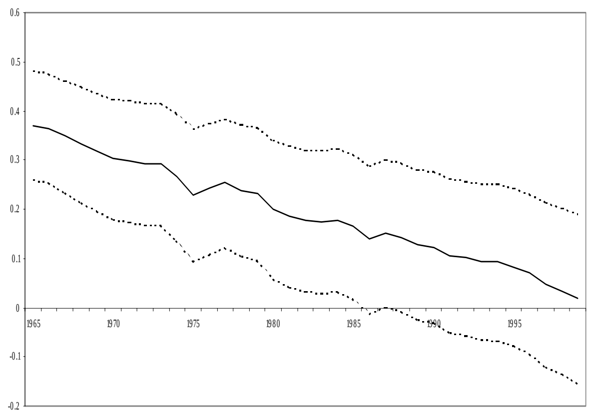


Figure 4.8: AES IT Capital

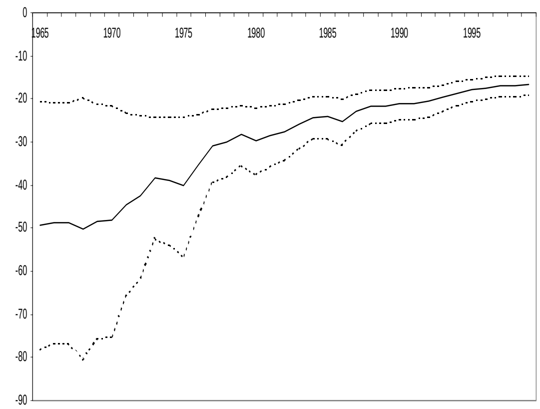


Figure 4.9: AES IT and Non IT

Figure 4.10: AES Non IT Capital

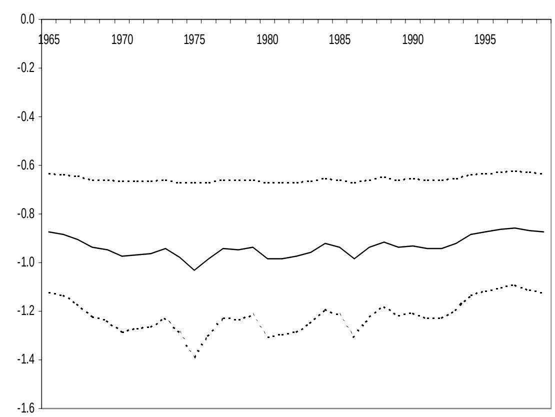


Figure 5.1: Skill Premium, normalized with 1996=1 (Actual and Predicted)

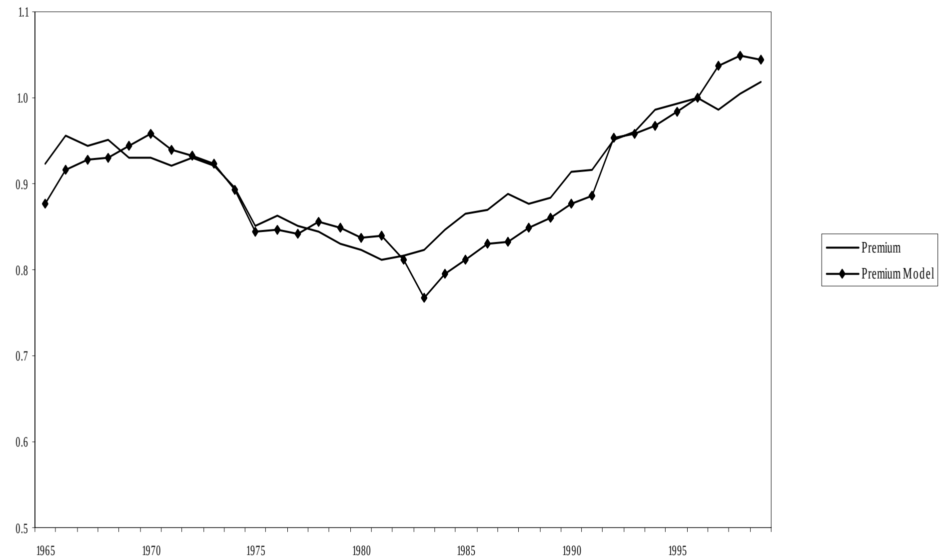


Figure 5.2: Relative Share of Skilled to Unskilled Labor (Actual and Predicted)

