The Decline in Capital-Skill Complementarity*

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Abstract

We revisit the capital-skill complementarity hypothesis and examine whether and under what conditions this mechanism can explain the developments in wage inequality and labor share in the 1963–2016 period. Krusell, Ohanian, Ríos-Rull, and Violante (2000) show that a model with capital-skill complementarity mechanism matches the data well and can account for the changes in wage inequality in the 1963–1992 period. We show that applying the model to the 1963–2016 period delivers a good fit for the skill premium; however, it does not predict the declining pattern in labor share in the last two decades. We modify the model to allow for a flexible technology structure and show that the degree of capital-skill complementarity is declining over time. The model with time-varying capital-skill complementarity can match the changes in skill premium and labor share in the 1963–2016 period.

JEL classification: E13, E25, J23, J31, O33
Keywords: capital-skill complementarity, technological change, skill-premium, labor share.

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1 Introduction

More than 50 years ago, Griliches (1969) provided evidence that capital and skilled labor are relatively more complementary than capital and unskilled labor, which led to the "capital-skill complementarity" hypothesis. Krusell, Ohanian, Ríos-Rull, and Violante (2000), hereinafter, KORV, develop a theoretical and empirical foundation for the capital-skill complementarity hypothesis. KORV propose a CES production function with four factors: skilled labor, unskilled labor, structures capital and equipment capital, general enough to accommodate a broad pattern of substitutability and complementarity within the four factors. KORV find that equipment-specific technological change can explain the patterns of skill premium and income inequality between 1963–1992; they show that the rise in skill-premium between the early 1980s and 1990s was due to the increased investment in the more efficient equipment capital, leading to the rise in ratio of capital inputs per skilled worker, and to an increase in the relative demand for skilled labor. The capital-skill complementarity mechanism has become a common feature of the neoclassical production technology; KORV estimated parameters have been used as inputs in a large number of studies.[1]

Since 1992, production processes, workplace environment and labor markets have all changed substantially. It is reasonable to consider that the degree of complementarity between capital and skill varies with the composition of technology

[1]See for example, Blankenau and Ingram (2002), Hendricks (2002), Caselli and Coleman (2002), Crifo-Tillet and Lehmann (2004), Lindquist (2004), Gilboa and Justman (2005), He and Liu (2008), Castro and Coen-Pirani (2008), Ben-Gad (2008), He (2012), Slavik and Yazici (2014), Goel (2017), Domeij and Ljungqvist (2019), among many others.

and its maturity. For example, Autor et al. (2003) show that computer technologies complement workers performing non-routine cognitive tasks but substitutes labor in routine cognitive and manual tasks. More recently, Beaudry, Green, and Sand (2016) argue that in the early 2000s, due to technology maturity and its widespread adoption, the demand for cognitive tasks with high educational skill underwent a reversal, pushing the high-skilled workers to move down the occupational ladder to jobs which require less education. Balleer and Van Rens (2013) argue that starting in the mid-1990s, technological improvements in capital substituted skilled workers more than unskilled workers. Our study proposes an extension to the KORV model to examine the changes in capital-skill complementarity over time.

We examine whether and under what conditions the capital-skill complementarity mechanism can be used to explain the rising wage inequality and declining labor share in the 1963–2016 period. There are two recent studies, Ohanian, Orak, and Shen (2021) and Maliar, Maliar, and Tsener (2020), which focus on extending the time period and re-estimating the KORV substitution elasticities. All studies agree that the estimated original KORV model for the extended time period performs well in explaining the changes in skill premium over time; however, it cannot explain the declining pattern in labor share. In fact, the KORV model with the original parameters generates an increase in labor share.

We extend the KORV model by allowing for a more flexible structure of technology. We do so by introducing a flexible time variation in all parameters of the KORV model; guided by estimation results, we narrow down the set of the relevant time-varying parameters. Further, we conduct a decomposition analysis over different time horizons to examine the roles of the capital-skill complementarity channel, changing complementary structure and relative supply effect channels on the evolution of skill premium and labor share.

