Econometrica, Vol. 68, No. 5 (September, 2000), 1029–1053

CAPITAL-SKILL COMPLEMENTARITY AND INEQUALITY: A MACROECONOMIC ANALYSIS

BY PER KRUSELL, LEE E. OHANIAN, JOSÉ-VÍCTOR RÍOS-RULL, AND GIOVANNI L. VIOLANTE[1]

The supply and price of skilled labor relative to unskilled labor have changed dramatically over the postwar period. The relative quantity of skilled labor has increased substantially, and the *skill premium*, which is the wage of skilled labor relative to that of unskilled labor, has grown significantly since 1980. Many studies have found that accounting for the increase in the skill premium on the basis of observable variables is difficult and have concluded implicitly that latent *skill-biased technological change* must be the main factor responsible. This paper examines that view systematically. We develop a framework that provides a simple, explicit economic mechanism for understanding skill-biased technological change in terms of observable variables, and we use the framework to evaluate the fraction of variation in the skill premium that can be accounted for by changes in observed factor quantities. We find that with capital-skill complementarity, changes in observed inputs alone can account for most of the variations in the skill premium over the last 30 years.

KEYWORDS: Capital-skill complementarity, wage inequality, technological change.

1. INTRODUCTION

THE SUPPLY AND PRICE OF SKILLED LABOR relative to unskilled labor have changed dramatically over the postwar period. Under education-based skill classifications, the quantity of skilled labor relative to that of unskilled labor has increased considerably, and the *skill premium*, defined as the wage of skilled labor relative to that of unskilled labor, has grown significantly since 1980. Why has the skill premium risen during a period of substantial growth in the relative supply of skilled labor? Many studies have found that answering that question on the basis of observable variables is difficult. These studies have concluded implicitly that latent skill-biased technological change must be the main factor responsible for the skill premium's increase.[2] However, there is no generally accepted economic framework for interpreting skill-biased technological change, measuring its rate of growth, or directly assessing its quantitative impor-

[1] Krusell, Ohanian, and Ríos-Rull thank the National Science Foundation. Krusell also thanks the Bank of Sweden Tercentanary Foundation, Ohanian also thanks the Alfred P. Sloan Foundation, and Ríos-Rull also thanks the University of Pennsylvania Research Foundation. We thank Michael Ben-Gad, Valentina Corradi, Larry Katz, Richard Rogerson, Randy Wright, the referees, seminar participants, and, in particular, a co-editor, for helpful comments. Special thanks go to Kathy Rolfe and Jenni Schoppers for very helpful editorial advice. The views expressed herein are those of the authors and not necessarily those of the Federal Reserve Bank of Minneapolis or the Federal Reserve System.

[2] See Bound and Johnson (1992) for a review of a number of explanations. They conclude that much of the variation in the skill premium is attributed to a residual trend component that is interpreted as skill-biased technological change.

tance.[3] In this paper, we develop such a framework and with it establish that the fraction of the historical variation in the skill premium that can be accounted for by changes in observed factor quantities is, in fact, quite large.

We conduct our analysis using a neoclassical aggregate production function in which the key feature of the technology is *capital-skill complementarity*. This means that the elasticity of substitution between capital equipment and unskilled labor is higher than that between capital equipment and skilled labor. A key implication of capital-skill complementarity is that growth in the stock of equipment increases the marginal product of skilled labor, but decreases the marginal product of unskilled labor. In our framework, skill-biased technological change reflects the rapid growth of the stock of equipment, combined with the different ways equipment interacts with different types of labor in the production technology. We hypothesize that capital-skill complementarity may be important for understanding wage inequality, because the stock of equipment, as measured in efficiency units by Gordon (1990), has been growing at about twice the rate of either capital structures or consumption over the postwar period, and its growth rate has accelerated since the late 1970s.

This hypothesis of capital-skill complementarity has been formalized by Griliches (1969). To illustrate how this mechanism can affect the skill premium, consider a three-factor production function similar to one used by Stokey (1996) in a study of inequality and trade. Output (y_t) is produced with capital equipment (k), unskilled labor (u), and skilled labor (s). Equipment and unskilled labor are perfect substitutes and have unit elasticity of substitution with skilled labor: $y_t = f(k_t, u_t, s_t) = (k_t + u_t)^{\theta} s_t^{1-\theta}$. The ratio of the marginal product of skilled labor to the marginal product of unskilled labor is

$$\frac{f_{s_t}}{f_{u_t}} = \left(\frac{1-\theta}{\theta}\right)\frac{k_t + u_t}{s_t}.$$

This example shows qualitatively that growth in the stock of equipment will increase the skill premium, since increases in the capital stock increase the marginal product of skilled labor, but decrease the marginal product of unskilled labor.

In this paper, we quantitatively evaluate how much capital-skill complementarity has affected the skill premium in the postwar period. To do this, we first modify the standard two-factor (capital and labor) aggregate production function by developing a four-factor aggregate production function that distinguishes among capital equipment, capital structures, skilled labor, and unskilled labor and that allows for different elasticities of substitution among the factors. Then, with time series observations, we read factor prices off the marginal product schedules and compare the skill premium in the model with the skill premium in the data.

[3] Some recent literature uses disaggregated or noncompetitive frameworks to explore how technological change may lead to wage inequality; see Violante (1998) for a quantitative theoretical analysis and Galor and Tsiddon (1997) and Acemoglu (1998) for qualitative theoretical analyses.

The values of the production function parameters that govern the substitution elasticities between capital equipment and skilled and unskilled labor are key elements of this quantitative analysis. We estimate the parameters of our model using U.S. time series data, and we find that the key substitution elasticities are consistent with capital-skill complementarity and are also very similar to estimates in the microeconomics literature.

Our main finding is that with empirically plausible differences in substitution elasticities, changes in observed factor inputs can account for most of the variation in the skill premium over the last 30 years. We also find that our four-factor production function preserves the success of the standard two-factor neoclassical production function: it too is consistent with the behavior of income shares and the returns on physical capital over time.

The paper is organized as follows. In Section 2, we discuss the factor price and quantity data we use in the analysis. In Section 3, we present the basic model. In Section 4, we describe the quantitative methodology and our results. In Section 5, we describe some implications of the results. In an Appendix, we discuss the construction of the data and the econometric technique.

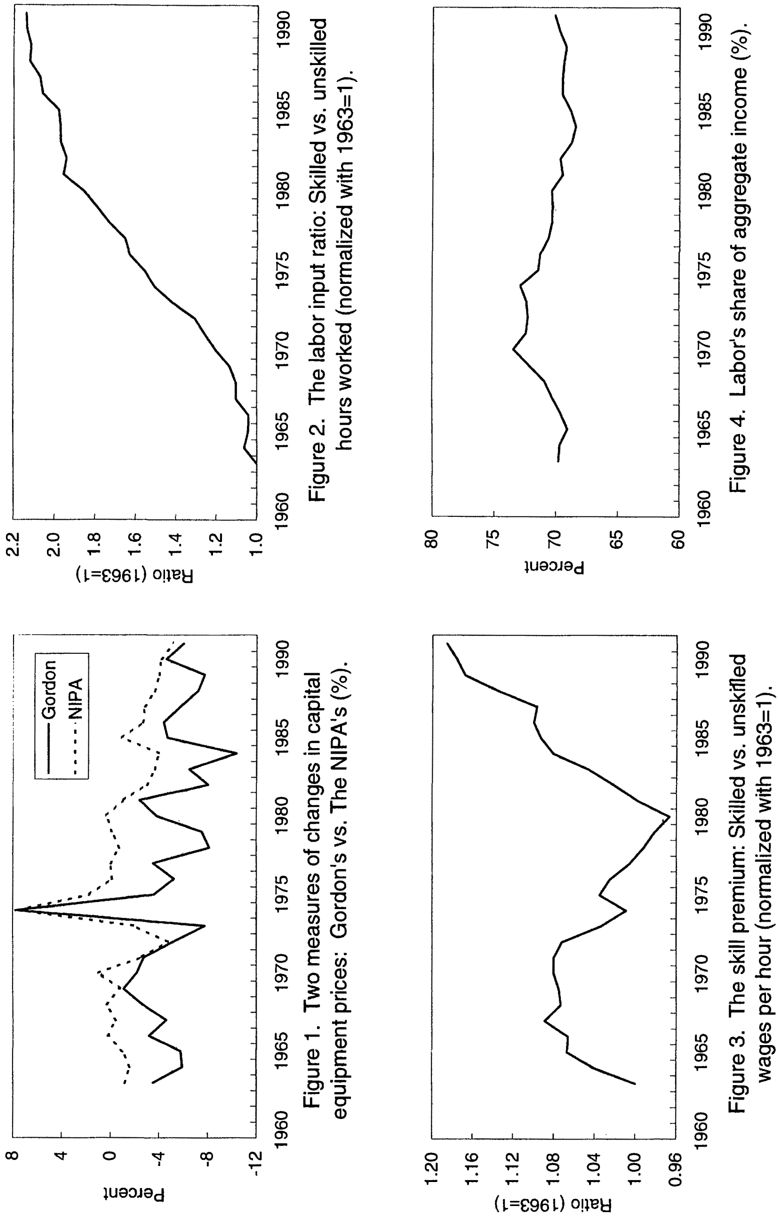
2. THE DATA

Our data consist of annual U.S. time series of capital and labor between 1963 and 1992.