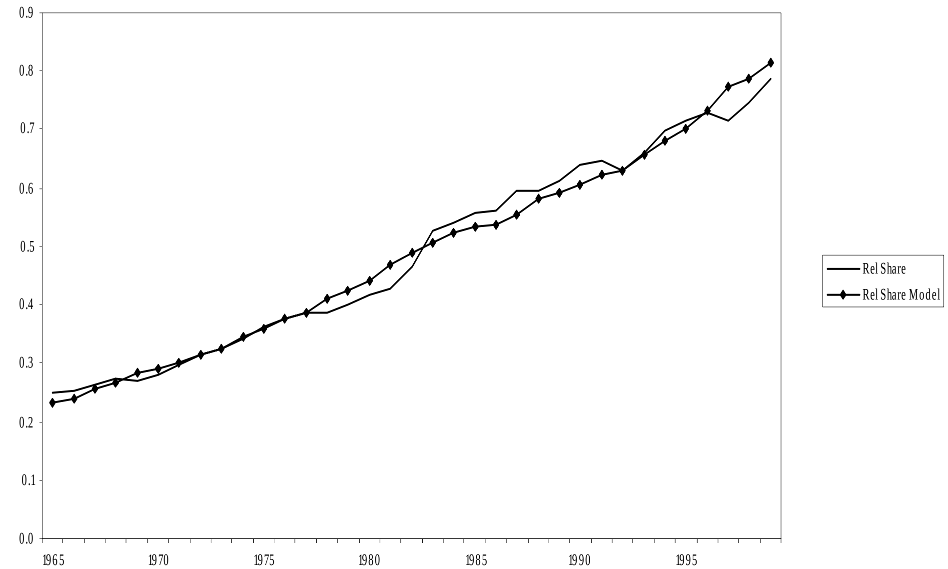


Figure 5.3: Input Shares (Actual and Predicted by IT Model)

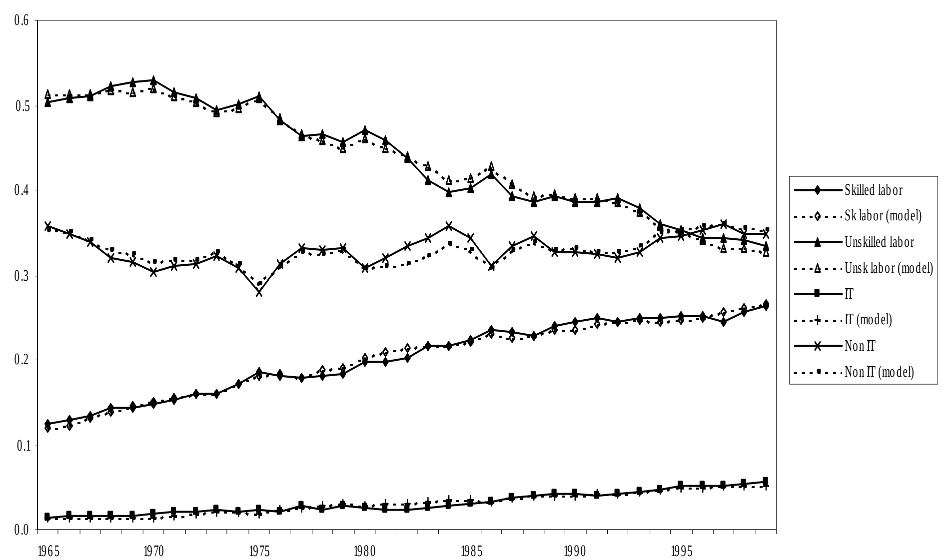
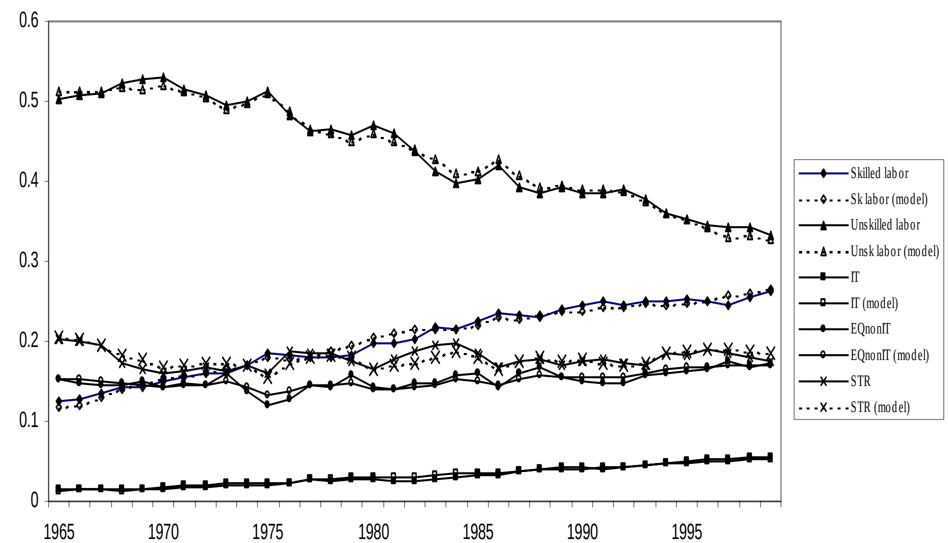


