Capital-Skill Complementarity and Inequality: A Sensitivity Analysis

Linnea Polgreen Pedro Silos*

University of Iowa Federal Reserve Bank of Atlanta

August 8, 2007

Abstract

In "Capital-Skill Complementarity and Inequality: A Macroeconomic Analysis", Krusell *et al.* (2000) analyzed the capital-skill complementarity hypothesis as an explanation for the behavior of the U.S. skill premium. We re-fit Krusell's model with two alternative capital equipment price series: one proposed by Greenwood *et al.* (GHK, 1997) and the official, revised National Income and Product Accounts (NIPA) data. We find that capital-skill complementarity is preserved, but other results were sensitive to the data used. Specifically, the fit of the model was similar to Krusell's using the NIPA data, but not the GHK data. Also, both series produce estimates of the elasticity of substitution between unskilled labor and equipment that are substantially larger than KORV's estimates.

Keywords: capital-skill complementarity, technological change, equipment prices

JEL Classification: C11, C82, E24, J31

*Beth Ingram, George Neumann and Charles Whiteman provided invaluable help. In addition, we have received useful comments from Siddhartha Chib, John Geweke, B. Ravikumar, Gianluca Violante, several anonymous referees, Narayana Kocherlakota (the Editor), and seminar participants at the University of Iowa and the Midwest Macroeconomics Meetings 2004.

Department of Clinical and Administrative Pharmacy, University of Iowa, Iowa City, IA 52242, 319-384-4516 (phone), 319-353-5646 (fax), linnea-polgreen@uiowa.edu.

Research Department, Federal Reserve Bank of Atlanta, 1000 Peachtree St. NE, Atlanta, GA 30309, 404-498-8630 (phone), 404-498-8956 (fax), Pedro.Silos@atl.frb.org

1 Introduction

Over the past thirty years, wages paid to college-educated workers have increased despite an increase in the supply of such workers. Explanations of this phenomenon increasingly focus on capital-skill complementarity (unskilled labor is more substitutable for equipment than skilled labor) and are supported by the estimates obtained in "Capital-Skill Complementarity and Inequality: A Macroeconomic Analysis" (2000) by Krusell, Ohanian, Ríos-Rull and Violante (KORV). The underlying contribution of KORV was to provide an empirical foundation for the theoretical notion of capital-skill complementarity.

KORV estimate the parameters of a constant-elasticity-of-substitution (CES) production function, using data on the prices and quantities of four factors: skilled labor, unskilled labor, structures and equipment. Their resulting production function is general enough to accommodate a broad pattern of substitutability and complementarity among the four factors. When KORV use this model to estimate the elasticities of substitution between skilled labor and equipment as well as that of unskilled labor and equipment, they find strong evidence of capital-skill complementarity. Furthermore, the model reproduces the major changes in the skill premium over time.

KORV's paper has been widely cited, and the data and parameters estimated in this model have been used to calibrate other models. Examples include Blankenau and Ingram (2002), Crifo-Tillet and Lehmann (2004), Hendricks (2002), Caselli and Coleman (2002), and Lindquist (2002).

However, KORV's measurement of capital equipment prices is problematic: they use a deflator for nominal equipment stock that is an extension of Gordon's (1990) series that implies very rapid growth in capital, particularly after 1975. To assess the robustness of their results, we estimated their model using two additional series: the official, revised National Income and Product Account (NIPA) series for equipment investment and a price series suggested by Greenwood, Hercowitz and Krusell (1997), which is an average of the NIPA series and the producer price index for capital equipment. The Bureau of

Economic Analysis (BEA) has undergone a substantial effort to provide a quality-adjusted price index for the equipment series, making that series a better choice for deflating the capital stock than it was when KORV's paper was written, almost a decade ago.

Using these two alternative data sets, we obtain several important results. First, capital-skill complementarity is extremely robust to any of the three price series used. Second, the fit of the skill premium is good for both the Gordon series used by KORV and the official NIPA series. The GHK price series, on the other hand, is not consistent with the increase in the skill premium observed since 1980. In addition, we provide researchers with additional estimates of elasticities of substitution between equipment and skilled labor, and equipment with unskilled labor. This should serve macroeconomists in parameterizing their models and assessing the robustness of their results to changes in the values of those elasticities. Lastly, we provide an alternative methodology to that used by KORV. This method is of interest in itself and can be applied to other non-linear state-space models.

2 KORV's Model

The theoretical model to be estimated is derived from a profit-maximizing firm's first-order conditions for choosing from among four factors of production: skilled labor (s_t), unskilled labor (u_t), structures (k_{st}) and equipment (k_{et}). The production-function form combines a CES aggregation of unskilled labor and an aggregation of equipment and skilled labor in a Cobb-Douglas function with structures:

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

where μ and λ are parameters that govern income shares, and σ and ρ are parameters that drive the elasticities of substitution between equipment and unskilled workers and equipment and skilled workers respectively. In this model, the elasticity of substitution between unskilled labor and skilled labor equals the elasticity of substitution between unskilled labor and equipment. Also, $\sigma > \rho$ implies that a rise in capital implies a rise in the skill premium, and this is the way we (and KORV) define capital skill complementarity [1]