In our analysis, we distinguish between two types of capital—structures and equipment—because they have grown at very different rates over the last 30 years. The standard measure of the stock of capital structures, from the National Income and Product Accounts (NIPA), grew at just a 3.2 percent rate through 1975 and at a 2.6 percent rate thereafter. The stock of capital equipment, meanwhile, has grown much more than that.

The NIPA data show strong growth in the capital equipment stock, but those data have been criticized by Gordon (1990) for overstating price changes by not adequately accounting for increases in the quality of equipment over time. We thus construct a measure of the capital equipment stock using Gordon's capital equipment price data, which are adjusted for quality changes. According to those data, the price of capital equipment relative to consumption declined considerably between 1963 and 1992, at a faster rate than the comparable NIPA price data. (See Figure 1.) The Gordon price series declines at a 4.5 percent rate through 1975 and at a 6 percent rate thereafter. We follow Greenwood, Hercowitz, and Krusell (1997) and interpret this relative price decline as reflecting technological change specific to the production of capital equipment. Our Gordon-based measure of the stock of capital equipment grew at a 6.2 percent rate through 1975 and at a 7.5 percent rate thereafter.[4]

[4] Gordon's (1990) data cover the sample period until 1984. The construction of the quality-adjusted stock of capital equipment and its relative price for the post-1983 period is described in the Appendix.



FIGURES 1–4.—Prices and quantities of factor inputs, 1963–91.

Since we are interested in the skill premium, we also distinguish between two types of labor—skilled and unskilled. It is standard in the literature to define the level of labor skill on the basis of the level of workers' education. Most education-based measures show a strong secular increase in the stock of skilled relative to unskilled labor input. Figure 2 shows the ratio of skilled labor hours worked to unskilled labor hours worked. *Skilled labor* is defined as requiring college completion or better (at least 16 years of school). The data are drawn from the U.S. Department of Commerce's *Current Population Survey* (*CPS*) over the 1963–92 period[5] and show an increase of more than 100 percent in the ratio of skilled labor input to unskilled labor input. Figure 3 shows three patterns in the skill premium over this period: a modest increase in the 1960's, a decline over much of the 1970's, and a sharp increase after 1980. Overall, the skill premium increased about 18 percent over the period.

Despite these strong trends in relative input quantities and prices, there are no trends in the shares of income earned by aggregate capital and aggregate labor over this period. This is clear in Figure 4, which displays the aggregate labor share of income. This labor share is defined as the ratio of labor income—wages, salaries, and benefits—to the sum of labor income plus capital income—depreciation, corporate profits, net interest, and rental income of persons.

In addition to the quantities and prices of these four inputs, we find that the ratio of the quantity of capital equipment to the quantity of skilled labor input is an important factor in our analysis. As we discuss in the following section, this ratio affects the skill premium through capital-skill complementarity. This ratio has grown consistently over the entire period, and its growth rate is somewhat higher after 1980.

3. THE MODEL

The standard neoclassical model has a household sector and a two-factor aggregate production function, with just capital and labor as the factors. We can simplify the analysis considerably by abstracting from the household sector and focusing on the aggregate production function. We develop, instead, a four-factor production function with different substitution elasticities between the two types of capital and the two types of labor.

In this model, there are three final goods: consumption c_t, structures investment x_{st}, and equipment investment x_{et}. Consumption and structures are produced with a constant returns to scale technology, and equipment is produced with the same technology scaled by equipment-specific technological progress q_t. Under these assumptions, the relative price of equipment is equal

[5] A description of these data is in the Appendix.

to $1/q_t$ and the aggregate production function is given by

$$(1) \qquad y_t = c_t + x_{st} + \frac{x_{et}}{q_t} = A_t G(k_{st}, k_{et}, u_t, s_t).$$

The production function G has constant returns to scale in capital structures k_s, capital equipment k_e, unskilled labor input u_t, and skilled labor input s_t. In addition to equipment-specific technological change, there is neutral technological change, A_t.

We assume that the production function is Cobb-Douglas over capital structures and a CES function of the three remaining inputs: $y = k_s^{\alpha} \tilde{y}^{1-\alpha}$. We choose the CES specification because it is simple, has relatively few parameters, and restricts substitution elasticities to be constant.[6] An alternative to the CES form is the translog function. This translog approach, however, has two drawbacks: the translog function has many more parameters, which would reduce degrees of freedom in our already small sample, and translog substitution elasticities vary over time, which would complicate quantifying the historical effects of changes in factor quantities on the skill premium.

There are three ways of nesting k_e, s, and u within a CES function, two of which allow for capital-skill complementarity: $\tilde{y}_1 = \Upsilon_1(s, \Upsilon_2(k_e, u))$ and $\tilde{y}_2 = \Upsilon_1(u, \Upsilon_2(s, k_e))$, where Υ_1 and Υ_2 are CES aggregators. The CES functional form imposes symmetry restrictions on substitution elasticities. For $\tilde{y}_1$, the elasticity of substitution between s and k_e is restricted to be the same as that between s and u. This restriction, however, is at variance with factor elasticity estimates that suggest that the substitution elasticity between skilled labor and unskilled labor is higher than the substitution elasticity between skilled labor and capital. (See Hamermesh (1993).)

For $\tilde{y}_2$, the CES function restricts the elasticity of substitution between unskilled labor and skilled labor to be the same as that between unskilled labor and equipment. This restriction, however, does not seem to be at variance with existing elasticity estimates. Moreover, we find that the first specification is not as consistent with the data as the second specification. Therefore, we use the second application in our analysis:[7]

$$(2) \qquad G(k_{st}, k_{et}, u_t, s_t) = k_{st}^{\alpha} \left[\mu u_t^{\sigma} + (1-\mu)(\lambda k_{et}^{\rho} + (1-\lambda) s_t^{\rho})^{\sigma/\rho} \right]^{(1-\alpha)/\sigma}$$

In this specification, μ and λ are parameters that govern income shares, and σ and ρ $(\sigma, \rho < 1)$ govern the elasticity of substitution between unskilled labor, capital equipment, and skilled labor. The elasticity of substitution between equipment (or skilled labor) and unskilled labor is $1/(1-\sigma)$, and the elasticity of substitution between equipment and skilled labor is $1/(1-\rho)$. Capital-skill

[6] Fallon and Layard (1975) have also used a CES production function with capital-skill complementarity. Their research analyzes substitution elasticities between skilled and unskilled labor.

[7] Goldin and Katz (1998) argue that early 20th century data are also consistent with this nesting.

complementary requires that $\sigma > \rho$. If either σ or ρ equals zero, the corresponding nesting is Cobb-Douglas.

The labor input of each type is measured in efficiency units: each input type is a product of the raw number of labor hours and an efficiency index: $s_t \equiv \psi_{st} h_{st}$ and $u_t \equiv \psi_{ut} h_{ut}$, where h_{it} is the number of hours worked and ψ_{it} is the (unmeasured) quality per hour of type i at date t. Clearly ψ_i can be given different interpretations: it can be human capital, accumulated by the agent, or it can represent a skill-specific technology level, brought about by research and development. Without direct measures of these two interpretations, however, they cannot be distinguished. We specify this unmeasured term later.

The Skill Premium From the Model

Now we see how the skill premium from this model is connected to the factor inputs.

We denote the skill premium by π. Since factor prices are equal to marginal products per unit of work, the skill premium can be expressed as a function of input ratios:

$$\text{(3)} \qquad \pi_t = \frac{(1-\mu)(1-\lambda)}{\mu} \left[\lambda \left(\frac{k_{et}}{s_t} \right)^{\rho} + (1-\lambda) \right]^{(\sigma-\rho)/\rho} \left(\frac{h_{ut}}{h_{st}} \right)^{1-\sigma} \left(\frac{\psi_{st}}{\psi_{ut}} \right)^{\sigma}.$$

To illustrate the implications of this expression for the skill premium, we log-linearize it and differentiate with respect to time. Log-linearizing yields

$$\ln \pi_t \simeq \lambda \frac{\sigma - \rho}{\rho} \left(\frac{k_{et}}{s_t} \right)^{\rho} + (1-\sigma) \ln \left(\frac{h_{ut}}{h_{st}} \right) + \sigma \ln \left(\frac{\psi_{st}}{\psi_{ut}} \right).$$

Differentiating with respect to time and denoting the growth rate of variable x by g_x, we obtain, after some algebra,

$$\text{(4)} \qquad g_{\pi t} \simeq (1-\sigma)(g_{h_{ut}} - g_{h_{st}}) + \sigma (g_{\psi_{st}} - g_{\psi_{ut}}) + (\sigma - \rho) \lambda \left(\frac{k_{et}}{s_t} \right)^{\rho} (g_{k_{et}} - g_{h_{st}} - g_{\psi_{st}}).$$

Equation (4) decomposes the growth rate of the skill premium into three components that have specific economic interpretations. This equation gives us a simple way to use our model to understand how changes in factor quantities affect the skill premium and allows us to isolate the effect of capital-skill complementarity.