Figure 5.4: Input Shares (Actual and Predicted by Five Input Model)



Figures 6.1-6.6: Contribution of Different Factors to the Growth in the Skill Premium. IT Model (in logs, normalized with 1965=0)

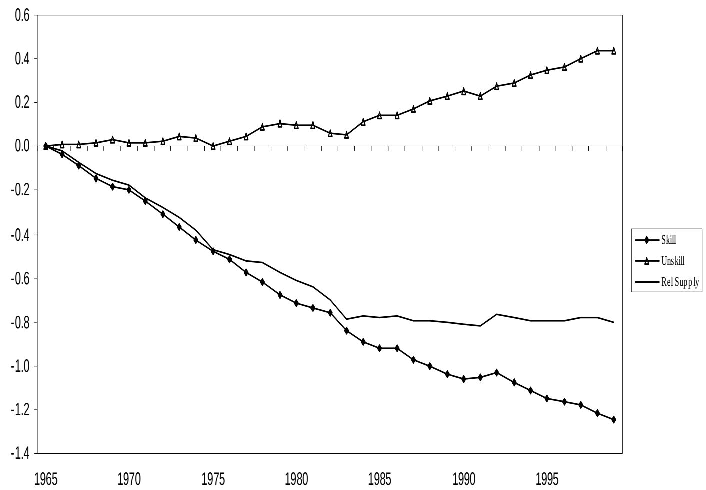


Figure 6.1: Relative Supply Effect

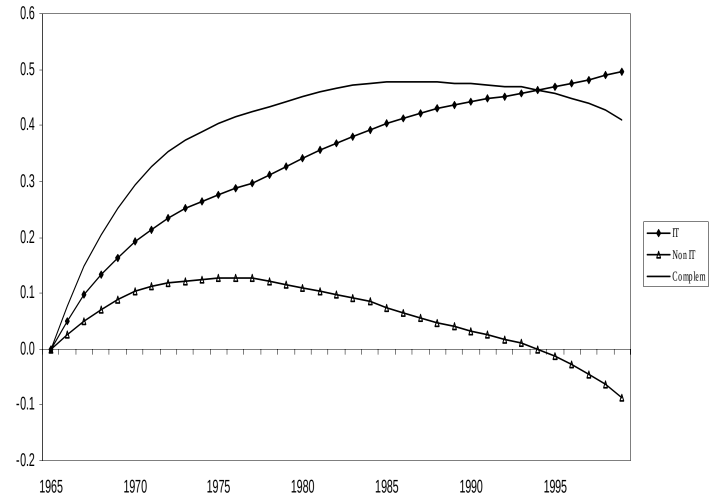


Figure 6.2: Complementarity Effect

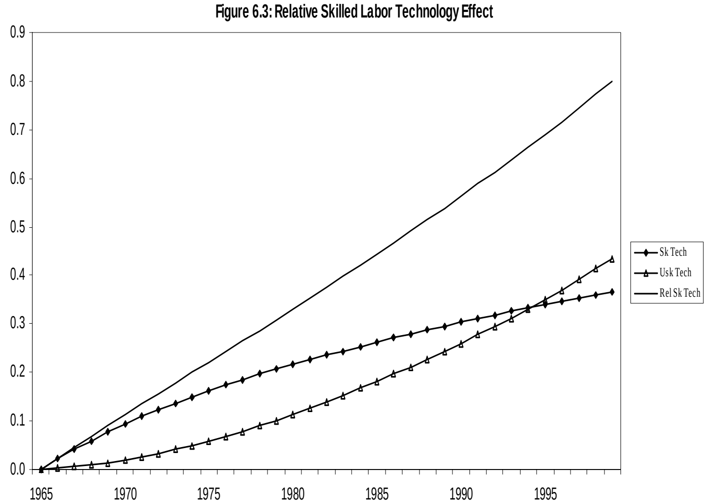