KORV define the elasticity of substitution between equipment and unskilled labor and equipment and skilled labor to be $\frac{1}{1-\sigma}$ and $\frac{1}{1-\rho}$ respectively. However, this is only true if all other factors are held constant. When other factors change, the definition of the elasticity of substitution changes; as a result, depending on one's definition of the elasticity of substitution, $\sigma > \rho$ may not imply that unskilled labor is more substitutable with capital than skilled labor is. Therefore, we compute, in addition to $\frac{1}{1-\sigma}$ and $\frac{1}{1-\rho}$, the Allen and Morishima elasticities of substitution, two frequently-used definitions of the elasticity of substitution within multi-input production functions. [2] In addition, the skilled and unskilled labor inputs, s_t and u_t are functions of hours (h_s and h_u) and efficiency indices (ψ_s and ψ_u): $s_t = \psi_{st}h_{st}$ and $u_t = \psi_{ut}h_{ut}$.

To estimate the model, the first-order conditions are simplified into three equations. The first equation,

$$\frac{w_{st}h_{st} + w_{ut}h_{ut}}{y_t} = (1-\alpha)\{\mu(h_{ut}\psi_{ut})^{\sigma} + (1-\mu)[\lambda k_{et}^{\rho} + (1-\lambda)(h_{st}\psi_{st})^{\rho}]^{\sigma/\rho}\}^{-1}$$
$$\{\mu(h_{ut}\psi_{ut})^{\sigma} + (1-\mu)[\lambda k_{et}^{\rho} + (1-\lambda)(h_{st}\psi_{st})^{\rho}]^{\frac{\sigma}{\rho}-1}(1-\lambda)(h_{st}\psi_{st})^{\rho}\}, \tag{2}$$

sets the share of labor in aggregate income ($\frac{w_{st}h_{st}+w_{ut}h_{ut}}{y_t}$) in the data equal to the analogue from the production function. The labor share is obtained in a manner similar to that explained in Cooley and Prescott (1995), taking the ratio of compensation of workers to personal income.

The second and third equations are obtained by rearranging the first order conditions for the choices of skilled and unskilled labor. The second equation,

$$\frac{w_{st}h_{st}}{w_{ut}h_{ut}} = \frac{1-\mu}{\mu}\sigma(1-\lambda)[\lambda k_{et}^{\rho} + (1-\lambda)(h_{st}\psi_{st})^{\rho}]^{\frac{\sigma}{\rho}-1}\frac{(h_{st}\psi_{st})^{\rho}}{(h_{ut}\psi_{ut})^{\sigma}}, \tag{3}$$

involves the ratio of the wage bill for skilled workers to that of unskilled workers. Equation

[1] We thank a referee from making us aware of this misconception.

[2] The interested reader is referred to Blackorby and Russell (1989) for a discussion of the different definitions of the elasticity of substitution.

(4) sets this ratio ($\frac{w_{st}h_{st}}{w_{ut}h_{ut}}$) in the data equal to the same ratio using the corresponding marginal products.

The third equation,

$$\frac{q_{t-1}}{q_t} = \frac{1}{(1-\delta_e)}\{(1-\delta_s) - G_{k_{st}} - q_{t-1}G_{k_{et}}\} + \epsilon_t, \tag{4}$$

is obtained from the marginal products of equipment and structures. It sets the expected return on equipment equal to the expected return on structures, where ϵ_t is an equipment-price-forecast-error with a known distribution.

Two sources of estimation error are given by the workers' abilities (ψ_{st}, ψ_{ut}), which are observed by the firm owner, but not the analyst. Also, the relative price of equipment (q_t) is not observed by the firm owner because production involves a one-period time-to-build feature: investment in equipment occurs in one period and the equipment is used in production during the following period. This uncertainty will be reflected by the forecasting error the firm owner makes when predicting prices.

Finally, KORV need to specify a stochastic process for the vector (ψ_{st}, ψ_{ut}), the latent abilities of workers. KORV are only interested in changes in the skill premium due to observable factors, so there is no trend in the ability factor:

$$\phi_t = \phi_0 + \nu_t, \tag{5}$$

where $\phi_t = [log(\psi_{st}), log(\psi_{ut})]'$ and $\nu_t \sim N(0, \Sigma)$.

3 Data

We estimate the model using KORV's original data for wages, structures, labor inputs and aggregate labor's share[3]. The series cover the period 1963-1992. We use two alternative series for capital equipment prices and the resulting real equipment stock, and re-evaluate KORV's model. Prior to estimation, we re-scale the labor input and structures series so

[3]The original KORV series are available online at G. Violante's website, http://www.econ.nyu.edu/user/violante/Journals/Data_KORV.

that in the initial period the ratio of capital equipment to structures and the two types of labor is constant across the different price series used. Note that this does not affect the growth rates of any of the variables. We then examine estimated parameter values and the ability of the model to explain the evolution of the skill premium.

Finding the real value of the stock of capital equipment requires an appropriate deflator. We consider three different series: the BEA's NIPA price series, the series used by KORV, and Greenwood, Hercowitz and Krusell's (1997) price series. The BEA provides a deflator for investment in equipment capital in its NIPA tables. This series has been criticized for not taking quality adjustment into account. Nevertheless, starting in the 1990s, the BEA has undertaken revisions to some price (and capital) series to correct this shortcoming. The two most important changes were the inclusion of software expenditures in fixed investment and the increase in the use of hedonic techniques for adjusting for quality when measuring price changes. The addition of software to the investment series was part of the comprehensive benchmark revision in 1999, and it is well documented in Moulton, Parker and Seskin (1999). The increasing use of hedonic techniques in statistical agencies is the subject of a report by Moulton (2001). For example, the BEA adopted a quality-adjusted price index for telephone switching equipment in 1997 and in 2001 it adopted one developed by the Federal Reserve for local area network (LAN) equipment (routers, hubs, etc...). In an Appendix we provide a more detailed description of the construction of Gordon's index and the quality adjustment in the Producer Price Index.