The first component, $(1-\sigma)(g_{h_{ut}} - g_{h_{st}})$, depends on the growth rate of skilled labor input relative to the growth rate of unskilled labor input—the *relative quantity effect*. Since $\sigma < 1$, relatively faster growth of skilled labor reduces the skill premium.

The second component, $\sigma(g_{\psi_{st}} - g_{\psi_{ut}})$, involves the growth of skilled labor efficiency relative to that of unskilled labor efficiency—the *relative efficiency effect*. The effect of a relative increase in the growth rate of skilled labor efficiency on the skill premium depends on σ, which governs the substitution elasticity between the two labor inputs. If $\sigma > 0$, so that the elasticity of substitution between the two types is greater than one, a relative improvement in the quality of skilled labor increases the skill premium. However, if $\sigma < 0$, so that the substitution elasticity is less than one, a relative improvement in the efficiency of skilled labor leads to a relative increase in the marginal product of unskilled labor, which results in a decline in the skill premium.

The third component, $(\sigma - \rho)\lambda(k_{et}/s_t)^{\rho}(g_{k_{et}} - g_{h_{st}} - g_{\psi_{st}})$, is the *capital-skill complementarity effect*. This component depends on two factors: the growth rate of equipment relative to the growth rates of skilled and unskilled labor input and the ratio of capital equipment to efficiency units of skilled labor input. If $\sigma > \rho$, skilled labor is more complementary with equipment than is unskilled labor. In this case, faster growth in equipment tends to increase the skill premium as it increases the relative demand for skilled labor.

The effect of $(k_{et}/s_t)^{\rho}$ on the skill premium depends on the shape of the isoquants of the technology. If equipment grows faster than skilled labor input, then the growth rate of the skill premium tends to increase over time when $\rho > 0$ (more substitutable than Cobb-Douglas), but to decrease when $\rho < 0$. With $\rho < 0$, the share of income paid to equipment relative to the share paid to skilled labor goes to zero in the limit, and income is thus divided solely between skilled and unskilled labor. Since the share of income paid to skilled labor is bounded, so is the growth rate of the skill premium.[8]

4. QUANTITATIVE ANALYSIS

Now we use our model to analyze quantitatively the sources of changes in the skill premium. We find those sources to be primarily changes in observed factor inputs.

Stochastic Specification

With values for the parameters of the production function, equation (4) can be used to assess how the skill premium has been affected by changes in factor inputs. We choose values for these parameters by calibrating some of the parameters and estimating others. The process of choosing parameter values has three steps: (i) specification of the stochastic elements in the model, (ii) specification of the equations to be estimated, and (iii) estimation of the parameters.

[8] A steady-state growth path exists if $\rho = \sigma = 0$ or if the long-run growth rates of all inputs in efficiency units are the same. Since we do not model household choices, our analysis does not have predictions for the long-run growth rates of these inputs.

(i) Stochastic Element Specification

Our model has two stochastic components. One is the relative price of equipment. This relative price plays a role in the construction of the rate of return on equipment investment, which we describe below. The model's other stochastic component is the pair of efficiency factors of the two types of labor. These efficiency factor variables are assumed to be unobserved by the econometrician. Since this study focuses on whether changes in observable variables can account for trend changes in the skill premium, our *benchmark specification* has no trend variation in labor quality of the two types. Thus, the skill premium in this specification is driven entirely by two factors: the relative quantity effect and the capital-skill complementarity effect.

To facilitate drawing a connection between our analysis and the literature, however, we conduct one analysis in which it is necessary to allow for trend differences in unmeasured labor quality. To make this interpretation, we specify the stochastic process governing labor quality of the two types as the following simple trend stationary process (in logs):

$$(5) \qquad \varphi_t \equiv \ln(\psi_t), \qquad \varphi_t = \varphi_0 + \gamma t + \omega_t,$$

where φ_t is a (2×1) vector of the log of labor quality of the two types, γ is a (2×1) vector of growth rates of the two types of labor quality, φ_0 is a (2×1) vector of constants specifying the value of the efficiency factors at the beginning of the sample, and ω_t is a vector shock process that we assume is multivariate normal and is i.i.d. with covariance matrix Ω: $\omega_t \overset{i.i.d.}{\sim} N(0, \Omega)$. The i.i.d. assumption simplifies parameter estimation considerably.[9] For our benchmark specification with no unmeasured trend changes, the elements of γ are zeroes.

(ii) Equation Specification

We will use the first-order conditions of a profit-maximizing firm, rewritten as income shares, to estimate the parameters of the model. This will let us assess easily the extent to which our model preserves the standard neoclassical growth model's consistency with the relative constancy of aggregate labor's share of income and the average rate of return on physical capital.

We use three equations in the estimation:

$$(6) \qquad \frac{w_{st}h_{st} + w_{ut}h_{ut}}{Y_t} = lsh_t(\varphi_t, X_t; \phi),$$

$$(7) \qquad \frac{w_{st}h_{st}}{w_{ut}h_{ut}} = wbr_t(\varphi_t, X_t; \phi),$$

[9] We identify neutral technological progress by using our production function and measures of output. We define *output* as the domestic product of the private sector, excluding the housing and farm sectors.

and

$$(8)\qquad (1-\delta_s)+A_{t+1}G_{k_s}(\varphi_{t+1},X_{t+1};\Phi) = E_t\left(\frac{q_t}{q_{t+1}}\right)(1-\delta_e)+q_tA_{t+1}G_{k_e}(\varphi_{t+1},X_{t+1};\phi).$$

Equations (6) and (7) are based on income shares implied by the firm's first-order conditions for hiring skilled and unskilled labor, and these equations are similar to those used by Griliches (1969) in his study of capital-skill complementarity. Equation (6) specifies that the total share of labor income in the model (lsh_t), defined by the marginal products from the production function, equals the aggregate labor share of income in the data. The data for the left side of the equation are the ratio of labor income to the sum of labor and capital income. Equation (7) requires that the share of income earned by skilled labor relative to that of unskilled labor in the data be equal to the corresponding production function object, which we denote by wbr_t. This condition for the *wage-bill ratio*, which is the ratio of earnings of skilled workers to unskilled workers, also follows from the firm's profit-maximizing decision in hiring skilled and unskilled labor. Note that lsh_t and wbr_t are functions of X_t and ϕ. The vector ϕ contains the parameters $\{\delta_s,\delta_e,\alpha,\mu,\lambda,\sigma,\rho,\eta_\varepsilon,\gamma,\Omega\}$ (η_ε is defined below), and X_t is the set of factor inputs $\{k_{st},k_{et},h_{st},h_{ut}\}$.

Since there are no standard measures of rental rates for equipment and structures, we must construct a proxy for these prices. To do so, we equate the expected net rate of return on investment in structures with that on investment in equipment. This is a simple way of ensuring that differences in rates of return between these two types of capital are not implausibly large. The left side of equation (8) is the date $t+1$ rate of return on structures investment. This is equal to the sum of two components: (i) the marginal product of structures, $A_{t+1}G_{k_s}(\varphi_{t+1},X_{t+1};\phi)$, where G_{k_s} is the partial derivative of the production function with respect to structures, and (ii) undepreciated capital structures $(1-\delta_s)$. The right side of equation (8) is the expected date $t+1$ rate of return on equipment investment. This also is equal to the sum of two components: (i) the marginal product of equipment investment, $q_tA_{t+1}G_{k_e}(\varphi_{t+1},X_{t+1};\phi)$, where G_{k_e} is the partial derivative of the production function with respect to equipment, and (ii) undepreciated capital equipment multiplied by the expected rate of change in the relative price of equipment: $E_t(q_t/q_{t+1})(1-\delta_e)$. Since the price of equipment has been falling over time, the term $E_t(q_t/q_{t+1})$ is the expected capital loss on undepreciated equipment.

In equation (8), we assume that there is no risk premium, which lets us abstract from the covariance between consumption and returns in the estimation procedure, and we assume that the tax treatments[10] of these two types of

[10] We have used the tax measures constructed by Cummins, Hassett, and Hubbard (1994) to explore the implications of this assumption and found that the results are similar.

investment are identical.[11] Our final simplifying assumption is to substitute the first term on the right side of equation (8) with $(1-\delta_e)q_t/q_{t+1}+\varepsilon_t$, where ε_t is the i.i.d. forecast error. This is assumed to be normally distributed: $\varepsilon \sim N(0, \eta_\varepsilon)$.

From our production function, it follows that $A_t = y_t/G(\cdot)$ in equation (1). Given the estimated parameters and observations on inputs and outputs, this function provides a simple way to identify neutral technical change residually.

