The B.E. Journal of Economic Analysis & Policy

Topics

Volume 11, *Issue* 1 2011 *Article* 65

Overestimating the Effect of Complementarity on Skill Demand

Brian K. Kovak*

*Carnegie Mellon University, bkovak@cmu.edu

Recommended Citation
Brian K. Kovak (2011) "Overestimating the Effect of Complementarity on Skill Demand," *The B.E. Journal of Economic Analysis & Policy*: Vol. 11: Iss. 1 (Topics), Article 65.
Available at: http://www.bepress.com/bejeap/vol11/iss1/art65

Overestimating the Effect of Complementarity on Skill Demand*

Brian K. Kovak

Abstract

Many recent studies estimate cost function parameters to measure the influence of capital-skill complementarity on changes in skill demand. This paper argues that standard cost function estimates assuming quasi-fixed capital systematically overestimate the effect of complementarity when subject to skill-biased technological change. While previous work has considered bias due to measurement error or general endogeneity concerns, this paper shows that upward bias results directly from cost minimizing behavior. I also develop a novel instrumental variables strategy based on the tax treatment of capital to more accurately measure the effect of complementarity. Although somewhat imprecise, the IV results support the model's prediction that the standard approach overestimates the effect of complementarity.

KEYWORDS: labor demand, technological change, capital-skill complementarity

*The author would like to thank Rebecca Blank, John Bound, Charlie Brown, Brian Cadena, John DiNardo, Michael Elsby, Juan Carlos Hallak, James Hines, Christopher House, Benjamin Keys, Stephan Lindner, James Sallee, Joel Slemrod, Doug Smith, Gary Solon, and seminar participants at the University of Michigan, the Midwest Economic Association, and the W.E. Upjohn Institute for Employment Research. Special thanks are due to Randy Becker, Eli Berman, and Wayne Gray for providing data. The author also gratefully acknowledges fellowship support from the University of Michigan Population Studies Center.

1 Introduction

Estimating capital-skill complementarity is fundamental to the study of labor demand. Complementarity estimates are used in calculating the elasticity of substitution between different types of labor, and in deciding how to aggregate different groups of workers when conducting empirical work. Such estimates are also necessary to predict the effect of capital subsidies on different workers' wages (Hamermesh, 1993). A large number of recent studies estimate cost function parameters in an effort to measure the effect of capital-skill complementarity on changes in skill demand. In this paper, I present a model of production incorporating capital-skill complementarity showing that cost minimizing behavior will lead these previous studies to overestimate the effect of complementarity when production is subject to skill-biased technological change. I then implement a novel instrumental variables strategy based on changes in the tax treatment of income from capital during the early 1980's to show that the standard complementarity estimates are likely biased upward in practice.

Cost function estimates with quasi-fixed capital were first introduced by Caves, Christensen, and Swanson (1981) in the context of measuring industry productivity growth.[1] Berman, Bound, and Griliches (1994) introduced the quasi-fixed capital approach to the literature on wage inequality, and a large number of subsequent papers have since utilized this approach.[2] The following intuition explains why estimates derived using this approach will be systematically biased toward overestimating the impact of capital-skill complementarity. The cost-function approach derives an estimating equation that relates changes in skill demand to changes in capital, with the regression coefficient on capital representing complementarity. The equation's error term represents skill-biased technological change (SBTC) in production. Firms experiencing SBTC will by definition increase their skill demand, but if complementarity is present, the increased use of skilled labor will also lead the firm to increase capital usage. Optimal firm behavior in the presence of complementarity implies a positive relationship between SBTC (the error term) and capital changes (the regressor of interest). Thus, the estimated coefficient on capital changes will be biased upward, overstating the impact of capital-skill complementarity on skill demand.

[1] More recent studies utilizing similar techniques include Bloch and Tang (2007), Casarin (2006), Lee (2008), and Nøstbakken (2006)

[2] Examples include Autor, Katz, and Krueger (1998); Berman and Machin (2000); Berman, Somanathan, and Tan (2005); Blonigen and Slaughter (2001); Caroli and Van Reenen (2001); Chun (2003); Doms, Dunne, and Troske (1997); Dunne, Haltiwanger, and Troske (1997); Goldin and Katz (1998); Haskel and Slaughter (2002); Machin and Van Reenen (1998); and Pavcnik (2003).

After demonstrating this intuition in a production framework that incorporates capital-skill complementarity, the analysis moves to determining the practical importance of the bias. I introduce a novel instrumental variable derived from policy changes in the tax treatment of capital that generated variation in the user cost of capital faced by different industries.[3] This approach is particularly well suited to identifying the role of complementarity, since it relies on exogenous variation in the price of capital across industries. The empirical results suggest that the theoretically predicted bias is realized in practice. Although the estimates are somewhat imprecise, the OLS point estimates overstate the importance of capital-skill complementarity relative to the IV estimates, as predicted by the theoretical analysis.

Previous papers in the wage inequality and complementarity literatures have noted the possibility of biased cost function estimates resulting from measurement error or endogeneity of cost function inputs. Dunne et al. (1997) and Duffy, Papageorgiou, and Perez-Sebastian (2004) respond to these concerns by using lagged values of production inputs and output as instrumental variables.[4] Krusell, Ohanian, Rios-Rull, and Violante (2000) utilize functional form restrictions and nonlinear estimation techniques to resolve potential endogeneity when estimating the effects of complementarity in the presence of skill-biased technological change.

The present analysis contributes to the previous literature in two ways. First, it refines the general endogeneity concerns discussed previously, demonstrating in a simple production model that optimal firm behavior itself will generate bias in a particular direction, overstating the role of complementarity. This bias is neither arbitrary, nor the result of measurement error, but results directly from cost minimizing behavior. Second, this paper uses a new policy-driven instrumental variables approach to consistently identify the effect of complementarity on changes in skill demand. This represents an alternative to the lagged-values instruments and simulation estimation approaches employed previously.

The analysis presented here has implications beyond the inequality literature. In general, OLS estimates of cost function parameters will be systematically biased when the following two conditions hold: 1) production is modeled with a quasi-fixed factor that exhibits different levels of substitutability across variable inputs, and 2) the production function is subject to factor-biased technical change. These conditions clearly hold in the wage inequality literature, but they are also likely to be relevant in industry studies of productivity growth that utilize the quasi-fixed factor assumption.

[3] See Triest (1998) for an overview of the use of tax policy changes to gain identification.

[4] Although Dunne et al. utilize different instruments, their long-difference IV cost function estimates also support this paper's conclusion. The IV analysis in Duffy et al. (2004) yields very imprecise estimates, making it difficult to infer bias by comparison with baseline estimates.

This paper has four remaining sections. The next section describes how cost function estimation has been employed in studies of changing skill demand and discusses the source of estimation bias. Section 3 presents a model that explicitly incorporates capital-skill complementarity, demonstrating that the standard estimation procedure will overestimate the effect of complementarity. Section 4 implements an instrumental variables strategy suggesting that the theoretically predicted bias is present in practice, and section 5 concludes.