KORV use an alternative series provided by Gordon (1990) that incorporates quality changes by means of hedonic regressions. The data cover the period 1963–1983. Since they want to estimate the model through 1992, they forecast Gordon's price series for 1984–1992. In particular, they estimate the "near" vector autoregression $P_t^G = \beta_0 + \beta_1 P_{t-1}^G + \beta_2 P_{t-1}^N + \epsilon_t$, where P_t^G is a 3×1 vector of prices in the "General Industrial Equipment", the "Transportation" and "Others" sectors, obtained from Gordon's dataset, and P_t^N is the official NIPA "capital equipment price index". Using the 21 annual observations available, they construct the forecast $\hat{P}_t^G$ for $t = 1984, \ldots, 1993$ using $\hat{P}_{t-1}^G$ and actual NIPA prices

P_t^N.[4]

To examine the robustness of KORV's results to alternative measurements, we also consider a deflator suggested by Greenwood, Hercowitz and Krusell (GHK). The GHK price series is the average between the Producer Price Index for capital equipment and the NIPA deflator for investment in capital equipment.

Figure 1 compares the growth rates of the three price series for our sample period. After 1984 the projected-Gordon series falls for all years except one. Alternatively, the GHK series has positive growth during the eighties. The average growth rates are -0.90% for the projected-Gordon series and 1.7% per year for the GHK series. The NIPA prices have grown little, and their average growth rate is 0.76%, a value between the other two alternatives.

These different ways of measuring prices imply very different capital stocks of equipment. Figure 2 shows the stock of equipment calculated using three different price series: the first from KORV's own data, the second based on the GHK series, and the third based on the NIPA data. The average annual growth rates over the period were 6.8% for the KORV-based stock of equipment, 3.2% for the NIPA series, and 2.4% for the GHK-based measure. For comparison, the stock of non-residential structures has averaged only 0.82% growth during this period. These three growth rates give very different pictures of the evolution of the stock of equipment: from the early 1960s to the early 1990s the stock of equipment has risen by a factor of 2 using the GHK measure, 2.6 using the NIPA series, and 7 using KORV's estimates.

We do not attempt to take a position on which series is more suitable for macroeconomic models. We simply provide alternative estimates for two different price series. KORV's series most likely over-estimates the growth rate of the stock of equipment, and the GHK series most likely under-estimates this growth[5]. Since KORV relies on a projec-

[4] Any changes in the quality adjustment procedure introduced in NIPA in the beginning of the 1980s would cause a large bias in this forecast.

[5] In fact, several other studies, e.g. Hobijn (2001), Bils and Klenow (2001) and Cummins and Violante (2002) find estimates for the growth rate of technical change that are close to KORV's numbers.

tion of Gordon's series that implies a large growth rate of capital, checking the robustness of KORV's model is a reasonable exercise.

4 Methodology

The three measurement equations and the stochastic specification for abilities form a non-linear state-space model, for which there are several estimation methods available. Ohanian *et al.* (1997) discuss several of these estimation methods and find that a version of simulated pseudo-maximum likelihood (SPML) works best in small samples. KORV take this route, which involves minimizing a loss function between artificially simulated data and observed US data. We adopt an alternative procedure based on the explicit assumption of measurement error, which allows us to work with the exact likelihood[6]. This method is related to work done in the Bayesian statistics literature by Gordon, Salmon and Smith (1993), Carlin, Polson and Stoffer (1992), and Geweke and Tanizaki (2000). Although computationally more expensive by some measures, Bayesian methods provide several advantages. The high dimensionality of the parameter space is less of a problem than in pseudo-maximum-likelihood methods, since we avoid any derivative-based numerical optimization. In addition, constraints that naturally arise from economic theory are generally easier to impose in a Bayesian framework than in alternative methods[7].

In our application, Bayesian inference involves specifying a prior distribution for the vector of parameters $\theta = \{\sigma, \rho, \mu, \lambda, \Omega, \Psi_0, \gamma, \Sigma\}$, and coupling it with the normal measurement-error likelihood function for the data, conditional on the parameters. By Bayes' theorem, the posterior distribution will be given by:

$$p(\theta|Y, X) \propto p(\theta)L(Y|\theta, X),$$

where $p(\theta)$ denotes the prior distribution, $L(Y|\theta, X)$ refers to the likelihood of the model,

[6]We do not provide an extensive explanation of our methodology. The interested reader can find all the details in our companion paper, Polgreen and Silos (2006).

[7]Regarding the assumption of measurement errors in the first two measurement equations, we think this assumption (made exclusively for technical reasons) is innocuous, given that variances of these errors turn out to be very small.

and Y and X are endogenous and exogenous variables respectively. The goal is a complete characterization of the moments of $p(\theta|Y,X)$, which are usually obtained by random sampling.