(*iii*) *Parameter Estimation*

The benchmark model is a nonlinear state-space model that takes the following form: measurement equations: $Z_t = f(X_t, \varphi_t, \varepsilon_t; \phi_t)$ and state equations: $\varphi_t = \varphi_0 + \omega_t$. The function $f(\cdot)$ contains the three nonlinear observational equations—the rate of return equality condition and the two share equations. The rate of return difference and the income shares are contained in the (3×1) vector Z_t, X_t is the set of inputs described above, φ_t is the (2×1) vector of unobservable logged quality factors which evolve according to the process specified in the state equation, and ε_t and ω_t are (3×1) and (2×1) vectors, respectively, of i.i.d. normally distributed disturbances.

This latent nature of φ_t and the nonlinearity of $f(\cdot)$ complicate estimation. Indicating with superscript T the vector of observations, we can write the joint probability distribution function (p.d.f.) of our model as $F(Z^T, \varphi^T | X^T, \phi)$. Since F^T is latent, we can only observe $F(Z^T | X^T, \phi)$. Therefore, to map the model into the data, we must collapse the first p.d.f. into the second. The joint presence of the nonlinearity of the measurement equations and the stochastic latent variables prevents us from using standard Kalman filtering methods. Therefore, we use simulation techniques to estimate the parameters.

In a companion paper (Ohanian et al. (forthcoming)), we analyze the econometric issues associated with the specification and estimation of our model and compare the performance of different simulation-based estimators. We conclude in that paper that when the unobservable variables are Gaussian trend stationary processes, simulated pseudo-maximum likelihood (SPML) estimation using the first and second moments is fast and produces parameter estimates with negligible bias in samples of size 30. We therefore use this technique for estimating the parameters of this model.[12]

We use a two-step version of SPML. (See White (1994).) This version of SPML is useful when some of the variables are potentially endogenous. We treat the date t stocks of capital equipment and capital structures as exogenous, but we allow for the possibility that date t values of skilled and unskilled labor input may respond to date t realizations of the technology and labor quality shocks. The two-step procedure we use takes into account this potential endo-

[11] For simplicity, we assume that A_{t+1} and φ_{t+1} are known when investment decisions are made. Thus, only q_{t+1} is unknown. This assumption simplifies estimation substantially, because it lets us abstract from specifying a separate stochastic process for A_t.

[12] See Gouriéroux, Monfort, and Trognon (1984) and Laroque and Salanié (1989, 1993, 1994).

geneity along the lines of two-stage least squares. In the first step, skilled and unskilled labor input are projected onto exogenous variables. In the second step, the fitted values of these two series are used in SPML. Further discussion of the estimation method is in the Appendix.

The parameter vector ϕ has a dimension of 15. Given our sample size of 30, we reduce the number of parameters that we estimate by calibrating some of the parameters and imposing some restrictions. Initially, we found that the covariance between the shock to skilled labor quality and unskilled labor quality was near zero ($2e-7$) and that the variances of these two shocks were very similar (0.04 versus 0.05). Therefore, we imposed the condition that the shocks had zero covariance and identical variances. This implies that we can rewrite the covariance matrix $\Omega = \eta_\omega^2 I_2$, where η_ω^2 is the common innovation variance and I_2 is the (2×2) identity matrix. Each of the parameters φ_{s0}, φ_{u0}, λ, and μ can act as a scaling factor, and one of these parameters must be fixed as a normalization. We choose to fix a priori the initial skill level of skilled labor efficiency φ_{s0}.

We also calibrate some of the parameters. We follow Greenwood, Hercowitz, and Krusell (1997) in choosing values for the depreciation rates of structures and equipment: $\delta_s = 0.05$ and $\delta_e = 0.125$. We also estimate an ARIMA model for the relative price of equipment, q_t, and use the estimated innovation variance as the variance of the one-step forecast error for the relative price: $\eta_\varepsilon^2 = 0.02$.[13]

There are seven remaining parameters to be estimated: the curvature parameters σ and ρ, which govern the substitution elasticities; α, which is structures' share of income; λ and μ, the weights in the CES nestings of the production function; ψ_{u0}, the initial value for unskilled labor efficiency; and η_ω^2, the variance of the labor efficiency shocks.

Findings

We estimate the parameters for the benchmark model using two-step SPML from 1963 to 1992. The estimates, based on 500 simulations, are presented in Tables I and II, with asymptotic standard errors in parentheses in Table I.

TABLE I

TWO-STEP SPML PARAMETER ESTIMATES, BENCHMARK MODEL

Parameter	σ	ρ	α	η_ω^2
Value	.401	−.495	.117	.043
(Std. error)	(.234)	(.048)	(.007)	(.003)

[13] We estimate the parameter η_ε as $(1-\delta_e)$ times the standard error of the residuals of a linear regression of q_{t+1}/q_t on the variables in the information set ξ_t. The results are robust to different specifications of the conditional mean. The estimated equation is $\hat{q}_t = 0.5 - 0.005t + 0.48\hat{q}_{t-1} - 1.07\varepsilon_{t-1} + \varepsilon_t$, where $\hat{q}_{t+1} \equiv q_{t+1}/q_t$, with $\bar{R}^2 = 0.49$ and $\hat{\sigma}_\varepsilon = 0.023$. See Hamilton (1994) for a discussion of estimation of ARMA models.

TABLE II

ESTIMATED SUBSTITUTION ELASTICITIES, BENCHMARK MODEL

Between Labor and Equipment:	
Unskilled $(1/(1-\sigma))$	1.67
Skilled $(1/(1-\rho))$	.67

The estimates are consistent with the theory of capital-skill complementarity: $\sigma > \rho$. Moreover, the substitution elasticities implied by these parameters are similar to those reported in the micro literature. The estimated substitution elasticity between unskilled labor and equipment and, by symmetry, unskilled labor and skilled labor is 1.67. This is similar to a substitution elasticity between unskilled labor and skilled labor of 1.5 reported by Johnson (1997) and is roughly in the middle of the range of elasticities between unskilled labor and capital surveyed by Hamermesh (1993). Similarly, the estimated substitution elasticity between skilled labor and equipment is 0.67, which is also well within the range of elasticities by Hamermesh (1993).[14] Note also that our estimate of capital structures' share of income (α)—at 11.7 percent—is very close to the 13 percent share calibrated by Greenwood, Hercowitz, and Krusell (1997).

Figures 5–8 show the behavior of the estimated equations in our benchmark model. These include ex post rates of return on equipment and structures computed from our model (Figure 5), aggregate labor's share of income in the model and in the data (Figure 6), and the share of labor income paid to skilled labor (the wage-bill ratio) in the model and in the data (Figure 7). The model statistics presented in these figures are generated by setting the i.i.d. shocks to labor quality to zero at every date. Consequently, fluctuations in the model's predictions are entirely due to changes in observable inputs.

We find that the predictions of the estimated benchmark model are broadly consistent with the data.

This is particularly true for the labor variables. The model is able to capture the behavior of the relative income shares of skilled and unskilled labor closely, because it reproduces the sharp increase over this 30-year period. The model is also consistent with the relative constancy of aggregate labor's share of income. This finding is interesting, because our nested CES production function places no restrictions on the behavior of income shares over time.

The model's predictions for the capital variables are reasonable, even though their levels are not restricted either. The ex post rate of return on structures computed from our model averages about 4 percent and fluctuates between 3 and 5 percent. The ex post rate of return on equipment computed from our

[14] Alternative definitions of substitution elasticities are sometimes used in the factor substitution elasticity literature, such as the Allen partial elasticity of substitution. Our definition of the substitution elasticity between skilled labor and equipment, which is solely a function of the curvature parameter ρ, differs from the Allen definition, which involves not only curvature parameters but also factor shares. Thus, directly comparing our estimate for this elasticity and some of the others in the literature is difficult.

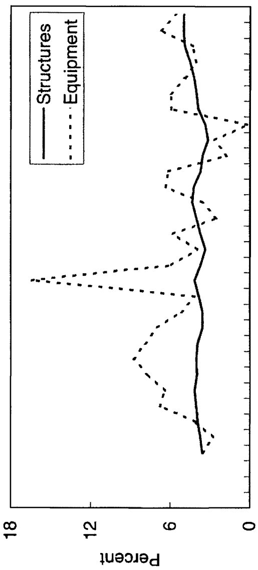


Figure 5. Ex post rates of return on capital equipment and structures (%).

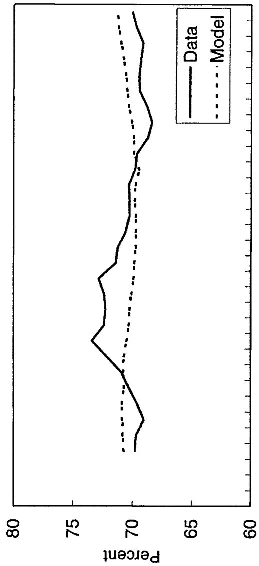


Figure 6. Labor's share of aggregate income (%).