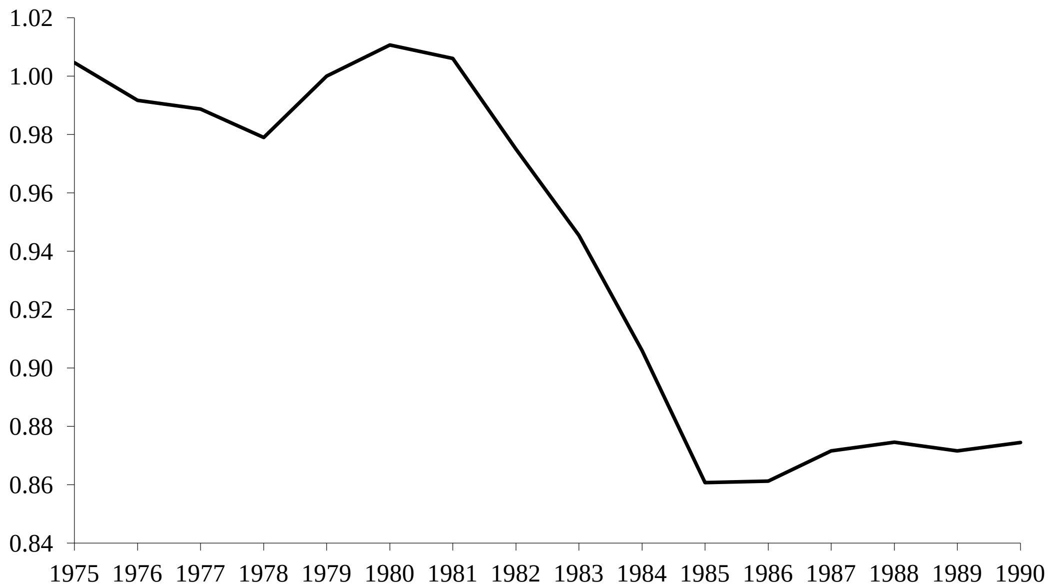
2 The Complementarity / SBTC Decomposition

Two potential causes of increased demand for skilled labor relative to unskilled labor are skill-biased technological change (SBTC) and capital-skill complementarity. SBTC is normally defined in a two-factor model, including skilled and unskilled labor. Berman, Bound, and Machin (1998) provide a concise definition: "A skill-biased technological change is an exogenous change in the production function that increases the [relative demand for skilled to unskilled labor] at the current wage level." An alternative driver of within-industry increases in relative skill demand is capital-skill complementarity combined with falling capital prices. A production function exhibits capital-skill complementarity if its derived factor demands imply that capital is more complementary with skilled labor than with unskilled labor. Under capital-skill complementarity, a fall in the price of capital will result in an increase in the demand for skilled labor relative to unskilled labor, given fixed relative wages. As shown in Figure 1, the price of new investment relative to production worker wages fell sharply during the first half of the 1980's.

Thus, both SBTC and capital-skill complementarity may have driven shifts in relative skill demand. Given the fundamental difficulty in directly measuring technological changes, studies generally seek to measure the effect of capital-skill complementarity and attribute residual shifts in relative skill demand to SBTC. In an effort to generate such an estimate of the effect of capital-skill complementarity on inequality, Berman et al. (1994), hereafter BBG, adapt a technique from Brown and Christensen (1981). They estimate an industry-level cost function using data on U.S. industries from the Annual Survey of Manufactures, and use the resulting parameter estimates to measure the effect of capital-skill complementarity on changes in industry skill share. The remainder of this section describes the BBG cost function estimation approach in order to highlight potential problems in the approach's ability to identify the effect of complementarity on skill share.

An estimation equation that distinguishes between the effects of capital-skill complementarity and SBTC can be derived from a translog variable cost function

Figure 1: The Price of New Investment Relative to Production Worker Wages



Source: Author's calculations based on Annual Survey of Manufactures data and price indices provided in the NBER Manufacturing Database (Bartlesman and Gray, 1996).
Notes: Production workers' wages calculated as production worker wagebill divided by production worker hours. Each yearly observation is a weighted sum of industry-level values for that year with weights equal to the industry's share of total yearly manufacturing wage bill. Values normalized to equal 1.0 in 1979.

of the form

$$
\begin{aligned}
\ln VC = {} & \alpha_0 + \alpha_y \ln Y + \sum_j \alpha_j \ln w_j + \beta \ln K + \frac{1}{2}\gamma_{YY}(\ln Y)^2 \\
& + \frac{1}{2}\sum_j \sum_k \gamma_{jk} \ln w_j \ln w_k + \frac{1}{2}\delta(\ln K)^2 + \sum_j \rho_{Y_j} \ln Y \ln w_j \\
& + \sum_j \rho_j \ln w_j \ln K + \pi \ln Y \ln K + \phi_t t + \frac{1}{2}\phi_{tt} t^2 + \phi_{tY} t \ln Y \\
& + \sum_j \phi_{tw_j} t \ln w_j + \phi_{tK} t \ln K
\end{aligned} \tag{1}
$$

where VC is variable cost, Y is value added, w_j is the cost of variable input j, K is capital, and t is time, representing technical change. BBG assume that capital is quasi-fixed, implying that firms do not maximize over capital, which accounts for its inclusion separate from other variable inputs in (1). Under this assumption, cost minimization yields a share equation which is then time differenced to yield

$$dS_j = \phi_{tw_j}dt + \rho_{Y_j}d\ln Y + \sum_k \gamma_{jk}d\ln w_k + \rho_j d\ln K \tag{2}$$

where S_j is the wagebill share of variable input j, and d is the long difference operator. Assuming linear homogeneity of the cost function, constant returns to scale production, and that all industries have the same elasticities of substitution between factors yields the following estimating equation for industry i:

$$dS_{S,i} = \gamma d\ln(w_{S,i}/w_{U,i}) + \rho d\ln(K_i/Y_i) + \phi_i dt \tag{3}$$

where $S_{S,i}$ is the wagebill share of skilled workers, $w_{S,i}$ is the wage of skilled workers, and $w_{U,i}$ is the wage of unskilled workers in industry i. γ is related to σ_{SU}, the elasticity of substitution between skilled and unskilled labor, and ρ measures the effect of capital-skill complementarity on increases in demand for skilled labor relative to unskilled labor. The technology term in this equation, $\phi_i dt$, includes an industry subscript, which can be interpreted as modeling a common cross-industry technology shock that has different effects on each industry.[5] In what follows, (3) will be referred to as the "decomposition equation."

In practice, the technology term in the decomposition equation, $\phi_i dt$, is interpreted as the error term of the estimating regression. (3) is generally estimated using industry or firm level data differenced over time spans ranging from 1 to 14 years. When determining how much of the changes in skill share can be attributed to capital-skill complementarity, one is primarily interested in estimating the parameter ρ in (3), which is identified by cross-industry variation in the change in capital intensity. By imposing the quasi-fixed capital assumption, the analysis assumes that changes in capital intensity are not the result of decisions by maximizing agents, and thus are exogenous to technology shocks in the error term.

Under the quasi-fixed capital assumption agents do not adjust capital, but the analysis simultaneously relies on capital intensity changes to identify the parameter of interest. Moreover, capital investment data almost certainly reflect the decisions of cost minimizing firms to some degree, so investment decisions are likely to be affected by changes in technology. Therefore, changes in capital intensity will be correlated with technology shocks in the error term, resulting in a biased estimate of the causal effect of complementarity on changes in skill share.[6]

[5] An observationally equivalent interpretation would impose a common effect of a given technology shock in all industries, but would allow for different shocks in each industry.