4.1 Priors

When the sample size is as small as in KORV's study, the choice of prior distributions could have a significant impact on the final results. For this reason, we have estimated the model using three different prior distributions, varying the prior means for ρ and σ: a "Neutral" prior, where both the prior means of ρ and σ are set to 0; the "KORV" prior, in which the means are set at KORV's own estimates and finally the "Other" prior where we use estimates from previous studies. However, estimates were so similar across the three specifications we report only results using the "Other" prior[8]. Specifically, we specified a prior Normal distribution with mean of 0.57 and standard deviation equal to 0.25 for σ[9], and a Normal with mean equal to -0.76 and a standard deviation of 0.25 for ρ[10].

The shares, λ and μ, were given prior Normal distributions truncated to the $[0,1]$ range, with a mean of 0.5 and a standard deviation of 0.2. The standard deviation of α was set at 0.005, with a mean of 0.11, which is the value estimated by KORV, which in turn is close to the value of 0.13 used in previous calibration studies (*e.g.* Greenwood, Hercowitz and Krusell, 1997). In all cases, the prior standard deviations were chosen so that a two-standard deviation band around the mean provided a reasonable range of estimates.

[8]Results with the other two specifications are certainly available upon request.

[9]The mean was chosen to match the estimate of Clark and Freeman (1977) in their annual (unpublished) sample of the manufacturing sector. The number is reported in Hammermesh's (1993) survey of labor demand. Note that in KORV's model the elasticity between unskilled labor and capital equals the elasticity between unskilled labor and skilled labor, but this relies on their specification of technology. We have used the reported elasticity of substitution between unskilled labor and capital (2.1) and not the elasticity of substitution between skilled labor and unskilled labor.

[10]This mean is halfway between the value of 0.08 from Berndt and White's unpublished 1978 paper on the demand for energy, and the value of -1.6 estimated in Dennis and Smith's 1978 study of the demand for real cash balances. Both of these studies focus on the manufacturing sector, roughly covering the period 1950-1973. Although both of these studies are rather dated, and energy and cash balances do not seem to be related to the topic at hand, these were the best estimates we could find.

5 Results

The results are given in Table 1. On the first line, labeled KORV1, we just re-write the estimates reported in KORV (2000). The last four lines show our own results: KORV2 uses KORV's original data and our methodology; KORV3 uses both KORV's data and methodology; NIPA uses the official NIPA series for capital equipment; and GHK refers to the GHK (1997) series.

Table 1: Results, "Other" Prior

		σ		ρ	
Capital Data	Years	Mean	Std. Dev.	Mean	Std. Dev.
KORV1	1963-1992	0.401	0.234	-0.495	0.048
KORV2	1963-1992	0.428	0.040	-0.415	0.028
KORV3 [11]	1963-1992	0.392	n.a.	-0.457	n.a.
NIPA	1963-1992	0.899	0.036	-0.567	0.052
GHK	1963-1992	0.917	0.061	0.010	0.074

The first two lines show that none of the results depend upon the estimation method: the first two lines use exactly the same data, and the resulting estimates for ρ and σ are very similar. Like KORV, all of our estimates imply capital-skill complementarity ($\sigma > \rho$), although the results for the GHK and NIPA series differ quantitatively from those obtained by KORV. Specifically, estimates for σ using the GHK and NIPA data are substantially larger. The values for ρ are 0.01 and -0.567, for the GHK and NIPA series respectively. Both are significantly different from the estimate of -0.415 we obtain with KORV's data. GHK and NIPA prices imply similar values for σ, close to 0.90, which are statistically different from the value around 0.4 we obtain with KORV's data. The posterior distributions of the difference between σ and ρ are shown in Figure 3. The dotted curve represents the GHK data, the solid curve represents KORV's data, and the dashed line represents the NIPA data. Although the difference is larger for the NIPA

[11] We were not able to compute standard errors for KORV's SPML approach. We nevertheless decided to report the point estimates for the parameters to show that none of the results rely on differences in methodology.

series, the capital-skill complementarity hypothesis is robust to any of the price series considered.

We now turn to the estimated elasticities of substitution. Since we are comparing our results to KORV, we will continue to call $\frac{1}{1-\sigma}$ and $\frac{1}{1-\rho}$ the elasticities of substitution, but we will also report other measures such as the Allen and the Morishima elasticities. The equipment-unskilled labor and equipment-skilled labor elasticities are given in the two panels of Table 2. The estimates for the elasticity of substitution between unskilled labor and equipment are between 0.8 and 19. Compared to the value obtained using KORV's data, the estimates using the alternative series are much higher for any of the definitions of the elasticity of substitution. The posterior distributions for $\frac{1}{1-\sigma}$ are given in Figure 4. Again, the solid line is the KORV data, the dashed line is the NIPA data and the dotted curve represents the GHK data[12]. The variance of the posterior using the KORV data is less than 3% of the variance of the posterior using the GHK data.

Considering the elasticity between equipment and skilled labor, all of our estimates for ρ are significantly different from those of KORV. Figure 5 gives the posterior distributions of $\frac{1}{1-\rho}$ using the KORV data (solid curve), the NIPA data (dashed curve), and the GHK data (dotted curve). The elasticities produced using GHK data are the largest.