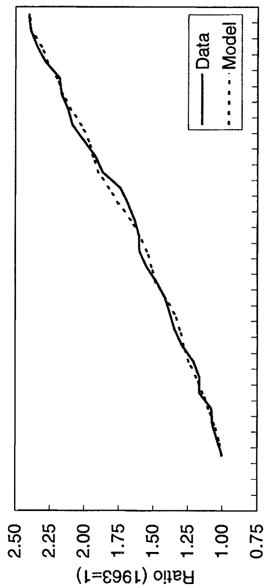


Figure 7. The wage-bill ratio: Skilled vs. unskilled total wages (normalized with 1963=1).

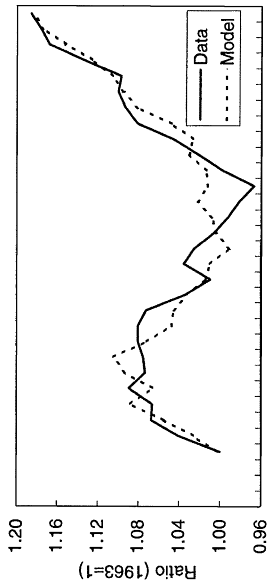


Figure 8. The skill premium: Skilled vs. unskilled wages per hour (normalized with 1963=1).

FIGURES 5–8.—The benchmark model's predictions for factor inputs, 1963–91.

model averages about 6 percent and is considerably more volatile than that of structures. This higher volatility is due to unexpected changes in the relative price of equipment. For example, the ex post return on equipment in 1974 is about 17 percent, which is due to a large unexpected increase in the price of equipment.[15] The 1974 return, along with a few other exceptionally high returns, is primarily responsible for the higher average return on equipment.[16]

The skill premium in the data and that predicted by the benchmark model are shown in Figure 8. Driven entirely by changes in observed factor quantities, our model captures the three main changes in the skill premium that occurred over this 30-year period: an increase in the skill premium in the 1960's, a decline in the 1970's, and a sharp increase after 1980.

To understand the specific role of capital-skill complementarity in the predictions of our model, we compute the skill premium without capital-skill complementarity. To do this, we maintain the substitution elasticity of 1.67 between skilled labor and unskilled labor, but restrict the substitution elasticity between equipment and the two types of labor to be the same. By shutting off the capital-skill complementarity effect, this exercise isolates the relative quantity effect on the skill premium. The prediction for the skill premium from this version of our model differs sharply from that in the benchmark model. The model without capital-skill complementarity predicts that the large increase in skilled labor would have reduced the skill premium by about 40 percent over this period. This stands in sharp contrast to the 20 percent increase predicted by our benchmark model.

These results indicate that both the relative quantity component, which has exerted downward pressure on the skill premium, and the capital-skill complementarity component, which has exerted upward pressure, have had quantitatively important effects over the period. Figure 9 and 10 show the effects of these two components in a historical decomposition of the log of the skill premium from the benchmark model into these two components. The relative quantity effect is shown in Figure 9. This effect is negative throughout the sample and clearly contributed significantly to the decline of the skill premium during the 1970's. This finding is consistent with Katz and Murphy (1992). The contribution of the capital-skill complementarity effect is shown in Figure 10. This factor is the driving force behind the increase in the skill premium. We estimate that the capital-skill complementarity effect increased the skill premium about 60 percent over the sample. We find that it was particularly important in the 1960's, when it increased the skill premium about 2.5 percent per year on average, and after 1980, when it increased the skill premium about 2.1 percent per year. In contrast, this component had a smaller positive effect

[15] The large increase in the relative price is evident both in the official national income and product accounts' (NIPA) equipment price index and in Gordon's (1990) quality-adjusted data.

[16] Besides the effect of a few influential observations, other factors may account for the difference between the ex post average returns on equipment and structures. In particular, equipment may yield a higher rate of return than structures because the volatility of equipment returns is so much higher. This could occur if investors were risk averse.

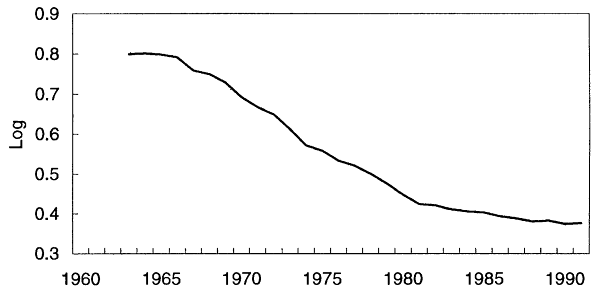


Figure 9. The relative quantity effect.

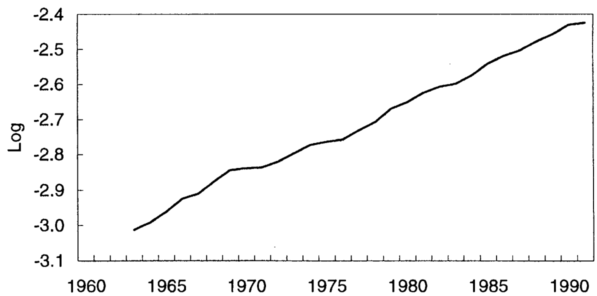


Figure 10. The capital-skill complementarity effect.

FIGURES 9–10.—A decomposition of the benchmark model's skill premium, 1963–91 (logs).

between 1969 and 1979, increasing the skill premium only about 1.4 percent per year. Overall, the capital-skill complementarity effect, which has driven the skill premium up to about 60 percent over the entire sample, dominates the relative quantity effect, which has driven the premium down about 40 percent.[17]

[17] We assessed the robustness of our results by considering two changes to our model. First, we used an alternative definition of *skill* in which skilled workers were those with at least some college education (13 or more years of school). The basic findings were similar, with the elasticity of substitution between skilled labor and equipment very similar to that in the benchmark case and a moderately higher elasticity of substitution between unskilled labor and equipment (1.89 versus 1.67 in the benchmark model). Second, we assessed the sensitivity of our results to differential tax treatment of structures and equipment. There are two sources of differences in tax treatment: different depreciation allowances and the use of the investment tax credit (ITC), which applies only to equipment purchases. Cummins, Hassett, and Hubbard (1994) construct annual time series on the ITC and the present value of depreciation allowances for equipment and structures over the 1953–88 period. We incorporated the ITC into our analysis, but could not use their data on depreciation allowances directly, since that would have required us to keep track of the entire distribution of equipment and structures. Thus, a comprehensive analysis of tax differences across assets is beyond the scope of this paper. Adding the ITC to our analysis did not change the findings in any important way. The results were very similar to those in the benchmark model—the elasticities of substitution were nearly identical. (The parameters are not strictly comparable to those reported in Section 4, since the model with the ITC can be estimated only through 1988.) The average net ex post rate of return on equipment is about 3 percent higher than that on structures with the tax benefit of the ITC, versus 2 percent higher in the benchmark model. We conclude that explicitly accounting for the ITC does not materially change our findings.

To evaluate how the recent increase in the growth rate of equipment has contributed to rising inequality, we conduct a counterfactual exercise in which we hold fixed the quantities of skilled and unskilled labor input and lower the average growth rate of equipment after 1975 to its average before and during 1975. We then compare the model's skill premium under this assumption to that generated under the actual time path of equipment. This analysis is summarized in Figure 11. We find that if equipment had grown at its average rate through 1975 in the years after 1975, the skill premium would have risen about 8 percent relative to its value in 1963. This is less than the 18 percent increase predicted by the model under the actual time path of the stock of equipment and suggests that the capital-skill complementarity effect may be a key factor in understanding the increase in inequality over the last 20 years.

Interpreting Skill-Biased Technological Change as Capital-Skill Complementarity

We now link our analysis, which focuses on the importance of capital-skill complementarity in accounting for the growth in skill premium, to other studies that have shown that a key component in accounting for that growth is an unmeasured trend or some other low-frequency component. Many economists (for example, Bound and Johnson (1992)) have interpreted this trend component as *skill-biased technological change* that has shifted the demand for skilled labor.