[6] Situations in which (3) is estimated using one-year differences may not suffer as much from this problem, as capital intensity may not have time to adjust to recent technology shocks over such

The same problem can be seen from another perspective when considering the potential sources of identifying cross-industry variation in capital intensity changes. The two most likely sources of variation are different capital price changes across industries and different arrival times of new technology to different industries. Since capital-skill complementarity implies that industries experiencing a decrease in the price of capital will increase their skill share, identification based on different capital price changes will be successful. Identification based on different arrival times of technology is more problematic. Variation in the error term is interpreted as resulting from skill-biased changes in technology. Industries experiencing large skill-biased technology shocks by definition will have more positive changes in skill share conditional on the change in capital intensity. If industry production functions exhibit complementarity, then increases in skill-share will raise the marginal product of capital and induce increased investment. Therefore, complementarity creates a causal link between SBTC and changes in capital intensity, which results in an overestimate of the effect of complementarity.

3 The Decomposition in a Model with Complementarity

In order to demonstrate the preceding intuition, this section presents a framework that explicitly imposes capital-skill complementarity (rather than simply allowing for complementarity as with the translog cost function). This framework demonstrates the resulting association between SBTC (the error term in (3)) and changes in capital intensity (the regressor of interest in (3)).

As defined by Griliches (1969), capital-skill complementarity implies that

$$\sigma_{KU} > \sigma_{KS} \tag{4}$$

where σ_{ij} is the Allen-Uzawa partial elasticity of substitution between factors i and j, and U, S, and K represent unskilled labor, skilled labor, and capital, respectively. The simplest three-factor production function that allows the imposition of capital-skill complementarity as defined in (4) is the two-level CES production function

a short time span. However, if technology shocks are serially correlated within industries, then the change in capital intensity in a given year, which is driven by the previous year's shock, will still be correlated with the error term, leading to bias. Since industries receiving new technologies are likely to experience the continued influence of technological developments, such serial correlation is quite likely in this case.

examined by Sato (1967):[7]

$$\begin{aligned} Y &= [\alpha Z^{\frac{\sigma-1}{\sigma}} + (1-\alpha)(g_U L_U)^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}} \\ \text{where } Z &= [\beta (g_K K)^{\frac{\psi-1}{\psi}} + (1-\beta)(g_S L_S)^{\frac{\psi-1}{\psi}}]^{\frac{\psi}{\psi-1}} \end{aligned} \tag{5}$$

The share parameters α and $\beta \in (0,1)$, the factor augmenting terms g_U, g_K, and $g_S > 0$, and the substitution parameters σ and $\psi > 0$ are all technology parameters, and K, L_S, and L_U represent capital, skilled labor, and unskilled labor inputs, respectively. Given this production function, the elasticities of substitution between capital and unskilled labor and between skilled labor and unskilled labor are $\sigma_{KU} = \sigma_{SU} = \sigma$, while the elasticity of substitution between capital and skilled labor is $\sigma_{KS} = \sigma + \frac{1}{\theta_{KS}}(\psi - \sigma)$, where $\theta_{KS} \in (0,1)$ is the cost share spent on capital and skilled labor combined.[8] The production function exhibits capital-skill complementarity as defined in (4) when $\sigma_{KU} > \sigma_{KS}$, which in this case is equivalent to $\sigma > \psi$.

Consider this production function in a partial equilibrium framework in which the price of the final good is normalized to one, and real factor prices are exogenous. In this framework, the first order conditions can be subjected to shocks to the different technology parameters, allowing one to observe the resulting comovement between the error term in the decomposition equation and capital intensity, the regressor of interest.[9] For notational convenience, I set $\psi = 1$ in the following expressions, corresponding to the case in which the inner CES aggregate reduces to Cobb-Douglas, and capital-skill complementarity is equivalent to $\sigma > 1$. The results are similar to those in the general case, but can be demonstrated using much simpler expressions.[10]

The dependent variable in the decomposition regression is the wagebill share of skilled labor. The two-level CES production function, (5), yields a particularly unruly form for this share. However, since the wagebill share of skilled

[7] This functional form is used here for illustrative purposes, but similar forms have been used directly in empirical estimation in Krusell et al. (2000) and Duffy et al. (2004).

[8] Although Sato (1967) does not include the factor-augmenting technology parameters, these elasticities can be derived following similar calculations to those in the appendix of Sato (1967).

[9] An alternative approach would be to derive the cost function implied by (5) and take a second order log approximation, which would correspond to (1). Unfortunately with capital fixed, no closed form solution for this cost function exists, and calculating the necessary derivatives to implement the second order approximation using the implicit function theorem quickly yields intractable mathematical expressions.

[10] The Appendix presents the analysis in the general case in which the only restriction placed on the elasticity parameters is the complementarity assumption that $\psi < \sigma$. The only substantive difference from the simpler $\psi = 1$ case concerns the parameters g_K and g_S. If $\psi \geq 1$ then the Cobb-Douglas case results continue to hold. Otherwise the signs of g_K's effect on K/Y and g_S's effect on L_S/L_U are ambiguous.

labor is increasing in L_S/L_U for a fixed wage ratio, one can infer the direction of change of the wagebill share of skilled labor by observing changes in L_S/L_U.[11] Taking the ratio of the first order conditions with respect to L_S and L_U and taking logs yields

$$\begin{aligned}\ln(L_S/L_U) =& \sigma\ln(\alpha/(1-\alpha)) + (1+(1-\beta)(\sigma-1))\ln(1-\beta) + \beta(\sigma-1)\ln\beta \\ & -(\sigma-1)\ln g_U + \beta(\sigma-1)\ln g_K + (1-\beta)(\sigma-1)\ln g_S + \sigma\ln w_U \\ & -(1+(1-\beta)(\sigma-1))\ln w_S - \beta(\sigma-1)\ln r\end{aligned} \tag{6}$$

where w_U, w_S, and r are the respective prices of unskilled labor, skilled labor, and capital. From this expression, it is clear that L_S/L_U is increasing in g_K, g_S, and α, and decreasing in g_U. Thus, in this model SBTC is associated with exogenous increases in g_K, g_S, and α, or decreases in g_U.[12]

The first order condition with respect to capital will demonstrate how capital intensity changes when the production function is subjected to SBTC parameter shocks. Taking logs of the first order condition with respect to capital yields

$$\begin{aligned}\ln(K/Y) =& \sigma\ln\alpha + (1-\beta)(\sigma-1)\ln(1-\beta) + (1+\beta(\sigma-1))\ln\beta + \beta(\sigma-1)\ln g_K \\ & + (1-\beta)(\sigma-1)\ln g_S - (1-\beta)(\sigma-1)\ln w_S - (1+\beta(\sigma-1))\ln r\end{aligned} \tag{7}$$

This expression shows that K/Y is increasing in g_K, g_S, and α, and invariant to g_U. The likely endogeneity in the decomposition equation is apparent given these comparative static results. The SBTC-inducing parameter changes directly cause increases in capital intensity, with the exception of g_U which has no effect on capital intensity. Thus, the capital intensity term in (3) is likely to be positively correlated with SBTC shocks in the error term, and the OLS estimate of ρ will be biased upward, overestimating the effect of complementarity on the relative demand for skilled labor.