Table 2a: Elasticities - Equipment and Unskilled Labor

Capital Data	$1/(1-\sigma)$	Allen	Morishima [13]
KORV	1.789	1.787	0.844
GHK	13.726	12.076	19.539
NIPA	9.887	9.881	14.464

[12]The Allen and Morishima elasticities of substitution have no distribution. We evaluated them at the median value of the parameter estimates.

[13]The elasticity of substitution gives a measure of how optimal factor shares change when there is a change in the price ratio. If we denote M_{ij} the Morishima elasticity between inputs i and j, in general, $M_{ij} \neq M_{ji}$. The reason is that the way this elasticity is computed, implies a change in the price of factor j in one case and factor i on the other. As a consequence, the effect on the other price ratios (there are multiple inputs) is different in each of the two cases. For details see Blackorby and Russell (1989). We show, for each pair of inputs, only one elasticity.

Table 2b: Elasticities - Equipment and Skilled Labor

Capital Data	$1/(1-\rho)$	Allen	Morishima
KORV	0.719	-1.197	0.565
GHK	1.016 [14]	1.010	0.768
NIPA	0.639	0.637	0.684

KORV use their model to predict the skill premium. Figure 6 displays the US skill premium along with the fit of the model using the KORV and NIPA series. As the figure shows, the fit with both measures is good: the general shape of the skill premium is replicated. Both the NIPA series and KORV's series explain the skill premium. However, in terms of the elasticities of substitution, the three series give quite different predictions. Given that the elasticity of substitution is an important object in many economic models, these different estimates could have large impact on the implications of those models for different fiscal or education policies. These results should therefore encourage more research devoted to obtaining better measurements of equipment prices as well as the elasticity of substitution.

Figure 7 shows the skill premium prediction for the GHK series. Here the fit is much worse. Not only is the skill premium over-predicted during the first part of the sample, but the series is not consistent with the large increase during the 1980s and 1990s. The GHK data have less-rapid growth in the capital stock. Rather than eliminating capital-skill complementarity, however, the elasticity of substitution between unskilled labor and capital becomes much larger. Note that, by assumption, skilled and unskilled labor also become more substitutable. From 1970 to 1982, the ratio of skilled workers to unskilled workers grew. Since skilled and unskilled labor are highly substitutable, the GHK series caused the predicted skill premium to fall.

[14] Given the skewness of the posterior distribution for σ with the NIPA and GHK series, we have decided to report the median elasticities instead of the mean elasticities.

6 Conclusion

We re-estimated the model in "Capital-Skill Complementarity and Inequality: A Macroeconomic Analysis" (2000) by Krusell, Ohanian, Ríos-Rull and Violante using a Bayesian methodology that can accommodate high-dimension problems with many constraints. We also considered alternative measurements for capital equipment prices. Regardless of the series used, like KORV, we find evidence of capital-skill complementary. However, the data used imply, in one case, a dramatically worse fit of the model to US data. Also, different data series gave substantially different values for the elasticities of substitution between capital and either skilled or unskilled labor. Using alternative capital equipment data obtained by using the series suggested by Greenwood, Hercowitz and Krusell (1997), and the official NIPA price series, we find unskilled labor to be more substitutable for equipment than KORV do. In fact, our estimates of the unskilled labor-equipment elasticity are up to six times larger than KORV's. This might have large quantitative implications in other models of inequality or in growth accounting. Future work should be directed toward finding a consensus about the value of the elasticity of substitution between equipment and different types of labor implied during the last forty years.

When KORV's model is estimated with the NIPA price series it provides a good fit to the observed skill premium. Using the newly revised NIPA series allows researchers to avoid ad-hoc projections of existing price series. Alternatively, the GHK series, while consistent with the capital-skill complementarity hypothesis, has difficulty predicting the skill premium observed in the data.

References

[1] Ernst R. Berndt, Zvi Griliches, and Neal J. Rappaport. Economic estimates of price indexes for personal computers in the 1990s. *Journal of Econometrics*, 68:243–268, 1995.

[2] Ernst R. Berndt and Catherine White. Technology, prices, and the derived demand for energy. unpublished paper, University of British Columbia, 1978.

[3] Mark Bils and Peter J. Klenow. Quantifying quality growth. *American Economic Review*, 91(4):1006–30, September 2001.

[4] Charles Blackorby and R. Robert Russell. Will the real elasticity of substitution please stand up? (a comparison of the Allen/Uzawa and Morishima elasticities). *American Economic Review*, 79(4):882–888, September 1989.

[5] William F. Blankenau and Beth F. Ingram. Welfare implications of factor taxation with rising wage inequality. *Macroeconomic Dynamics*, 6:408–28, 2000.

[6] Kenneth H. Brown and Shane M. Greenstein. How much bigger is bigger, faster and cheapter? buyer benefits from innovation in mainframe computers in the 1980s. manuscript, National Bureau of Economic Research, 1995.

[7] B.P. Carlin, N.G. Polson, and D.S. Stoffer. A monte-carlo approach to nonnormal and nonlinear state-space modeling. *JASA*, 87(418):493–500, 1992.

[8] F. Caselli and W.J. Coleman. The U.S. technology frontier. *American Economic Review*, 92(2):148–152, May 2002.

[9] Kim Clark and Richard Freeman. Time-series models of the elasticity of demand for labor in manufacturing. unpublished paper, Harvard University, 1977.