Figure 6.3: Relative Skilled Labor Technology Effect

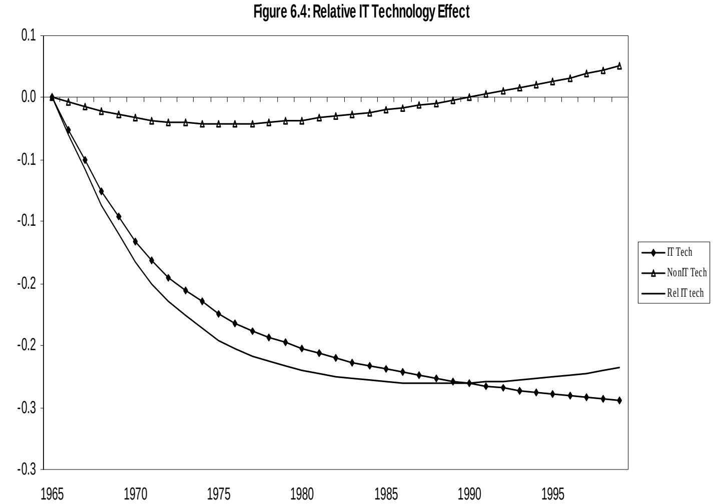


Figure 6.4: Relative IT Technology Effect

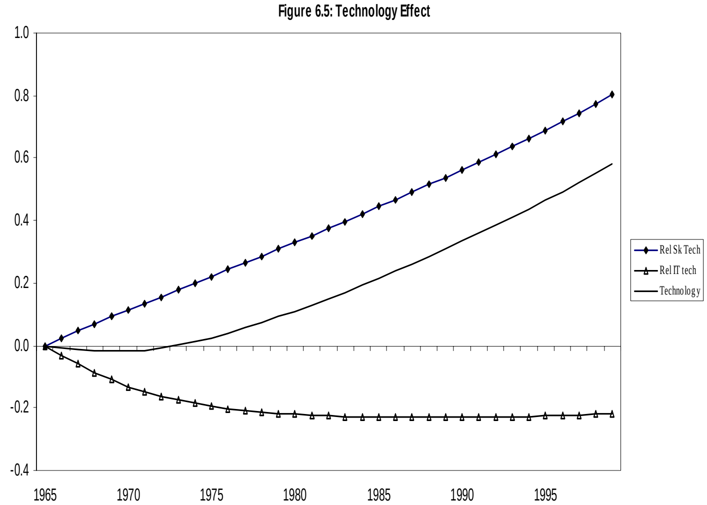


Figure 6.5: Technology Effect

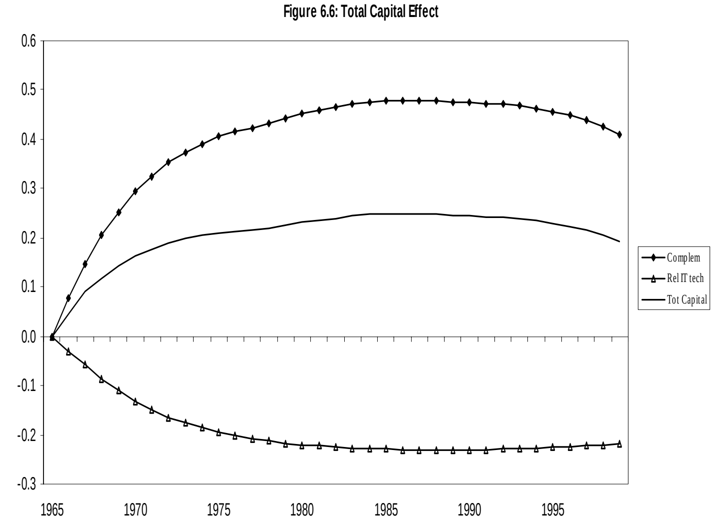


Figure 6.6: Total Capital Effect

Figures 7.1-7.2: Contribution of Three Main Factors to the Growth in the Skill Premium. IT Model (in logs, normalized with 1965=0)