[11] The wagebill share of skilled labor is defined as

$$\frac{w_S L_S}{w_S L_S + w_U L_U} = \frac{\frac{w_S}{w_U}\frac{L_S}{L_U}}{\frac{w_S}{w_U}\frac{L_S}{L_U}+1}$$

which is increasing in $\frac{L_S}{L_U}$ for a fixed wage ratio.

[12] The effects of changes in β on $\ln(K/Y)$ and $\ln(L_S/L_U)$ depend on the value of other parameters and input prices, and thus cannot be signed in general. However, taking the partial derivatives of (6) and (7) with respect to β, one can show that $\frac{\partial\ln(K/Y)}{\partial\beta} > 0$ whenever $\frac{\partial\ln(L_S/L_U)}{\partial\beta} > 0$. If this is the case, increases in β will induce positive bias in estimating ρ, as is the case with the other parameters. However, the bias could be negative or zero in other cases.

To see this bias more clearly, it is possible to use (6) and (7) to calculate the OLS estimate of ρ in (3) that would be obtained if the data used in estimation reflect the production technology just described. Following the previous literature, assume that the relative wage term in (3) is constant across industries and is therefore absorbed into the intercept term (see section 4 below). In this case,

$$\operatorname{plim}\hat{\rho} = \frac{\operatorname{Cov}\left(dS_{S,i}, d\ln\frac{K_i}{Y_i}\right)}{\operatorname{Var}\left(d\ln\frac{K_i}{Y_i}\right)}. \tag{8}$$

For small changes in $\frac{L_S}{L_U}$, the definition of $S_{S,i}$ implies that $dS_{S,i} = (S_{S,i} - S_{S,i}^2)\, d\ln\frac{L_{S,i}}{L_{U,i}}$. Assuming for simplicity that all industries begin with the same skill share, (8) can be restated as

$$\operatorname{plim}\hat{\rho} = \frac{(S_S - S_S^2)\operatorname{Cov}\left(d\ln\frac{L_{S,i}}{L_{U,i}}, d\ln\frac{K_i}{Y_i}\right)}{\operatorname{Var}\left(d\ln\frac{K_i}{Y_i}\right)}. \tag{9}$$

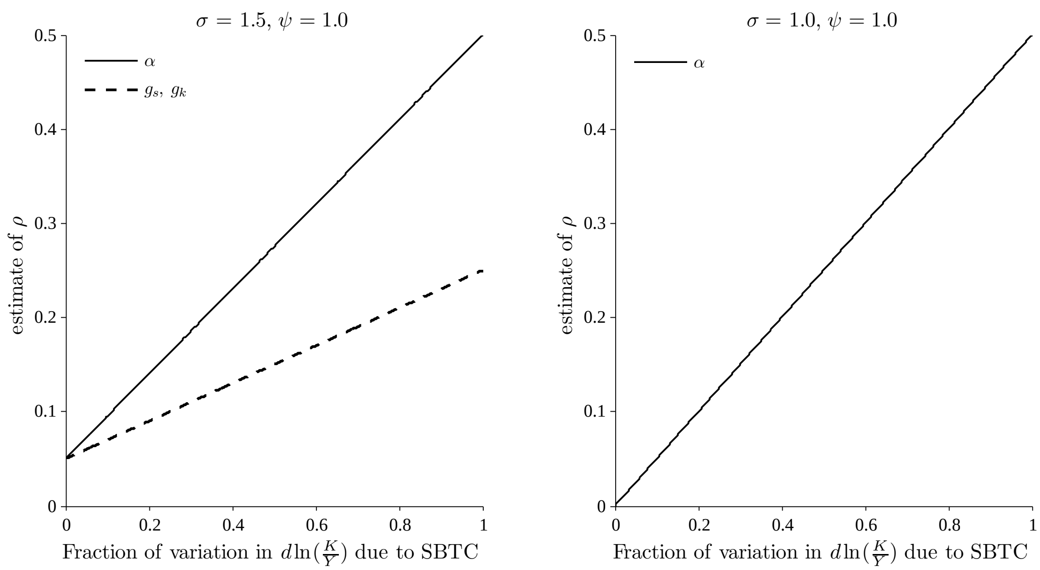
Given information on the variation in factor prices and technology parameters across industries, the covariance and variance terms in (9) can be calculated directly from (6) and (7), yielding the corresponding estimate of ρ.

In practice, the researcher estimating (3) observes variation in $d\ln(K_i/Y_i)$ that may be driven by capital price variation or by SBTC. Figure 2 uses (9) to show that the estimate of ρ increases as the variation in $d\ln(K_i/Y_i)$ is more heavily driven by SBTC, even when the degree of complementarity is held fixed. As an example of how the estimates in Figure 2 were calculated, consider the case where capital variation is driven only by cross-industry variation in the capital price r and the technology parameter α, and these two drivers are independent. The variation in $d\ln(K_i/Y_i)$ is then given by

$$\operatorname{Var}\left(d\ln\frac{K_i}{Y_i}\right) = \sigma^2\operatorname{Var}(d\ln\alpha_i) + (1+\beta(\sigma-1))^2\operatorname{Var}(d\ln r_i), \tag{10}$$

with the first term on the right hand side describing the portion of the variation in $d\ln(K_i/Y_i)$ due to α-based SBTC and the second term describing the remainder of the variation due to r. The x-axis in Figure 2 represents the fraction of the total variation in $d\ln(K_i/Y_i)$ due to variation in the relevant SBTC parameter, so when this value is 0, all of the capital variation comes from r, and there is no variation in SBTC. The line labeled α in the left panel of Figure 2 shows how the estimate of ρ increases as the fraction of the variation in $d\ln(K_i/Y_i)$ due to α-based SBTC increases from 0 to 1 in the presence of complementarity (since $\sigma > \psi$). The line's intersection with the y-axis shows the correctly identified estimate of ρ, which is

Figure 2: Complementarity estimates implied by 2-Level CES production function

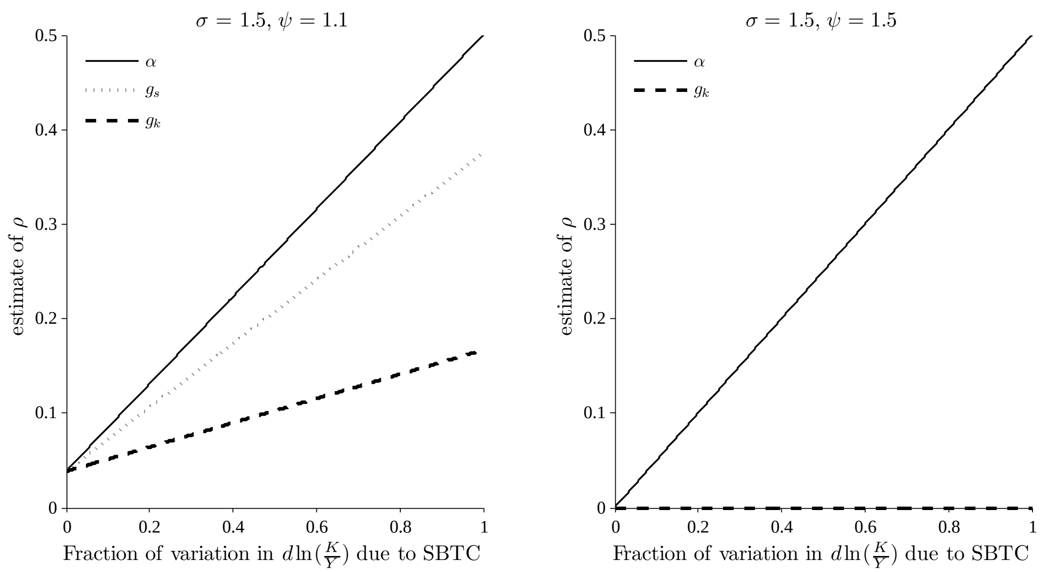


positive, indicating the presence of complementarity. As the variation in SBTC is increased, however, the ρ estimates increase, in spite of the fact that the substitution parameters are unchanged. A similar pattern is seen in the right panel of Figure 2, in which production does not exhibit capital-skill complementarity (since $\sigma = \psi$). The ρ estimates only reflect the absence of complementarity when all of the capital variation is driven by variation in r, and the estimates of ρ are increasingly upward biased as SBTC variation becomes more important.