[10] R. Cole, Y. Cehn, J. Barquin-Stolleman, E. Dulberger, N. Helvacian, and J. Hodge. Quality-adjusted price indexes for computer processors and selected peripherals equipment. *Survey of Current Business*, January 1986.

[11] U.S. Department of Commerce. *Statistical Abstract of the United States*. U.S. Bureau of the Census, Washington D.C., 1991, 1992.

[12] T.F. Cooley and E.C. Prescott. *Frontiers of Business Cycle Research*. Princeton University Press, Princeton, NJ, 1995.

[13] P. Crifo-Tillet and E. Lehmann. Why will technical change not be permanently skill-biased? *Review of Economic Dynamics*, 7(1):157–180, January 2004.

[14] Jason G. Cummins and Giovanni L. Violante. Investment-specific technical change in the United States (1947–2000): Measurement and applications. *Review of Economic Dynamics*, 5(2):243–84, April 2002.

[15] Enid Dennis and V. Kerry Smith. A neoclassical analysis of the demand for real cash balances by firms. *Journal of Political Economy*, 86:793–814, 1978.

[16] J. Geweke and H. Tanizaki. Bayesian estimation of state-space models using the Metropolis-Hastings algorithm within Gibbs sampling. manuscript, Kobe University, 2000.

[17] N.J. Gordon, D.J. Salmon, and A.F.M. Smith. Novel approach to nonlinear/non-Gaussian Bayesian state estimation. *IEE-Proceedings-F*, 140:107–113, 1993.

[18] Robert J. Gordon. *The Measurement of Durable Goods Prices*. The University of Chicago Press, Chicago, IL, 1990.

[19] Jeremy Greenwood, Zvi Hercowitz, and Per Krusell. Long-run implications of investment-specific technological change. *American Economic Review*, 87(3):342–62, June 1997.

[20] Lutz Hendricks. How important is human capital for development? Evidence from immigrant earnings. *American Economic Review*, 92(1):198–219, March 2002.

[21] Bart Hobijn. Embodiment in u.s. manufacturing. manuscript, Federal Reserve Bank of New York, March 2001.

[22] Michael Holdway. Quality-adjusting computer prices in the producer price index: An overview. http://www.bls.gov/ppi/ppicomqa.htm, October 1990.

[23] Per Krusell, Lee E. Ohanian, José Víctor Ríos-Rull, and Giovanni L. Violante. Capital-skill complementarity and inequality: A macroeconomic analysis. *Econometrica*, 68(5):1029–53, September 2000.

[24] Bureau of Labor Statistics. Handbook of methods, Ch. 14: Producer prices. http://www.bls.gov/opub/hom/homch14_b.htm, September 2003.

[25] Matthew J. Lindquist. Capital-skill complementarity and inequality over the business cycle. working papers in economics, Stockholm University, 2002.

[26] Brent Moulton. The expanding role of hedonic methods in the official statistics of the United States. manuscript, Bureau of Economic Analysis, 2001.

[27] Brent Moulton, Robert Parker, and Eugene Seskin. A preview of the 1999 comprehensive revision of the National Income and Product Accounts: Definitional and classificational changes. *Survey of Current Business*, 79:7–20, August 1999.

[28] Lee Ohanian, Giovanni L. Violante, Per Krusell, and José Víctor Ríos-Rull. Simulation-based estimation of a non-linear, latent factor aggregate production function. In Robert S. Mariano, Tel Schuelrmann, and Melvyn Weeks, editors, *Simulation-Based Inference in Econometrics: Methods and Applications*, pages 359–99. Cambridge University Press, Cambridge, U.K., 2000.

[29] Linnea Polgreen and Pedro Silos. Crude substitution: The cyclical dynamics of oil prices and the college premium. WP-2006-14, Federal Reserve Bank of Atlanta, 2006.

[30] James Sinclair and Brian Catron. An experimental price index for the computer industry. *Monthly Labor Review*, pages 16–24, October 1990.

7 Appendix

Our data cover the period from 1963 to 1992. Even though the NIPA equipment-price series has been recently improved, in the past, many economists argued that this series understated quality changes. So, in addition to using the NIPA data, we also used data from KORV (2000) and GHK (1997) in this paper. KORV's data was based on Gordon's (1990) series of quality-adjusted equipment prices. However, Gordon's data ended in 1983, so the data from 1984-1992 are forecasted. They consider four categories of equipment: office information processing, general industrial, transportation and other (aggregations of the 16 categories used by Gordon). They estimate a vector autoregression (VAR) for each of the four categories of equipment prices using past values, the lagged official NIPA price index, and a lagged business-cycle indicator.

The prices for three of the four categories were stable during this period, so KORV assumed that the relationship between the Gordon's quality-adjusted- and official-price indices was also stable during this period. However, the price series for office-information-processing equipment changed dramatically during this period, so they split this category into two groups: 1) computers and peripherals and 2) other. The other category was forecast using the VAR, but the computers-and-peripherals category was estimated differently. The price series was estimated using price series for peripherals from 1972-1984 (Cole, 1986), mainframes from 1985-1991 (Brown and Greenstein, 1995), and personal computers from 1989-1992 (Berndt, Griliches and Rappaport, 1995), and estimating the shares of these items in business expenditure from data in the Statistical Abstract of the United States (1991, 1992).