The quantitative importance of a trend component has been reported by Katz and Murphy (1992) (KM). They find that a simple supply/demand model

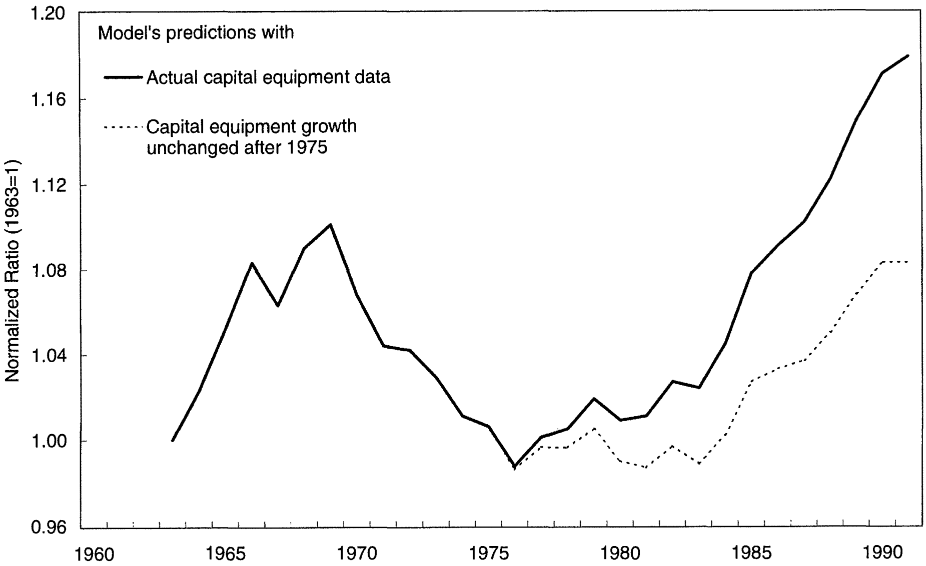


FIGURE 11.—A counterfactual experiment: What capital equipment growth has contributed to the skill premium, 1963–91.

specifying the log of the skill premium[18] as a function of a linear time trend, which represents a relative demand shifter for skilled labor, and the log of the ratio of unskilled to skilled labor input can account for much of the variation in the skill premium over time. They estimate their equation using ordinary least squares and report the following coefficient estimates:[19] $\ln \pi_t = 0.709 \ln(h_{ut}/h_{st}) + 0.03t$.

The KM finding has led many economists to ask what explicit economic factors lie behind the time trend in this equation. The results from our benchmark model suggest that one possible factor is capital-skill complementarity. If this is true, then the capital-skill complementary effect should have important low-frequency components. Our analysis shows that it does—the correlation between the capital-skill complementarity effect and the time trend is about 0.98. We also generated the predicted skill premium from our benchmark model and used this prediction to estimate the KM model. That estimated model fits the skill premium from our benchmark model well, with a significant coefficient on the time trend variable.[20] These findings suggest that the KM time trend variable may be a proxy for capital-skill complementarity.

While capital-skill complementarity may be a reasonable interpretation for the KM trend, there are other interpretations. One is that the trend is due to different growth rates of unmeasured labor efficiency of unskilled and skilled workers.[21] This can be assessed by deriving the KM model from our model with equal elasticities of substitution between skilled labor and capital and between unskilled labor and capital (with no capital-skill complementarity) and trend differences in the growth of unmeasured labor quality. Given the specification for the log of labor quality (5), the log of the skill premium in this version is

$$\ln \pi_t = (1-\sigma)\left(\frac{h_{ut}}{h_{st}}\right) + \sigma(\gamma_s - \gamma_u)t. \tag{9}$$

A comparison of the log of the skill premiums from our model with no capital-skill complementarity and from the KM model indicates that the coefficient on the time trend in the KM model can be interpreted as the product of σ, the curvature parameter governing the elasticity of substitution between

[18] Katz and Murphy (1992) consider skilled workers to be those with college completion and unskilled those with high school completion.

[19] Fitting the KM equation to our data, which differ somewhat from KM in the definition of unskilled workers, yields very similar results.

[20] We also tried to estimate the equation with both the trend term and the capital-skill complementarity effect. Since these two terms are very highly correlated, the estimates suffered from multicollinearity.

[21] Laitner (1998) develops this point.

skilled and unskilled labor and the difference in the trend growth rates of skilled and unskilled labor quality, $(\gamma_s - \gamma_u)$. Based on the Katz-Murphy OLS estimates, the implied annual growth rate of skilled labor quality is more than 11 percentage points higher than that of unskilled labor quality. This means that skilled labor quality has increased by a factor of about 30 relative to unskilled labor quality over this 30-year period.

While this alternative interpretation of the KM trend can account for changes in the skill premium, it requires a substantial difference in the growth rates of unmeasured labor quality. We are unaware of any data consistent with this large difference. The fact that labor quality is unobserved, combined with the lack of evidence supporting changes of the required magnitude, suggests that this alternative interpretation of the KM trend is less compelling than that of capital-skill complementarity.

5. IMPLICATIONS

While the development of better and cheaper capital equipment benefits the economy as a whole, our results show how this development drives down the wages of unskilled workers and has implications for the efficacy of alternative public policies. One popular proposal to try to narrow the gap between skilled and unskilled labor has been to increase trade barriers to protect domestic unskilled labor from competition with low-wage foreign labor. However, our findings suggest that this type of policy may not be as successful as its proponents believe because low-wage foreign labor is not the only factor competing with domestic labor. Unskilled labor is also competing with persistently cheaper and better capital equipment. Thus, our results suggest, the key to narrowing inequality is better education and training for unskilled workers. By improving skills, workers can use new equipment and raise their own productivity, rather than be replaced by new machines.

Dept. of Economics, University of Rochester, Rochester, NY 14627, U.S.A.,

Dept. of Economics, University of California at Los Angeles, 405 Hilgard Avenue, Los Angeles, CA 90024, U.S.A.; Dept. of Economics, University of Minnesota, Minneapolis, MN 55455, U.S.A.; and Research Department, Federal Reserve Bank of Minneapolis, Minneapolis, MN 55480, U.S.A.,

Dept. of Economics, University of Pennsylvania, 3719 Locust Walk, Philadelphia, PA 19096, U.S.A.,

and

Dept. of Economics, University College London, Gower Street, London WC1E 6BT, U.K.

Manuscript received August, 1997; final revision received July, 1999.

APPENDIX

Data Construction and Model Estimation

1. DATA CONSTRUCTION

Labor Input

The sources of our labor input data are the U.S. Department of Commerce's *CPS* Annual Demographic Uniform March Files for the years 1964–88 and the *CPS* Annual Demographic March Files for the years 1989–93. We include all people between 16 and 70 years old, excluding the self-employed. We construct the series for skilled and unskilled labor input and wages in two steps. In the first step, we construct several hundred demographic groups and record some variables in each group. In the second step, we sort these groups into two categories: skilled labor and unskilled labor. The variables are aggregated across groups to obtain category-specific averages.

For each person, we record the following characteristics: age, race, sex, years of education, and the *CPS* sampling weights. We also record current employment status, weeks worked last year, hours worked last week, and labor income earned last year.[22] We use the index i for workers and the index t for the current year.

Age is divided into 11 five-year groups. The race variable is grouped into white, black, and others. There are two sexes. Finally, education status is grouped so that $E_i \leq 11$ means no high school diploma, $E_i = 12$ means high school graduate, $12 < E_i \leq 15$ means some college, and $E_i > 15$ means college graduate and more.

Each worker is assigned to one group defined by age, race, sex, and education. There are 264 groups, which generate a partition of the population in the sample and which we denote by $g \in G$. For each partition, we construct an average measure of the labor input and the labor earnings. For the computation of the group labor input, we must take into account the labor input of those workers who reported zero hours worked last week. (This can occur although they worked last year for a positive number of weeks: the week before the survey they were either unemployed or, if employed, not at work.) We make this correction by assuming that their weekly supply of hours is equal to that of the average worker with nonzero hours worked belonging to the same group. Hourly wage is the ratio between last year's labor income and last year's measure of labor input (in hours). We obtain the following measures of individual labor input l_{it} and hourly wage w_{it}: $l_{i,t-1} = h_{it} wk_{i,t-1}$ if worked last week and $l_{i,t-1} = \bar{h}_{gt} wk_{i,t-1}$ if did not work last week, where

$$\bar{h}_{gt} = \frac{\Sigma_{i \in g} 1(lfs_{it} = e) h_{it}\, \mu_{it}}{\Sigma_{i \in g} 1(lfs_{it} = e)\, \mu_{it}}.$$

Then we have $w_{i,t-1} = y_{i,t-1}/l_{i,t-1}$. Therefore, for the group g, we obtain

$$l_{g,t-1} = \frac{\Sigma_{i \in g} l_{i,t-1}\, \mu_{it}}{\Sigma_{i \in g}\, \mu_{it}},$$

$$w_{g,t-1} = \frac{\Sigma_{i \in g} w_{i,t-1}\, \mu_{it}}{\Sigma_{i \in g}\, \mu_{it}},$$

and $\mu_{g,t-1} = \Sigma_{i \in g}\, \mu_{it}$.

We aggregate the set G of 264 groups indexed by g into skilled and unskilled categories and compute measures of the total annual labor input for skilled workers N_{st} and of their hourly wage W_{st} and total annual labor input for the unskilled N_{ut} and their hourly wage W_{ut}.

[22] No correction has been made for top-coded earnings. For instance, Juhn, Murphy, and Pierce (1993) impute earnings as 1.33 times the top-coded value, but they report that their results are not sensitive to this correction.