Figure 7.1: Decomposition of Skill Premium. Main Effects

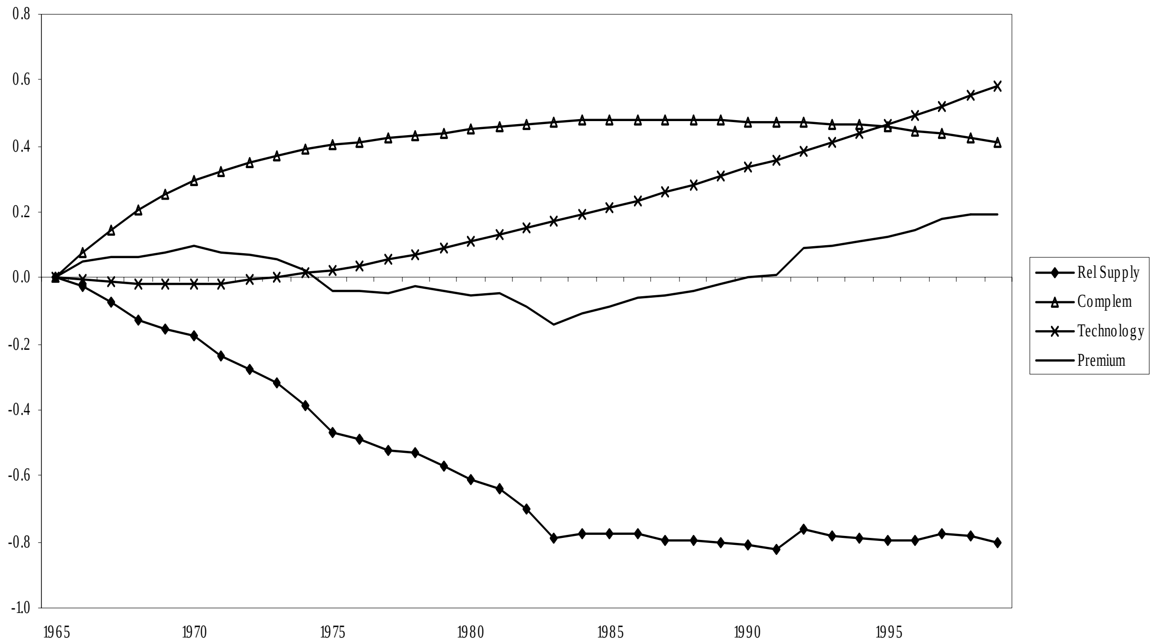
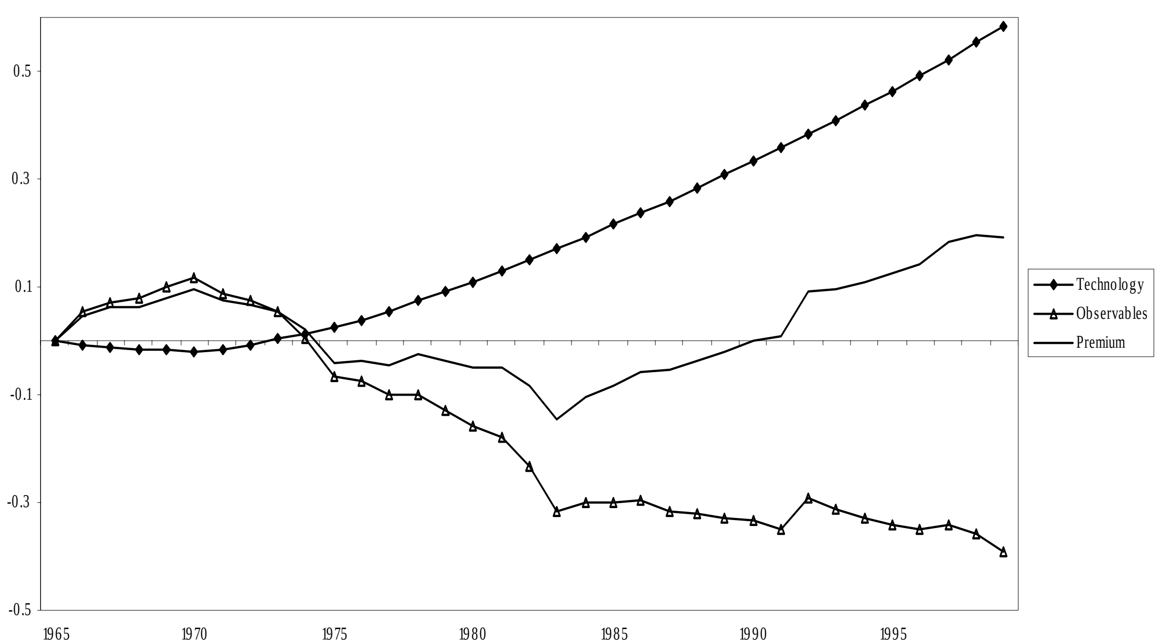


Figure 7.2: Decomposition Skill Premium. Obsservables vs Technology



Figures 8.1-8.6: Contribution of Different Factors to the Growth in the Skill Premium. Five Input Model (in logs, normalized with 1965=0)