Figure 2 presents similar results for SBTC based upon variation in g_S and g_K, yielding the same conclusion. The degree of complementarity is correctly identified only when capital variation is driven by r and is overestimated when SBTC is present. Note that the estimates for g_S and g_K variation are identical in the left panel due to the Cobb-Douglas assumption ($\psi = 1$), and are absent from the right panel because neither parameter affects $d\ln(K_i/Y_i)$ in the absence of complementarity, so the x-axis is undefined. Estimate plots generated without the Cobb-Douglas restriction on ψ are presented in Figure 3, yielding the same qualitative conclusions.

This section has demonstrated that cost minimization implies that SBTC drives changes in both skill share and capital intensity. Therefore OLS estimates of the decomposition equation overestimate the effect of complementarity on skill de-

Figure 3: Complementarity estimates implied by 2-Level CES production function - without Cobb-Douglas restriction on ψ



mand.[13] The estimate plots in Figures 2 and 3 support this conclusion, and suggest that consistent identification can be achieved by using variation in capital intensity that is driven by cross-industry variation in the price of capital. The following section operationalizes this observation using an instrumental variables estimation strategy based on the tax treatment of capital.

4 Disentangling the Effects of Complementarity and SBTC

The preceding theoretical discussion suggests that the decomposition equation overestimates the effect of capital-skill complementarity on relative skill demand. In an

[13] BBG and others have included proxies of SBTC such as computer investment or R&D expenditures in an effort to directly measure the effects of technical change. While previous studies appear to have included these proxy variables for reasons other than concerns with endogeneity, a perfect measure of SBTC would completely remove it from the error term and resolve the endogeneity problem just discussed. However, the data previously used appear to be quite weak proxies for SBTC, and any cross-industry variation in SBTC that is not accounted for by the proxy will remain in the error term, continuing to cause biased parameter estimates.

effort to assess this theoretical prediction, the remainder of this paper presents an instrumental variables analysis that takes advantage of changes in the U.S. corporate income tax code during the early 1980's. These changes resulted in cross-industry variation in the tax treatment of industry capital, which provide an instrument for the change in industry capital intensity. The results suggest that the theoretically predicted bias is realized empirically.

4.1 Corporate Income Tax and Effective Marginal Tax Rates

The corporate income tax in the U.S. is similar to a tax on corporate profits, allowing businesses to deduct input and materials costs that are incurred in generating revenues. Since capital inputs provide services over a long period of time and are "used up" slowly through economic depreciation, a textbook profits tax would allow businesses to deduct the value of economic depreciation incurred each year rather than the full price of the capital asset at the time of purchase. In practice, the U.S. corporate income tax has deviated from the textbook profits tax by providing investment tax credits allowing firms to immediately reduce tax liability by a fraction of a capital good's purchase price and by creating statutory depreciation schedules that differ substantially from economic depreciation rates. These deviations result in effective marginal tax rates that differ from the statutory tax rate.[14] Since the size of the investment tax credit and the gap between economic and statutory depreciation rates vary across capital assets, income from investment in different capital assets faces different effective marginal tax rates even though the statutory tax rate is the same across income from all assets. The empirical analysis presented here utilizes estimates of effective marginal tax rates on 28 different capital assets generated by Gravelle (2001) using the Hall and Jorgenson (1967) user cost of capital formula, which accounts for investment tax credits, statutory depreciation, economic depreciation, inflation, and interest rates.

During the time period being examined, legislative changes greatly affected the tax treatment of capital investment.[15] The overall effect of these legislative

[14]The effective marginal tax rate is defined as the marginal tax rate on true economic profits that would yield the same incentive to invest as the tax structure actually faced by the firm.

[15]The Economic Recovery Tax Act of 1981 redefined depreciation categories, substantially increasing depreciation rates for most assets, and decreased the statutory tax rate on income from capital from 47% to 46%. Legislation during the 1981-85 period reduced the very large investment incentives of the 1981 Act. Finally, the Tax Reform Act of 1986 decreased the tax rate to 34% and sought to bring the system back in line with true economic depreciation by repealing many investment incentives and creating more variation in statutory depreciation rates across asset classes. See Auerbach, Aaron, and Hall (1983); Gravelle (1994); and Gravelle (2001) for detailed summaries of the relevant changes in tax law.

changes was to generate significant variation in effective marginal tax rates across assets. In order to utilize this variation as an instrument for capital intensity in the decomposition regression, it is important that the investment incentives were not targeted toward capital assets that may embody SBTC. If such targeting did take place, the changes in tax rates might be correlated with SBTC shocks in the decomposition's error term and would not yield a valid instrument for changes in capital intensity. In its Report on the Economic Recovery Tax Act of 1981, the U.S. Senate Committee on Finance (1981) stated that "tax reductions are urgently needed to stimulate capital formation," and goes on to note that the Act provides broad accelerated depreciation allowances for both plant and equipment capital assets. Neither the report nor the individual senators' additional comments mention targeting particular types of assets. These apparently ad-hoc investment incentives appear to have changed marginal tax rates in ways that do not exhibit any systematic pattern across asset classes.

Table 1 reports the difference in the time averaged effective marginal tax rates in the 1975-79 and 1980-87 periods, and ranks the 28 asset classes by how much each was affected by the early 1980's tax changes. The policy changes had very different effects on effective marginal tax rates for different capital assets. This variation comes from explicit differences in the tax treatment of different assets, with some facing larger investment tax credits and shorter depreciation schedules, and also from differences in each asset's true economic rate of depreciation, since a given investment tax credit favors shorter-lived assets.[16] Similar assets are quite evenly distributed throughout this ranking. For example, the six different classes of structures fall at ranks 7, 10, 15, 24, 25, and 26. High-tech equipment assets that are generally associated with SBTC, Office/Computing, Instruments, and Communications Equipment, fall at ranks 1, 19, and 27, respectively. Thus, it appears that the tax changes did not target particular types of capital assets, and rather attempted to promote investment in general while affecting individual assets in essentially random ways. This evidence argues against targeted investment incentives that could have invalidated the use of tax changes as an instrument for changes in capital intensity.

[16]Consider two assets with the same purchase price and both eligible for a 10% investment tax credit, with the second asset much longer lived (depreciates more slowly) than the first. The investment tax credit amount is identical for the two assets, given identical purchase prices. However, the longer lived asset has a larger present value of tax payments, since it provides returns for more years. Hence, the tax credit represents a larger share of the overall tax burden and stronger incentive for investment in the shorter lived asset. Another way to see this difference is to note that shorter lived assets are replaced more frequently, allowing more frequent opportunities to benefit from the credit (Gravelle, 1994).