We assume that the groups within a class are perfect substitutes, and for the aggregation, we use as weights the group wages of 1980. Let $j = s$, u indicate the skilled and the unskilled type, respectively. Then the total labor input (in hours) for the two categories is $N_{j,t-1} = \Sigma_{g \in G_{jt}} l_{g,t-1} w_{g,80}\, \mu_{gt}$. The average hourly labor income is

$$W_{j,t-1} = \frac{\Sigma_{g \in G_{jt}} w_{g,t-1} l_{g,t-1}\, \mu_{gt}}{N_{j,t-1}}.$$

Since wages and labor input data in the survey refer always to one year earlier, our sample spans the period 1963–92.

Capital Equipment

Many economists have argued that the standard measure of capital equipment is deficient: it understates quality changes. Gordon (1990) has constructed quality-adjusted measures of equipment prices from 1947 to 1983 that can be used to construct an alternative measure of the stock of capital equipment. We use Gordon's (1990) data to do this, and we consider the following four categories of equipment:

- Office information processing (OIP): office computing and accounting machinery (OCAM) (made up of computers and peripherals (COMP) and other (OFF)); and other office and information processing (OTHOIP) (made up of communications (COMM) and instruments, photocopy, and related equipment (INST)).
- General industrial equipment (INDEQ).
- Transportation (TRANSP).
- Others (OTHER).

Gordon (1990) uses a Törnqvist (TORN) index to aggregate the quality-adjusted prices. For N goods, labeled $i = 1, \dots, N$, the change of the TORN price index from $t-1$ to t is

$$\Delta TORN_t = \sum_{i=1}^{N} \log\left(\frac{p_t^i}{p_{t-1}^i}\right)\frac{(s_t^i + s_{t-1}^i)}{2},$$

where p_t^i is the price level of good i in year t and s_t^i is the nominal expenditure on good i in year t. This index is an annual chain-weighted index. For rapidly changing prices and shares, chain-weighted indices provide better approximations than fixed-weight indices.

For the sample period after 1983, we know of no existing quality-adjusted series for the categories above, except for computers. To construct these series, we aggregate the 16 primary categories used by Gordon (1990) into the four main groups: OIP, INDEQ, TRANSP, and OTHER. The share for OIP doubled between 1947 and 1983, with much of the increase occurring in the early and mid-1980s. The other price indices, however, did not change dramatically. Therefore, we assume that the relationships between the quality-adjusted and the official-price indices were stable over time for these categories. We forecast the quality-adjusted prices for 1983–92 using the series of the official NIPA price indices, which are available up to 1992.

We estimate a vector autoregression (VAR) for the period 1963–83 for the quality-adjusted price indices for INDEQ, TRANSP, and OTHER in levels using their past values, the lagged official NIPA price indices, and a lagged indicator of the business cycle.[23] Then we forecast recursively up to 1992, exploiting the fact that the exogenous variables are observable for that period. (Details about the estimated equations are available on request.) Until 1983, the values are from Gordon's (1990) series; starting from 1984, values are forecasted.

Constructing a quality-adjusted series for OIP is important, because this is the category with the largest change in price and relative share. We first split the OIP category into COMP and equipment

[23] Our lagged indicator is a composite index of four lagged indicators, named DLAGG in the Citibase data set.

other than computers and peripherals (OFF, COMM, and INST). For communications equipment and instruments, we use the same forecasting technique as before, but we fit two separate equations this time, because the data before 1984 do not show any strong comovements. (Results are available on request.) These equations are then used to forecast prices after 1983. For the OFF category, we use the official NIPA price index.

For computers and peripherals, a large literature on quality-adjusted price indices is available. The COMP category is composed of personal computers (PCs), other computers (mainframes, supercomputers, workstations, and midrange computers), and peripherals. Computers and peripherals held by consumers are not relevant for our measure of capital input; therefore, we consider only the durables used in the business sector. The *Statistical Abstract of the United States* (U.S. Department of Commerce (1991, 1992)) reports that the share of PCs in the business sector increased from 37 percent to 57 percent of the total expenditure on PCs in the decade considered.[24] Assuming that all other types of computers are held by the business sector and that peripherals are shared by the home and business sectors in the same proportion as computers, we estimate that between 1983 and 1992 the share of mainframes, workstations, and other computers in the total expenditure on COMP declined from 46 percent to 35 percent, while the share of PCs increased from 9 percent to 21 percent. The share of peripherals was constant at around 44 percent of total COMP.

The only existing adjusted price index for peripherals is that computed by Cole et al. (1986) for the period 1972–84. It shows an average annual decline of 10 percent, which is lower (in absolute value) by a factor of 1.3 than the corresponding magnitude for the total adjusted price series for OCAM taken from Gordon (1990). Using the shares of the categories, we compute that the ratio of the decline in the price of peripherals to that of PCs and mainframes is 0.65. We assume that this ratio also holds for the period 1984–92. Given the adjusted price indices for different types of computers, we can also recover that of peripherals. Brown and Greenstein (1995) compute an adjusted series for prices of mainframes, and they find that in the period 1985–91, prices declined 30 percent, on average, every year. We assume that that percentage change also holds for all other computers, except PCs. Berndt, Griliches, and Rappaport (1995) compute a hedonic-adjusted price index for PCs from 1989 to 1992 and conclude that the price declined more than 29 percent a year. Moreover, they report a result from an earlier study that covered 1983–88, in which the average decline was 22 percent. For the missing years, we assume that the change in price is an average of the change in the preceding and following years, when the point of the sample is interior, as in 1989 for PCs. Otherwise, we assume that the price change is equal to that for the closest year for which an observation is available, as for 1983, 1984, and 1992 for mainframes. Our results confirm the widely held view that the NIPA index still underestimates the true decline in price for COMP.

We aggregate the price indices for the four main categories with the TORN procedure. We construct the relative price index by dividing the aggregate TORN price series by the deflator for nondurable and service consumption.

We construct investment in capital equipment in efficiency units by deflating the nominal series of investment in equipment from NIPA through our quality-adjusted price index for equipment. We obtain the series for capital equipment starting from a value of capital that matches the investment/capital ratio in Gordon (1990, Table 12.6) for 1963 and recursively constructing capital the next period with investment and the depreciation ratio of 0.125 calibrated as described in Section 4 of the paper. Table AI summarizes the average growth rates of the relative price and the capital stock in efficiency units for our computation and for the NIPA data before and after 1980, the key year in the time pattern of the skill premium.

2. ECONOMETRIC TECHNIQUES

To estimate the model, we used a simulated pseudo-maximum likelihood estimation (SPMLE) algorithm originally developed by Laroque and Salanié (1989, 1993, 1994). They also prove consistency and asymptotic normality of SPMLE.

[24] For the share of different types of computers, the share of peripherals, and the fraction sold to business, see U.S. Department of Commerce (1991), Tables 1273, 1274, 1277, pp. 754–755) and (1992, Tables 1256 and 1258, p. 771).

TABLE AI

AVERAGE ANNUAL PERCENTAGE CHANGES OF MAIN SERIES

Series	% Change During 1963–79	% Change During 1980–92
Relative Price		
NIPA	−0.3	−2.6
TORN	−3.6	−6.0
Capital Equipment		
NIPA	4.6	3.4
TORN	6.8	7.4

To allow for the possible dependence of hours worked on shocks, we use the two-stage SPML developed by White (1994), which is similar in spirit to two-stage least squares. We treat skilled and unskilled labor input as endogenous, and we project these variables onto a constant, current, and lagged stock of capital equipment and structures, the lagged relative price of equipment, a trend, and the lagged value of the U.S. Commerce Department's composite index of business cycle indicators. We then use the fitted (instrumented) values of skilled and unskilled labor input from this first-stage regression in a second-stage analysis described below. We define the vector $\tilde{X}_t$ as consisting of the stocks of equipment and structures and of the instrumented values of skilled and unskilled labor input.

In the second stage of the analysis, we use the instruments and the instrumented values of the labor input series with SPMLE. This proceeds as follows: given the distributional assumptions on the error terms, for each date t observation, we generate S realizations of the dependent variables, each indexed by i, by following two steps.

(A1) Step 1: $\varphi_t^i = \varphi_0 + \gamma t + \omega_t^i.$

Step 2: $Z_t^i = f(\tilde{X}_t, \psi_t^i, \varepsilon_t^i; \phi).$

In Step 1, we draw a realization of ω_t from its distribution and use it to construct a date t value for $\varphi_t = \log(\psi_t)$. In Step 2, this realization of ψ_t, together with a draw of ε_t, let us generate a realization of Z_t.