The four resulting series are then combined using a chain-weighted Tornqvist index

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

Where p is the price level of good i in year t and s is the nominal expenditure on good i in year t. The resulting series is then used to deflate the nominal investment in equipment series from NIPA.

The second equipment price series, proposed by Greenwood Hercowitz and Krussell (1997), is an average of the implicit producer-durable-equipment-price deflator from NIPA and the fixed-weight price index (PPI) for producer durable equipment. This index was suggested by Gordon as an alternative to the time-consuming index used in his book and also by KORV. The PPI is a chain-weighted Laspeyres index of prices producers receive for their products. At the beginning of our sample, the PPI was called the Wholesale Price Index (WPI). The WPI covered prices for less than half of the manufacturing sector, and the product list was weighted toward commodities and high-volume products in large industries. Also, all firms in an industry were weighted equally, no matter the firm's size. For the most part, the current PPI began in 1978, although changes were not fully implemented until 1986. The commodity-based focus was shifted to a finished-goods focus, and items are now weighted by value-of-shipments data contained in the latest economic census. The price series is developed from 100,000 prices from 25,000 firms. These firms are rotated periodically and are chosen by probability sampling. Most goods manufactured in the U.S. are included (BLS, 2007).

Since the Bureau of Labor Statistics (BLS) samples the same products each period, and many products change over time, some form of quality adjustment has been necessary. To adjust for quality changes, The BLS collects data from firms on the costs connected to the quality change. The change in the index will reflect only that amount, not the nominal price increase. If the production cost difference between an old item and a new one is unavailable, or if an explicit comparison is not feasible, the BLS assumes that any difference in price between the old and the new items is due entirely to differences in quality. The previous method does not work for many products, like computers, for which this year's computer may be of higher quality, but also carries a lower price than last year's model. The PPI did not include computers in its index until 1991, at which time the BLS introduced cross-section, hedonic regressions to estimate the relationship between specific computer characteristics and the computer's price. Resulting implicit prices for computer characteristics are then used to value the quality improvement resulting from changes in computers (Holdway, 2001, Sinclair, 1990).

As you can see from Figures 1 and 2, the GHK series and the NIPA series follow a similar path. This is because the BEA uses the PPI for many equipment components when constructing its series. However, there are substantial differences between the two indexes as well. For example, the BEA uses its own price indexes for telephone equipment and photocopying equipment, and software. In addition, it uses the BLS import price index for all imported capital except transportation.