Table 1: Changes in Average Effective Marginal Tax Rates

Rank	Asset	Average MTR 1975-79	Average MTR 80-87	Difference
1	Office/Computing	-8.0	9.0	17.0
2	Trucks/Buses/Trailers	7.0	10.1	3.1
3	Construction Machinery	5.0	8.0	3.0
4	Agricultural Equipment	4.0	6.8	2.8
5	Tractors	6.0	8.6	2.6
6	Furniture and Fixtures	5.0	7.3	2.3
7	Mining Structures	12.0	11.5	-0.5
8	Other Equipment	13.0	9.4	-3.6
9	Railroad Equipment	28.0	24.4	-3.6
10	Public Utility Structures	30.0	26.1	-3.9
11	Other Electrical Equipment	12.0	8.1	-3.9
12	Special Industrial Equipment	12.0	7.9	-4.1
13	Engines and Turbines	36.0	31.5	-4.5
14	Metalworking Machinery	13.0	8.4	-4.6
15	Farm Structures	44.0	37.8	-6.3
16	Mining/Oilfield Equipment	17.0	10.3	-6.8
17	Autos	19.0	12.0	-7.0
18	Aircraft	18.0	11.0	-7.0
19	Instruments	22.0	14.9	-7.1
20	Electric Transmission Equipment	33.0	25.6	-7.4
21	General Industrial Equipment	23.0	14.0	-9.0
22	Fabricated Metal	30.0	20.4	-9.6
23	Service Industry Equipment	22.0	10.9	-11.1
24	Commercial Structures	51.0	39.4	-11.6
25	Other Structures	57.0	45.4	-11.6
26	Industrial Structures	54.0	42.0	-12.0
27	Communications Equipment	25.0	9.0	-16.0
28	Ships and Boats	32.0	10.0	-22.0

Source: Author's calculations based on data presented in Gravelle (2001)

4.2 Data and Estimation

Equation (3) is estimated using data from the Annual Survey of Manufactures (ASM) in the NBER Manufacturing Productivity Database (Bartlesman and Gray, 1996). As is common in studies of wage inequality, nonproduction and production workers respectively define skilled and unskilled workers. For comparison with previous results in the literature, this analysis follows a number of choices made by Berman, Bound, and Griliches (1993) in implementing the estimation of (3). The relative wage term in the share equation is dropped due to a lack of data in the

ASM on nonproduction worker hours.[17] Y is measured as shipments rather than value-added due to the lack of appropriate price deflators for industry value-added. As already mentioned, the technology term in (3), representing SBTC, is left in the error term. In an effort to reduce noise induced by measurement error in smaller industries in the ASM, data are weighted using the industry's share of the total manufacturing wagebill.[18] Finally, the results presented examine changes between 1979 and 1987.

I use the change in the industry effective marginal tax rate on capital income as an instrument for the change in industry capital intensity. This approach corresponds directly the definition of complementarity based upon elasticities of substitution - it examines changes in relative skill demand resulting from exogenous changes in the price of capital assets. The industry effective marginal tax rate is calculated as follows. Given the effective marginal tax rates for assets a in years t from Gravelle (2001), and assuming that a marginal investment will have the same asset mix as the industry's investments at a given point in time, t_0, an overall marginal tax rate on capital income in industry i can be constructed using a weighted average[19]

$$\tau_i^t = \sum_a \kappa_{a,i}^{t_0} m_a^t \tag{11}$$

where τ_i^t is the industry-level measure of the effective marginal tax rate on capital income in industry i at year t, $\kappa_{a,i}^{t_0}$ is the weight for asset a in industry i at a given point in time t_0, and m_a^t is the effective marginal tax rate on asset a at year t. The asset weights, $\kappa_{a,i}^{t_0}$, reflect how much each industry utilizes each asset class, calculated here as the fraction of total industry i investment allocated to asset a as reported in the 1977 Benchmark Input-Output Accounts Capital Flow Tables (Silverstein, 1985). This data set is published using the I-O Accounts industrial classification system, which includes 52 manufacturing industries corresponding to the 2- or 3-digit SIC level, each of which is assigned a tax rate for each year using equation (11). The change in the time averaged tax rate between the periods 1975-1979 and 1980-1987 is then used as an instrument for the change in capital intensity from 1979 to 1987. Since capital asset use data is available only by the I-O Accounts classification, the instrument varies only at the I-O Accounts industry level. Thus, all empirical results are reported with standard errors adjusted for 52 clusters at the

[17] BBG assume that "the price of quality-adjusted production and nonproduction labor does not vary across industries..." If this is the case, any variation across industries in observed relative wages actually reflects unobserved worker quality variation. The quality-adjusted relative wage would then be constant across industries and absorbed by the constant term if properly measured.

[18] See Berman et al. (1993, p.23) for a detailed discussion.

[19] Similar approaches are employed in Auerbach et al. (1983), Fullerton and Karayannis (1993), Gravelle (1982), Gravelle (1983), Gravelle (1994), and King and Fullerton (1984)

Table 2: Share Equation Estimates - All Industries

dependent variable: change in non-production workers' wage bill share (d Ss)

Equation	(1) OLS	(2) IV	(3) OLS	(4) IV
d ln(K/Y)	0.028	-0.012		
	(0.018)	(0.031)		
d ln(E/Y)			0.030	-0.041
			(0.017)$^{+}$	(0.034)
Constant	0.437	0.482	0.414	0.542
	(0.073)**	(0.067)**	(0.070)**	(0.067)**
R^2	0.028		0.036	
1st stage coefficient		-1.499		-0.959
on tax instrument		(0.507)**		(0.424)*
1st stage F		8.74		5.11
Hausman test P-value		0.131		0.046*

Sample: Annual Survey of Manufactures, 450 manufacturing industries.
Notes: Standard errors adjusted for 52 clusters at the I-O accounts industry classification level. The d operator represents long differences over the 1979-1987 range, divided by 8 for yearly changes. Data weighted by industry share of total manufacturing wage bill, averaged between 1979-1987.
+ significant at 10%; $*$ significant at 5%; $**$ significant at 1%

I-O Accounts classification level, using the mapping from 4-digit SIC industries in the ASM to the I-O Accounts in Young (1991). As discussed above, changes in the tax treatment of capital do not appear to have targeted particular types of assets associated with skill-biased technological change. As an additional piece of evidence suggesting that the instrument just described is likely exogenous to SBTC, I measure the correlation between the instrument and industry R&D expenditures in 1974, using data from Scherer (1984), which has been used previously as a proxy for SBTC (Berman et al., 1994). The correlation is -0.0012, indicating that the variables are essentially unrelated, which provides further suggestive evidence that the instrument is valid in this context.