First, we estimate the KORV parameters using the extended time period, adding 25 years of data. We closely replicate the KORV results and our findings for the extended time period are similar to those reported in Ohanian, Orak, and Shen (2021) and Maliar, Maliar, and Tsener (2020). For the full sample period from 1963 to 2016, the KORV model can reasonably account for the changes in the skill premium profile. Our estimated substitution elasticities are around 1.95 between unskilled labor and capital equipment and 0.83 between skilled labor and capital equipment, well within the range suggested by Polgreen and Silos (2008) and consistent with more recent studies. The model provides a good fit for the skill premium and delivers consistent rates of return on capital, however, it is not successful in matching the declining pattern in labor share. Similar results are reported in Ohanian, Orak, and Shen (2021) and Maliar, Maliar, and Tsener (2020).

Second, we analyze the dynamics of the capital-skill complementarity mechanism. To do so, we allow all parameters of the model to vary over time by performing an estimation for each of the 30-year period rolling-windows within the 1963–2016 period, such that the first rolling window captures exactly the same time period as in KORV. We find that the elasticity of substitution between unskilled labor and capital equipment remains relatively stable across the rolling windows; whereas the elasticity of substitution between capital equipment and skilled labor exhibits an increasing trend when more recent years are included in the sample. Other parameters of the model are fairly constant across the rolling windows.

Third, guided by these findings, we re-estimate the model for the 1963–2016 period, allowing for the parameter governing the elasticity between equipment capital and skilled labor to be time dependent. Incorporating this time-varying complementarity channel, our "augmented" KORV model predictions are not only consistent with the skill premium patterns but also provide a good match for the declining labor share, something the original KORV model does not generate. Further, a decomposition exercise confirms that the capital-skill complementarity effect is still the dominant force in driving the skill premium patterns in the last half-century. Skill-premium decomposition analysis shows that 52.6 percent of the variation in the skill premium can be attributed to the capital-skill complementarity channel with capital deepening, or the rapid growth in the stock of capital equipment, driving the increased demand for skilled workers. The time-varying complementarity and relative supply effect channels explain 11.5 and 35.9 percent of the evolution in skill premium, respectively.

The decline in capital-skill complementarity implies that a decrease in the price of capital equipment will lead to a smaller increase in the demand for skilled labor in the more recent years. Both versions of the KORV model, with and without time-varying capital-skill complementarity, deliver a good fit for the skill premium, wage-bill ratio and are consistent with the observed rates of return on equipment capital. However, the KORV model without a declining trend in capital-skill complementarity cannot explain the decline in labor share, whereas a model with the trend can.

The decline in capital-skill complementarity may reflect the adoption and routinization of new technologies, which leads to a decline in comparative advantage of the skilled workers. Theoretical framework developed in Greenwood and Yorukoglu (1997) shows how a technological advancement is followed by a transitory increase in the demand for skilled labor that is needed to implement the new technologies; following the initial adoption of the new technology, the relative demand for skilled labor declines towards its original steady state level. Castro and Coen-Pirani (2008) utilize a one-off decline in capital-skill complementarity to explain the increase skilled hours volatility since mid 1980s; they argue that Greenwood and Yorukoglu (1997) mechanism could provide a theoretical explanation for the decline in capital-skill complementarity. Beaudry et al. (2016) also argue that in the early 2000s the demand for skill underwent a reversal due to the widespread adoption and maturity of new technologies. Occupational transition of high-educated workers to jobs which require less education can explain the observed decline in capital-skill complementarity.

The rest of the paper is organized as follows. Section 2 describes the model and the analytical derivation of skill premium. Section 3 details the estimation strategy, followed by the description of data in Section 4. Section 5 describes the estimated parameters and the decomposition results. We discuss the implications of our findings in Section 6. Section 7 concludes the paper.

2 Model

Our model extends the one developed in KORV, allowing for a more flexible technology structure. The KORV model is a two sector model of the production side of the economy. One sector produces capital equipment, and the other produces consumption good and capital structures.

$$
\begin{aligned}
c_t + I_{st} &= A_t G(k_{st}, k_{et}, u_t, s_t) \qquad (1) \\
I_{et} &= A_t q_t G(k_{st}, k_{et}, u_t, s_t) \qquad (2)
\end{aligned}
$$

where I_{st} and I_{et} are investments in capital structures and capital equipment in year t, and c_t is consumption. Inputs of the same factor in each sector are different, superscript indicators are omitted to simplify notation. Production technology requires two types of capital, capital structures (k_s) and capital equipment (k_e); and two types of labor input, unskilled (u) and skilled (s) workers. Labor inputs are defined by hours and efficiency units.[2] There are two types of productivity shocks, aggregate neutral shock is denoted by A_t and investment-specific technology shock is denoted by q_t. The function $G(.)$ is common to both sectors and homogeneous of degree one, which allows to define total output in consumption units and aggregate both sectors.