Figure 8.1: Complementarity Effect

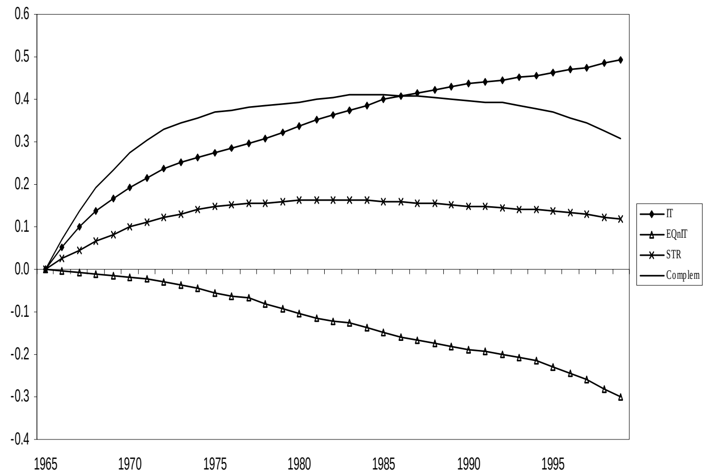


Figure 8.2: Relative Capital Technology Effect

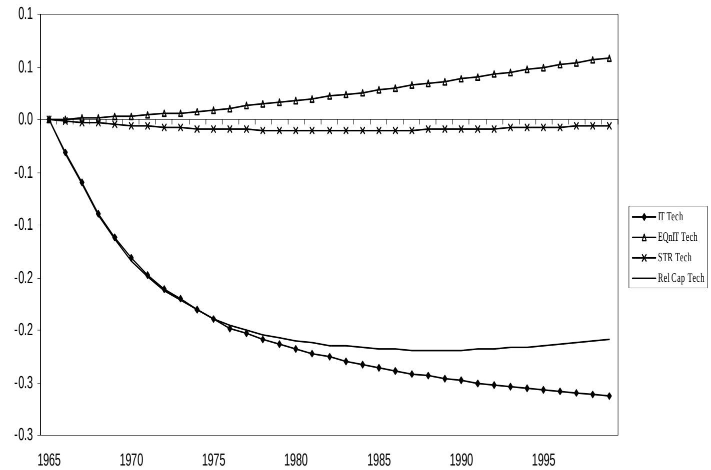


Figure 8.3: Technology Effect

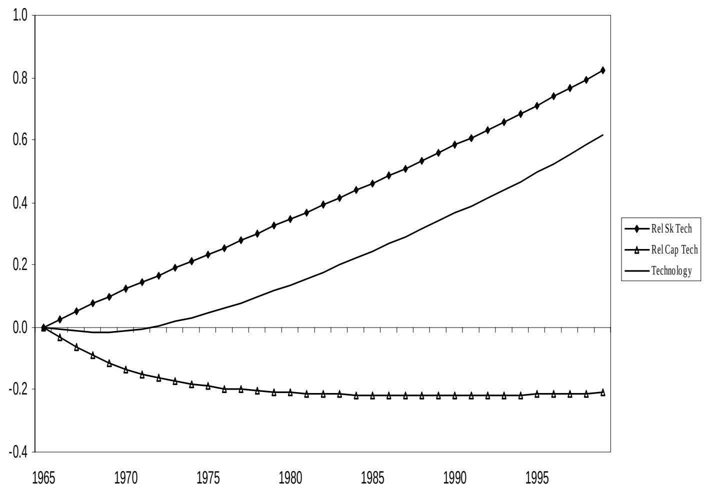


Figure 8.4: Total Capital Effect

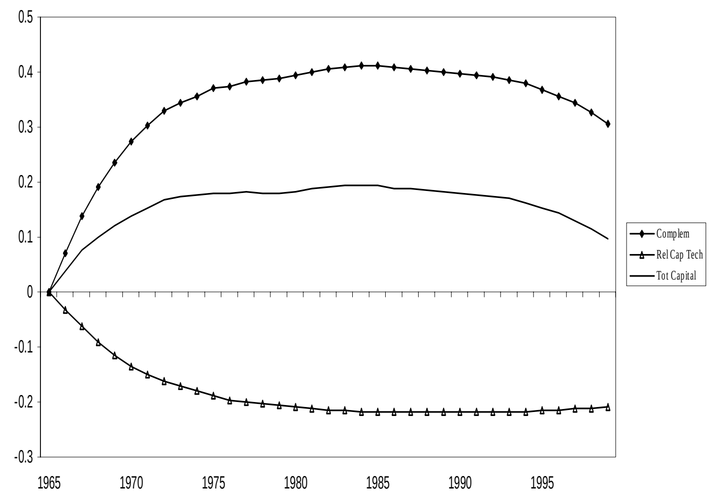


Figure 8.5: Decompostion of Skill Premium. Main Effects

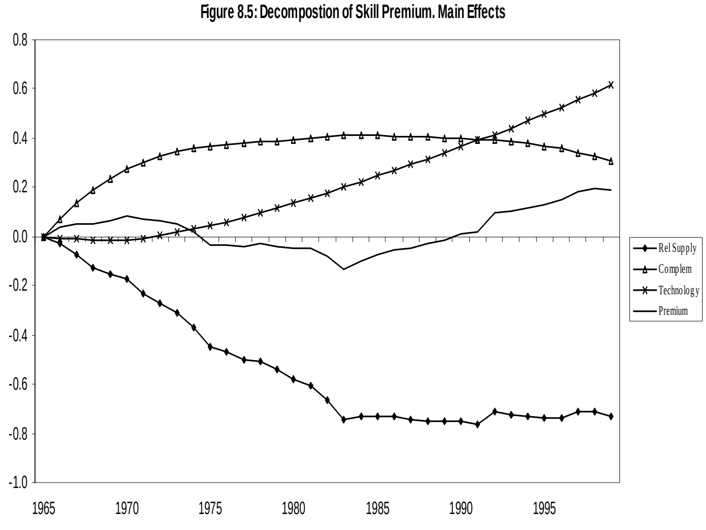