Table 2 presents OLS and IV estimates of the decomposition equation, (3), and Table 3 presents regression variable means. The OLS point estimates in column (1) of Table 2 are identical to those in BBG Table 11, column (1), although the standard errors presented here are somewhat larger due to clustering at the I-O industry level. As seen in previous work, the coefficient on $d\ln(K/Y)$ is positive,

Table 3: Regression Variable Means - All Industries

Variable	Mean
d Ss	0.468
d ln K	2.807
d ln E	3.492
d ln Y	1.693
d ln(K/Y)	1.113
d ln(E/Y)	1.799

Sample: Annual Survey of Manufactures, 450 manufacturing industries.
Notes: All differences represent changes over the 1978 - 1987 range, divided by 8 for average yearly changes. Data weighted by industry share of total manufacturing wage bill, averaged between 1979 and 1987.

suggesting the presence of complementarity. Column (2) presents the IV results for the same specification, using the change in the industry effective marginal tax rate on capital income as an instrument for the change in capital intensity. As expected, the first-stage results indicate that industries facing larger tax cuts exhibited larger increases in capital intensity. The first-stage F statistic is 8.74. Based on the results in Stock and Yogo (2005), this F statistic is just large enough to allay concerns regarding large size distortions due to weak instruments.[20] The IV complementarity estimate is negative, though sufficiently imprecisely estimated that small positive coefficients cannot be ruled out. In fact, the P-value for a Hausman endogeneity test of the difference between the OLS and IV estimates is 0.131, indicating that the two estimates are not statistically different at conventional significance levels. While these results are consistent with the theoretical prediction that OLS overstates the amount of complementarity, the imprecise negative point estimate and marginal instrument strength prohibit a decisive conclusion.

In keeping with the intuitive notion that equipment assets are more relevant to complementarity than structures, columns (3) and (4) report OLS and IV regressions examining equipment assets rather than combining equipment and structures. In this case, the instrument is calculated using only tax rates on equipment assets.

[20]The F statistic of 8.74 is large enough to reject the null hypothesis that the actual size of a 5% test is greater than 20%, given the critical value of 6.66 in Stock and Yogo (2005) (Table 5.2, $n = 1$ $K_2 = 1$). It is nearly large enough to rule out smaller distortions as well - the critical value for the actual size of a 5% test being greater than 15% is 8.96.

The results are very similar to those in the first two columns, though the decreased variation in the instrument resulting from the restricted set of assets renders it sufficiently weak that large size distortions cannot be ruled out. In spite of the resulting imprecision and potential weak-instrument bias of the IV estimates toward the OLS estimates, the associated Hausman test of equality between the IV and OLS estimates is rejected. Again, the negative point estimate and weak instrument rule out strong conclusions, but these results also suggest that the OLS estimates are biased upward.

Previous work often includes changes in structures intensity along with changes in equipment intensity and a separate regression term for changes in output to account for deviations from constant returns to scale. These terms are omitted from the present analysis due to a lack of available instruments. It is conceptually feasible to instrument for changes in structures intensity, just as for equipment intensity in column (4) of Table 2. Unfortunately, this is not practically possible in this case, due to the nature of the policy variation driving cross-industry variation in the instrument. Nearly all structures investment in manufacturing industries involves assets in the Industrial Structures and Commercial Structures classifications. As seen in Table 1, these two assets experienced nearly identical tax changes during the period being examined, so there is essentially no cross-industry variation in the tax treatment of structures that could be used to instrument for changes in structures intensity. However, with data on more detailed structures assets or a different tax policy change, the current methodology could in principle be used to generate a structures instrument. Output changes are omitted because they, like capital, are likely to be endogenous, but no instruments are readily available beyond the tax changes already being used to instrument for changes in capital intensity.[21] Thus, the approach developed here utilizes the constant returns assumption, which obviates the need for a separate term measuring changes in output.

The results presented here provide suggestive evidence against the strong complementarity found in previous studies estimating the share equation and support the theoretical finding that OLS estimates are biased upward. However, the IV estimates are somewhat imprecisely estimated, and there are concerns about instrument strength. Thus, although the present results do suggest upward bias in previous estimates, they should not be taken as strong evidence against smaller levels of complementarity. The IV approach developed here could be used to generate more precise estimates given more detailed data on how industries use different

[21] Dunne et al. (1997) and Duffy et al. (2004) instrument for changes in capital intensity and changes in output with flexible functional forms of lagged levels and changes in the regression variables. Given concerns about serially correlated SBTC shocks within industry potentially invalidating the exogeneity of lagged values as instruments, I have chosen to focus on policy-based instruments in this analysis.

capital assets. Since the capital asset data used here vary only across 52 industries, clustering at this level implies that the analysis essentially uses only 52 observations. Hopefully future studies using the approach developed here will have access to capital asset use data at a finer level of industrial detail.[22]

5 Conclusion

This analysis has demonstrated that cost function estimates in many recent studies systematically overstate the influence of capital-skill complementarity on increases in relative skill demand. This bias results from the assumption of quasi-fixed capital in the presence of skill-biased technological change. Although this finding is consistent with the inequality literature's consensus that complementarity alone cannot account for the observed increases in skill demand during the 1980's, an accurate measure of complementarity is of independent interest in many areas of labor demand and when evaluating policies that affect the price of capital. Although somewhat imprecise, the instrumental variables analysis suggests that the standard OLS estimates overestimate complementarity. Since much of the recent evidence regarding the degree of complementarity comes from studies utilizing the cost function approach with quasi-fixed capital, these results suggest a need to further investigate the extent of capital-skill complementarity in manufacturing production using alternative methods. The tax-based instrumental variables approach presented here represents one approach that could be used to examine complementarity following future tax changes.

[22]The U.S. Census Bureau's Annual Capital Expenditures Survey included questions regarding investment by detailed asset class in its 1998, 2003, and 2008 surveys, with the expectation of continuing to ask these questions every five years (U.S. Census Bureau, 2005). Sadly, the survey utilizes a highly aggregated industry definition, including 29 manufacturing industries in 1998 and 37 in 2003 and 2008, so it is unlikely to provide enough information to overcome the imprecision in the current analysis.

Appendix: Two-Level CES Production Function with General Parameter Values

The analysis presented above imposes $\psi = 1$ in (5) for simplicity. Without imposing the restriction that $\psi = 1$, the primary complication is that the unit price of Z, the capital-unskilled labor aggregate, has the following form:

$$\lambda = \left[\beta^{\psi}\left(\frac{r}{g_K}\right)^{1-\psi} + (1-\beta)^{\psi}\left(\frac{w_S}{g_S}\right)^{1-\psi}\right]^{\frac{1}{1-\psi}}$$

As this term does not log-linearize to a convenient expression, it generates very complex comparative static results for factor demands. For completeness, the general case factor demands are as follows.

$$\frac{L_U}{Y} = \left(\frac{1-\alpha}{w_U}\right)^{\sigma} {g_U}^{\sigma-1}$$

$$\frac{K}{Y} = \alpha^{\sigma}\beta^{\psi}{g_K}^{\psi-1}r^{-\psi}\lambda^{\psi-\sigma}$$

$$\frac{L_S}{Y} = \alpha^{\sigma}(1-\beta)^{\psi}g_S^{\psi-1}w_S^{-\psi}\lambda^{\psi-\sigma}$$

As described in the text, taking logs of these factor demands allows determination of the effect of each parameter on the elements of the decomposition regression, K/Y and L_S/L_U. Given the complementarity assumption that $\psi < \sigma$, the results of this exercise are as follows.