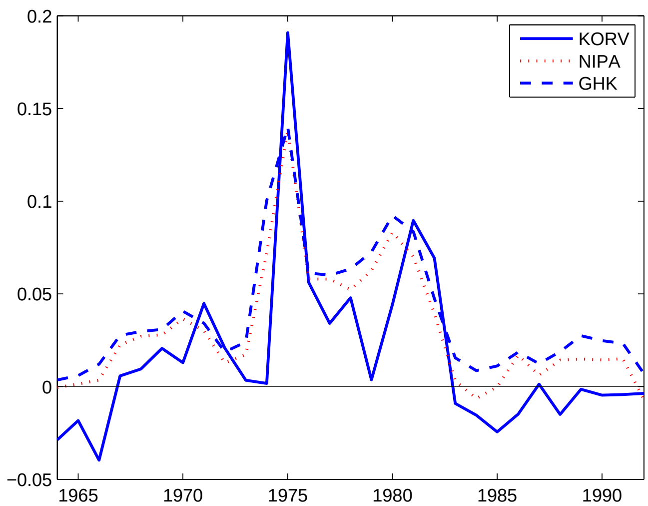

Figure 1: Growth Rates in Equipment Prices - Three Alternative Measures

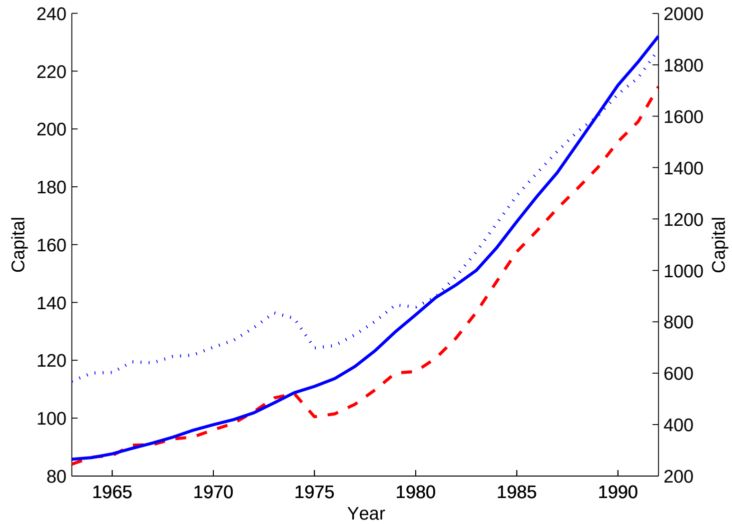

Figure 2: Capital Stocks Implied by Different Price Series

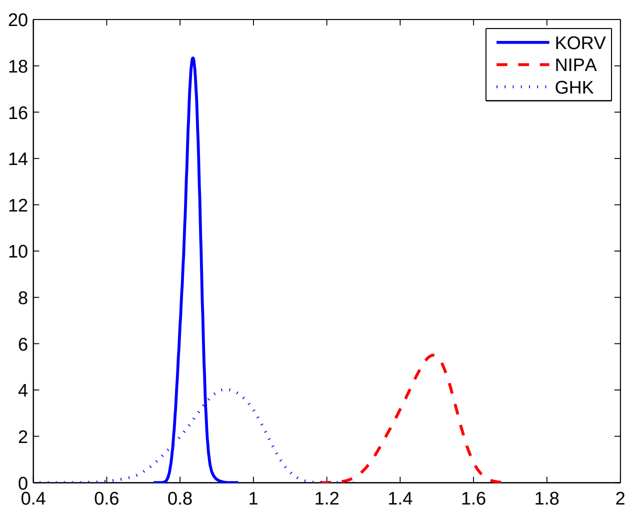

Figure 3: $\sigma - \rho$

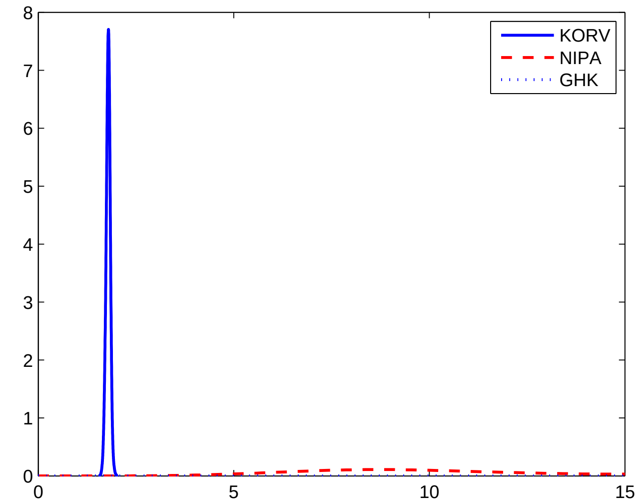

Figure 4: $1/(1-\sigma)$

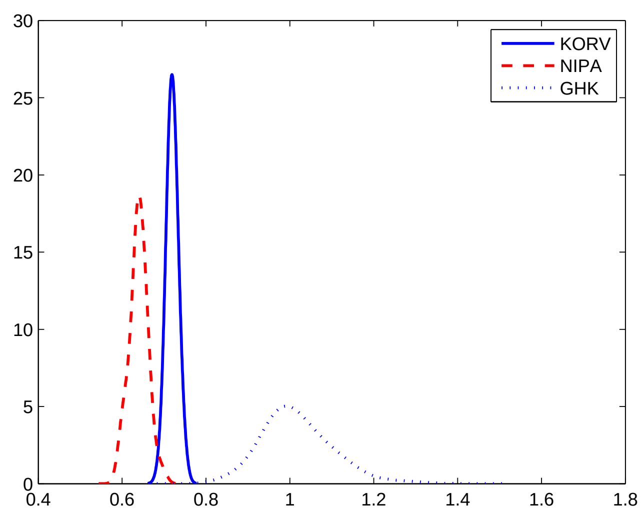

Figure 5: $1/(1-\rho)$

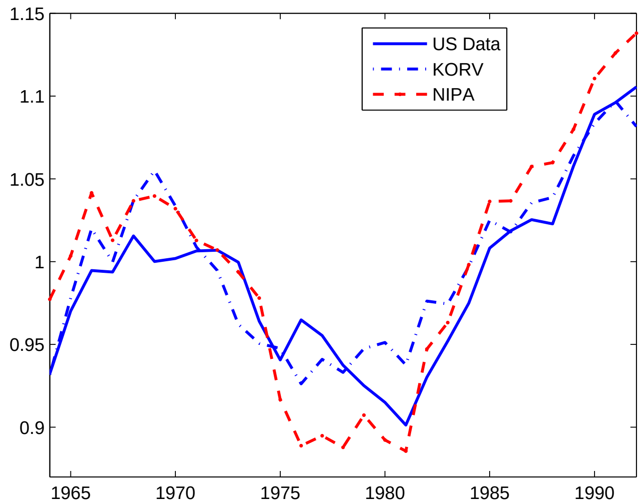

Figure 6: Skill Premium - KORV and NIPA Data

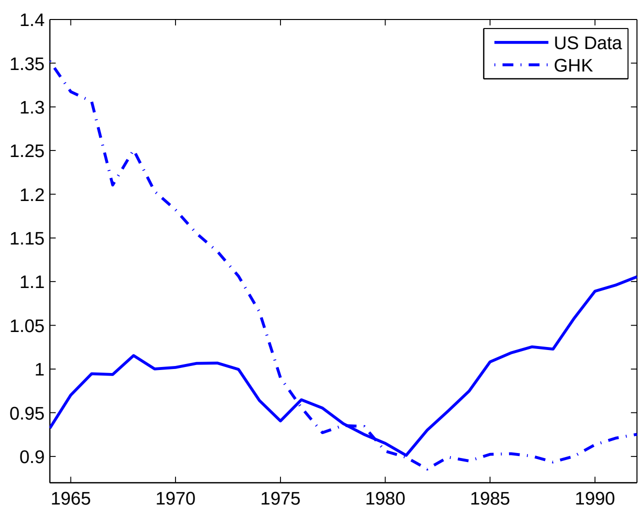

Figure 7: Skill Premium - GHK Data