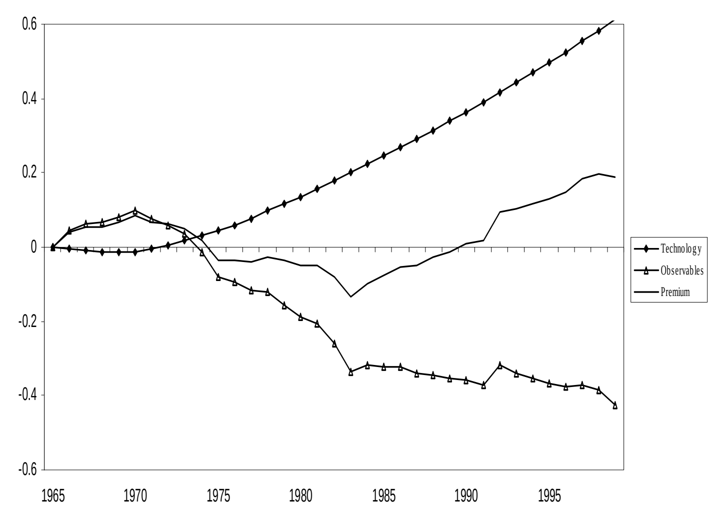


Figure 8.6: Decomposition of Skill Premium. Observables vs Technology



Figures 9.1-9.2: Contribution of Main Factors to the Growth in the Relative Share of Skilled Labor. IT Model

Figure 9.1: Decomposition of the Relative Share of Skilled Labor. Main Effects

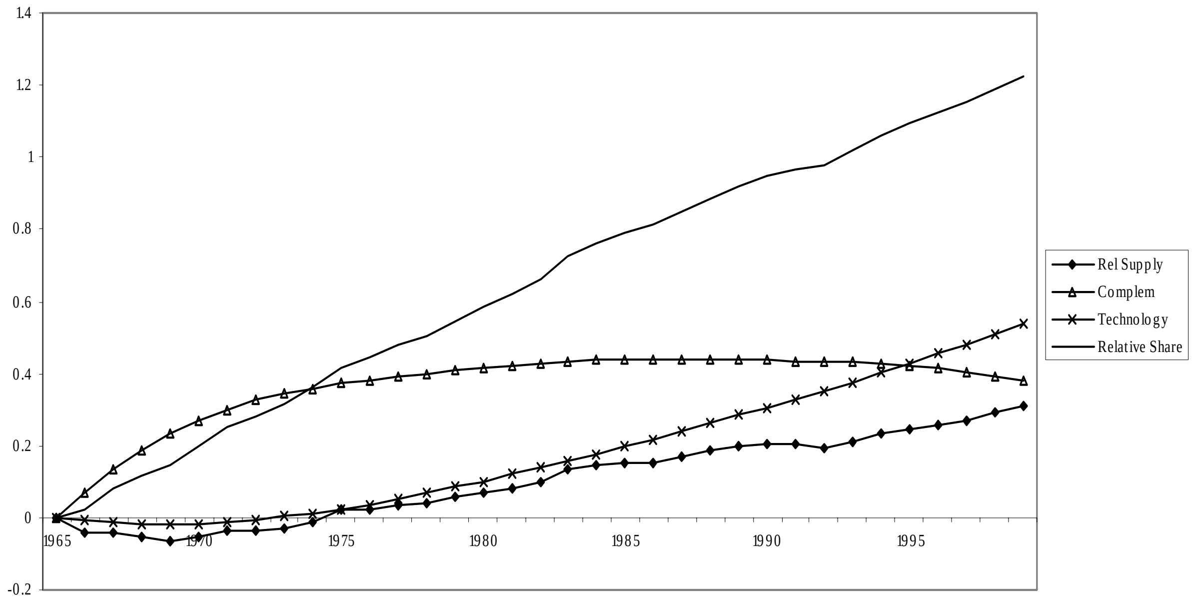


Figure 9.2: Decomposition of the Relative Share of Skilled Larbor. Observables vs Technology