Positive changes in α cause positive changes in both L_S/L_U and K/Y. The effects of β remain ambiguous. Increases in g_U have no effect on K/Y and cause positive (negative) changes in L_S/L_U if $\sigma < 1$ ($\sigma > 1$). Increases in g_K cause positive changes in L_S/L_U and cause positive changes in K/Y if $\psi \geq 1$ (otherwise the effect on K/Y is ambiguous). Increases in g_S cause positive changes in K/Y and cause positive changes in L_S/L_U if $\psi \geq 1$ (otherwise the effect on L_S/L_U is ambiguous). Thus the conclusions in the text hold, with the added restriction that $\psi \geq 1$ to determine the effects of g_K and g_S. Note, however, that Krusell et al. (2000) estimate $\psi = 0.67$ and $\sigma = 1.67$, which is consistent with the complementarity assumption, but not with the restriction that $\psi \geq 1$.

References

Auerbach, A. J., H. J. Aaron, and R. E. Hall (1983): "Corporate taxation in the United States," *Brookings Papers on Economic Activity*, 2, 451–513.

Autor, D. H., L. F. Katz, and A. B. Krueger (1998): "Computing inequality: Have computers changed the labor market?" *Quarterly Journal of Economics*, 113, 1169–1213.

Bartlesman, E. J. and W. Gray (1996): "The NBER manufacturing productivity database," *NBER Technical Working Paper*, 205.

Berman, E., J. Bound, and Z. Griliches (1993): "Changes in the demand for skilled labor within U.S. manufacturing industries: Evidence from the Annual Survey of Manufacturing," *NBER Working Paper*, 4255.

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, 367–397.

Berman, E., J. Bound, and S. Machin (1998): "Implications of skill-biased technological change: International evidence," *Quarterly Journal of Economics*, 113, 1245–1279.

Berman, E. and S. Machin (2000): "Skill-biased technology transfer," *mimeo*.

Berman, E., R. Somanathan, and H. W. Tan (2005): "Is skill-biased technological change here yet? Evidence from Indian manufacturing in the 1990's," *World Bank Policy Research Paper*, 3761.

Bloch, H. and S. Tang (2007): "The effects of exports, technical change and markup on total factor productivity growth: Evidence from Singapore's electronics industry," *Economics Letters*, 96, 58–63.

Blonigen, B. A. and M. J. Slaughter (2001): "Foreign-affiliate activity and U.S. skill upgrading," *Review of Economics and Statistics*, 83, 362–376.

Brown, R. S. and L. R. Christensen (1981): "Estimating elasticities of substitution in a model of partial static equilibrium: An application to U.S. agriculture, 1947 to 1974," in E. R. Berndt and B. C. Field, eds., *Modeling and Measuring Natural Resource Substitution*, Cambridge, MA: MIT Press, 209–229.

Caroli, E. and J. Van Reenen (2001): "Skill-biased organizational change? Evidence from a panel of British and French establishments," *Quarterly Journal of Economics*, 116, 1449–1492.

Casarin, A. A. (2006): "Efficient industry configurations in downstream gas markets. an empirical assessment," *Energy Economics*, 29, 312–328.

Caves, D. W., L. R. Christensen, and J. A. Swanson (1981): "Productivity growth, scale economies, and capacity utilization in U.S. railroads, 1955 - 74," *American Economic Review*, 71, 994–1002.

Chun, H. (2003): "Information technology and the demand for educated workers: Disentangling the impacts of adoption versus use," *Review of Economics and Statistics*, 85, 1–8.

Doms, M., T. Dunne, and K. R. Troske (1997): "Workers, wages, and technology," *Quarterly Journal of Economics*, 112, 253–290.

Duffy, J., C. Papageorgiou, and F. Perez-Sebastian (2004): "Capital-skill complementarity? Evidence from a panel of countries," *Review of Economics and Statistics*, 86, 327–344.

Dunne, T., J. Haltiwanger, and K. R. Troske (1997): "Technology and jobs: Secular changes and cyclical dynamics," *Carnegie Rochester Conference Series on Public Policy*, 46, 107–178.

Fullerton, D. and M. Karayannis (1993): "United States," in D. W. Jorgenson and R. Landau, eds., *Tax Reform and the Cost of Capital: An International Comparison*, Washington: Brookings Institution.

Goldin, C. and L. Katz (1998): "The origins of technology-skill complementarity," *Quarterly Journal of Economics*, 113, 693–732.

Gravelle, J. G. (1982): "Effects of the 1981 depreciation revisions on the taxation of income from business capital," *National Tax Journal*, 35, 1–20.

Gravelle, J. G. (1983): "Capital income taxation and efficiency in the allocation of investment," *National Tax Journal*, 36, 297–307.

Gravelle, J. G. (1994): *The Economic Effects of Taxing Capital Income*, Cambridge, MA: MIT Press.

Gravelle, J. G. (2001): "Whither tax depreciation?" *National Tax Journal*, 54, 513–526.

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

Hall, R. E. and D. W. Jorgenson (1967): "Tax policy and investment behavior," *American Economic Review*, 57, 391–414.

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

Haskel, J. E. and M. J. Slaughter (2002): "Does the sector bias of skill-biased technical change explain changing wage inequality?" *European Economic Review*, 46, 1757–1783.

King, M. A. and D. Fullerton, eds. (1984): *The Taxation of Income from Capital: A Comparative Study of the United States, United Kingdom, Sweden, and West Germany*, Chicago: University of Chicago Press.

Krusell, P., L. Ohanian, J. Rios-Rull, and G. Violante (2000): "Capital-skill complementarity and inequality: A macroeconomic analysis," *Econometrica*, 68,1029–1053.

Lee, M. (2008): “Environmental regulation and production structure for the Korean iron and steel industry,” *Resource and Energy Economics*, 30, 1–11.

Machin, S. and J. Van Reenen (1998): “Technology and changes in skill structure: Evidence from seven OECD countries,” *Quarterly Journal of Economics*, 113, 1215–1244.

Nøstbakken, L. (2006): “Cost structure and capacity in the Norwegian pelagic fisheries,” *Applied Economics*, 38, 1877–1887.

Pavcnik, N. (2003): “What explains skill upgrading in less developed countries?” *Journal of Development Economics*, 71, 311–328.

Sato, K. (1967): “A two-level constant-elasticity-of-substitution production function,” *Review of Economic Studies*, 201–218.

Scherer, F. M. (1984): “Using linked patent and R&D data to measure interindustry technology flows,” in Z. Griliches, ed., *R&D, Patents and Productivity*, Chicago: University of Chicago Press.

Silverstein, G. (1985): “New structures and equipment by using industries, 1977,” *Survey of Current Business*, 65, 26–35.

Stock, J. H. and M. Yogo (2005): “Testing for weak instruments in linear IV regression,” in D. W. K. Andrews, ed., *Identification and Inference for Econometric Models*, New York: Cambridge University Press.

Triest, R. K. (1998): “Econometric issues in estimating the behavioral response to taxation: A nontechnical introduction,” *National Tax Journal*, 51, 761–772.

U.S. Census Bureau (2005): *Annual Capital Expenditures: 2003*, volume ACE/03, Washington D.C.: U.S. Government Printing Office.

U.S. Senate Committee on Finance (1981): *Report of the Committee on Finance, United States Senate on H.J. Res. 266, Together with Additional and Minority Views*, Washington D.C.: U.S. Government Printing Office.

Young, P. C. (1991): “Benchmark input-output accounts for the U.S. economy, 1982,” *Survey of Current Business*, 71, 30–71.