By simulating the model through equation (A1), we can obtain the first and second moments, respectively, of Z_t:

$$m_s(X_t; \phi) = \frac{1}{S} \sum_{i=1}^{S} f(\tilde{X}_t, \psi_t^i, \varepsilon_t^i; \phi),$$

and

$$V_S(X_t; \phi) = \frac{1}{S-1} \sum_{i=1}^{S} (Z_t^i - f(\tilde{X}_t^i, \psi_t^i, \varepsilon_t^i; \phi))(Z_t^i - f(\tilde{X}_t^i, \psi_t^i, \varepsilon_t^i; \phi))'.$$

On the basis of these moments constructed for each $t = 1, \ldots, T$, we can write the second-stage objective function

$$\text{(A2)} \qquad \ell_S^2(Z^T; \phi) = \frac{1}{2T} \sum_{t=1}^{T} \Big\{ [Z_t - m_s(\tilde{X}_t; \phi)]' (V_S(\tilde{X}_t; \phi))^{-1} \times [Z_t - m_S(\tilde{X}_t; \phi)] \ln \det(V_S(\tilde{X}_t; \phi)) \Big\},$$

where $\ell_s^2(Z^t; \phi)$ denotes the second-stage objective function. The SPML estimator $\hat{\phi}_{ST}$ is the maximizer of equation (A2). Note that throughout the maximization procedure of the objective function, the same set of $(T \times S)$ random numbers for each component of the three-dimensional vector of shocks must be used to ensure that the likelihood is deterministic.

In another paper, Ohanian et al. (forthcoming), we present a detailed Monte Carlo analysis on the properties of this estimator in small samples and with trending variables. There we find, in general, very little mean and median basis, even for $S = 10$. For $S = 50$, the mean bias is essentially zero.

We compute standard errors for the parameter estimates using White's (1994) formulae. The computations of the exact asymptotic standard errors take into account the first-stage parameter uncertainty in the instrumental variable estimation.

Define the set of potentially endogenous variables as X^T and the set of instruments as W^T. The first-stage likelihood function is $\ell^1(X^T; W^T, \theta)$, and the second-stage likelihood function is $\ell^2(Z^T; \tilde{X}^T(W^T, \theta^*), \phi)$, where $\tilde{X}^T(W^T, \theta^*)$ is the linear projection of X^T in the space of W^T. The "$*$" parameters denote the pseudo-true values.

Let $\nabla_\theta \equiv \partial \ell^1 / \partial \theta$ and $\nabla_{\theta\theta} \equiv \partial^2 \ell^1 / \partial \theta \, \partial \theta'$ and similarly for the other parameters. Moreover, define the matrices

$$H^* = \begin{bmatrix} \nabla_{\theta\theta} \ell^1(\theta^*) & 0 \\ \nabla_{\theta\phi} \ell^2(\theta^*, \phi^*) & \nabla_{\phi\phi} \ell^2(\theta^*, \phi^*) \end{bmatrix},$$

and

$$I^* = \begin{bmatrix} \nabla_\theta \ell^1(\theta^*) \nabla_\theta' \ell^1(\theta^*) & \nabla_\theta \ell^1(\theta^*) \nabla_\theta' \ell^2(\theta^*, \phi^*) \\ \nabla_\theta \ell^2(\theta^*, \phi^*) \nabla_\theta' \ell^1(\theta^*, \phi^*) & \nabla_\theta \ell^2(\theta^*, \phi^*) \nabla_\theta' \ell^2(\theta^*, \phi^*) \end{bmatrix}.$$

Theorem 6.11 in White (1994) establishes that the asymptotic variance-covariance matrix of $\hat{\phi}_T$ is $\operatorname{var}(\hat{\phi}_T) = H_{22}^{*-1}[I_{22}^* - H_{21}^{*\prime} H_{11}^{*-1} I_{12}^* - I_{21}^* H_{11}^{*-1} H_{21}^* + H_{21}^{*\prime} H_{11}^{*-1} I_{11}^* H_{11}^{*-1} H_{21}^*] H_{22}^{*-1}$.

Notice that the first term of the matrix multiplication $(H_{22}^{*-1} I_{22}^* H_{22}^{*-1})$ would be the asymptotic variance of $\hat{\phi}$ if we had not estimated θ in the first step, but had taken it as given. The remaining three terms in the brackets thus sum to a positive definite matrix. To compute the asymptotic variance of our simulation-based estimates of the parameters, we replace in the above expressions θ^* by $\hat{\theta}^T$ as well as ϕ^* and $\hat{\phi}_T$ by $\hat{\phi}_{ST}$.

REFERENCES

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

BERNDT, ERNST R., ZVI GRILICHES, AND NEAL J. RAPPAPORT (1995): "Econometric Estimates of Price Indexes for Personal Computers in the 1990's," *Journal of Econometrics*, 68, 243–268.

BOUND, JOHN, AND GEORGE JOHNSON (1992): "Changes in the Structure of Wages in the 1980's: An Evaluation of Alternative Explanations," *American Economic Review*, 82, 371–392.

BROWN, KENNETH H., AND SHANE M. GREENSTEIN (1995): "How Much Bigger Is Bigger, Faster & Cheaper? Buyer Benefits From Innovation in Mainframe Computers in the 1980's," Working Paper 5138, National Bureau of Economic Research.

COLE, ROSANNE, Y. C. CHEN, JOAN A. BARQUIN-STOLLEMAN, ELLEN DULBERGER, NURHAN HELVACIAN, AND JAMES H. HODGE (1986): "Quality-Adjusted Price Indexes for Computer Processors and Selected Peripheral Equipment," *Survey of Current Business*, 66, 41–50.

CUMMINS, JASON G., KEVIN A. HASSETT, AND R. GLENN HUBBARD (1994): "A Reconsideration of Investment Behavior Using Tax Reforms as Natural Experiments," *Brookings Papers on Economic Activity*, 0, 1–59.

FALLON, P. R., AND P. R. G. LAYARD (1975): "Capital-Skill Complementarity, Income Distribution, and Output Accounting," *Journal of Political Economy*, 83, 279–301.

GALOR, ODED, AND DANIEL TSIDDON (1997): "Technological Progress, Mobility, and Economic Growth," *American Economic Review*, 87, 363–382.

GOLDIN, CLAUDIA, AND LAWRENCE F. KATZ (1998): "The Origins of Technology-Skill Complementarity," *Quarterly Journal of Economics*, 113, 693–732.

GORDON, ROBERT J. (1990): *The Measurement of Durable Goods Prices*, National Bureau of Economic Research Monograph Series. Chicago: University of Chicago Press.

GOURIÉROUX, CHRISTIAN, ALAIN MONFORT, AND ALAIN TROGNON (1984): "Pseudo Maximum Likelihood Methods: Theory," *Econometrica*, 52, 681–700.

GREENWOOD, JEREMY, ZVI HERCOWITZ, AND PER KRUSELL (1997): "Long-Run Implications of Investment-Specific Technological Change," *American Economic Review*, 87, 342–362.

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

HAMERMESH, DANIEL S. (1993): *Labor Demand*. Princeton, N.J.: Princeton University Press.

HAMILTON, JAMES D. (1994): *Time Series Analysis*. Princeton N.J.: Princeton University Press.

JOHNSON, GEORGE E. (1997): "Changes in Earnings Inequality: The Role of Demand Shifts," *Journal of Economic Perspectives*, 11, 41–54.

JUHN, CHINHUI, KEVIN M. MURPHY, AND BROOKS PEIRCE (1993): "Wage Inequality and the Rise in Returns to Skill," *Journal of Political Economy*, 101, 410–442.

KATZ, LAWRENCE F., AND KEVIN M. MURPHY (1992): "Changes in Relative Wages, 1963–1987: Supply and Demand Factors," *Quarterly Journal of Economics*, 107, 35–78.

LAITNER, JOHN (1998): "Earnings Within Education Groups and Overall Productivity Growth," Manuscript, Department of Economics, University of Michigan.

LAROQUE, GUY, AND BERNARD SALANIÉ (1989): "Estimation of Multi-Market Fix-Price Models: An Application of Pseudo Maximum Likelihood Methods," *Econometrica*, 57, 831–860.

——— (1993): "Simulation-Based Estimation of Models with Lagged Latent Variables," *Journal of Applied Econometrics*, 8, S119–S133.

——— (1994): "Estimating the Canonical Disequilibrium Model: Asymptotic Theory and Finite Sample Properties," *Journal of Econometrics*, 62, 165–210.

OHANIAN, LEE E., GIOVANNI L. VIOLANTE, PER KRUSELL, AND JOSÉ-VICTOR RÍOS-RULL (forthcoming): "Simulation-Based Estimation of a Nonlinear, Latent Factor Aggregate Production Function," in *Simulation-Based Inference in Econometrics: Methods and Applications*, ed. by Robert S. Mariano, Til Schuermann, and Melvyn Weeks. Cambridge, U.K.: Cambridge University Press.

STOKEY, NANCY L. (1996): "Free Trade, Factor Returns, and Factor Accumulation," *Journal of Economic Growth*, 1, 421–447.

U.S. DEPARTMENT OF COMMERCE (1963–93): *Current Population Survey*. Washington, D.C.: U.S. Bureau of the Census.

——— (1991, 1992): *Statistical Abstract of the United States*. Washington, D.C.: U.S. Bureau of the Census.

VIOLANTE, GIOVANNI L. (1998): "Technological Progress and Skill Dynamics: A Solution to the Wage Dispersion Puzzle?" Manuscript, Department of Economics, University College London.

WHITE, HALBERT (1994): *Estimation, Inference and Specification Analysis*, Econometric Society Monographs, No. 22. Cambridge, U.K.: Cambridge University Press.