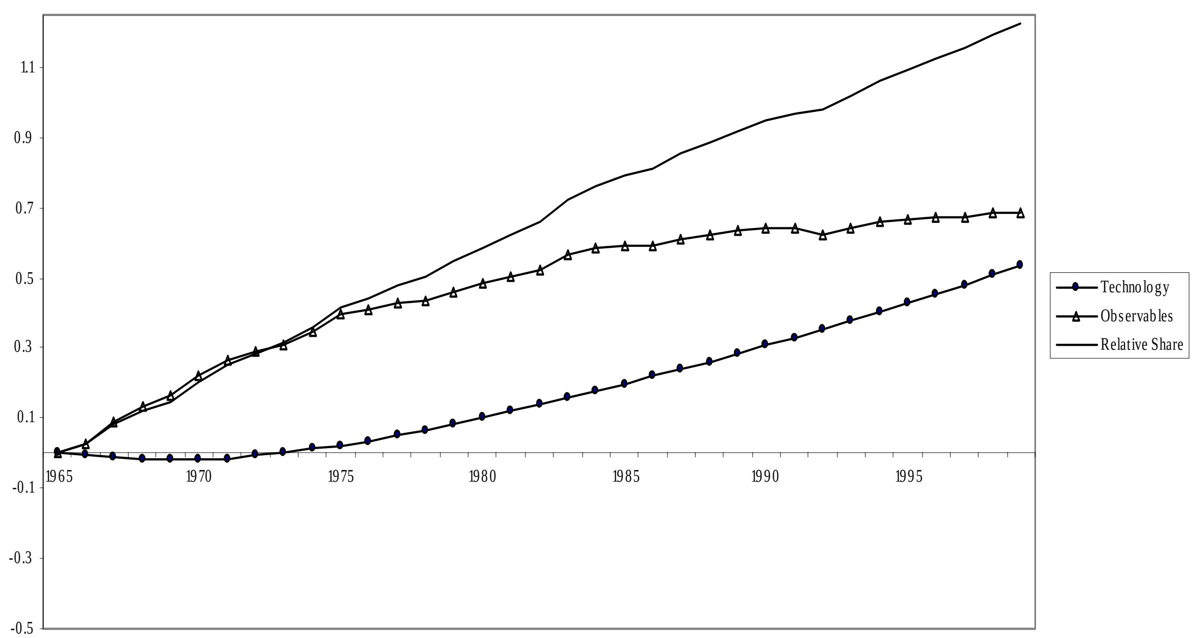


Table A1: Hausman Exogeneity Tests

	Degrees of Freedon	Wald Statistic	p_value	p_value*15
I1	5	22.36	0.00	0.01
I2	5	2.49	0.78	11.67
I3	3	7.61	0.05	0.82
I4	5	0.44	0.99	14.91
I5	4	3.19	0.53	7.90
I6	4	0.86	0.93	13.96
I7	5	6.36	0.27	4.10
I8	4	0.87	0.93	13.93
I9	5	3.91	0.56	8.44
I10	2	1.12	0.57	8.57
I11	3	5.07	0.17	2.50
I12	5	2.16	0.83	12.39
I13	7	14.23	0.05	0.71
I14	4	3.53	0.47	7.09
I15	4	3.79	0.44	6.53

Note: the instruments used in the analysis are the following:

I1	Constant
I2	Average Marginal Tax Rate on Personal Labor Income
I3	Effective Corporate Income tax rate
I4	Average Marginal Tax Rate on Dividends
I5	Rate of Taxation on Consumption Goods
I6	Time Endowment in 1999 dollars
I7	Lagged Price of personal Consumption Expenditures
I8	Lagged Price of Leisure and Unemployment
I9	Lagged Capital Service Price
I10	Logarithm Level of Technology
I11	Lagged Price Index of Private Domestic Labor Input
I12	Lagged Real Full Consumption
I13	Lagged Private Wealth Including Claims on Government and the ROW
I14	US Population
I15	Government Demand

High p-values indicate that we cannot reject the null hypothesis of exogeneity.
The last column presents p-values adjusted due to simultaneous inference.