[2]As such, $u_t = h_{ut}\psi_{ut}$ and $s_t = h_{st}\psi_{st}$ where h and ψ correspond to hours and efficiency units, respectively.

The following laws of motion define the evolution of capital.

$$k_{st+1} = (1-\delta_{st})k_{st} + I_{st} \quad (3)$$

$$k_{et+1} = (1-\delta_{et})k_{et} + I_{et} \quad (4)$$

where the parameters δ_{st} and δ_{et} denote capital specific depreciation rates.

The production function is a Cobb-Douglas in capital structures and a combination of nested CES functions of the remaining factor inputs.

$$G(k_{st}, k_{et}, u_t, s_t) = A_t k_{st}^{\alpha_t} \left[\mu_t u_t^{\sigma_t} + (1-\mu_t)\left(\lambda_t k_{et}^{\rho_t} + (1-\lambda_t) s_t^{\rho_t}\right)^{\frac{\sigma_t}{\rho_t}}\right]^{\frac{1-\alpha_t}{\sigma_t}} \quad (5)$$

where $G(\Omega_t)$ is the aggregate output, $\Omega_t \equiv \{k_{st}, k_{et}, u_t, s_t\}$ are factor inputs.

The parameters $\alpha_t,\ \mu_t,\ \lambda_t \in (0,1)$ govern the income shares and $\sigma_t,\ \rho_t, \in (-\infty, 1)$ govern the elasticities of substitution. In particular, $\frac{1}{1-\sigma_t}$ $\left(\frac{1}{1-\rho_t}\right)$ measures elasticities of substitution between capital equipment and unskilled (skilled) labor. We allow for a more flexible framework allowing all the model parameters to be time dependent. Capital-skill complementarity hinges on $\sigma_t > \rho_t$ and KORV uses the difference between the two parameters to gauge the degree of capital-skill complementarity.

We assume a competitive factor model and define skill premium as the ratio of skilled wage over unskilled wage. Skill premium is expressed as:

$$\pi_t = \frac{(1-\mu_t)(1-\lambda_t)}{\mu_t}\left[\lambda_t\left(\frac{k_{st}}{s_t}\right)^{\rho_t} + (1-\lambda_t)\right]^{\frac{\sigma_t-\rho_t}{\rho_t}}\left(\frac{h_{ut}}{h_{st}}\right)^{1-\sigma_t}\left(\frac{\psi_{ut}}{\psi_{st}}\right)^{\sigma_t} \quad (6)$$

where ψ measures the labor efficiency of each type of worker.

Equation 6 specifies the skill premium as a function of relative factor inputs. We analyze the changes in the skill premium using a decomposition exercise proposed by KORV and further elaborated in Lindquist (2005). First, using g_x to denote the growth rate of variable x, changes in skill premium (g_π) can be decomposed into capital-skill complementarity (CSC), relative quantity (RQ) effects and relative efficiency effect (RE).[3]

The original KORV specification and studies that adopted the KORV approach assume a time invariant technology structure. Under this assumption, the decomposition of changes in the skill premium takes the following form,

$$g_{\pi_t} \simeq \underbrace{\lambda(\sigma-\rho)\left(\frac{k_{et}}{s_t}\right)^{\rho}(g_{k_{et}} - g_{h_{st}} - g_{\psi_{st}})}_{\text{Capital-skill complementarity (CSC) effect}} + \overbrace{(1-\sigma)(g_{h_{ut}} - g_{h_{st}})}^{\text{Relative quantity (RQ) effect}} + \underbrace{\sigma\,(g_{\psi_{st}} - g_{\psi_{ut}})}_{\text{Relative efficiency (RE) effect}} \quad (7)$$

In equation 7, the capital-skill complementarity (CSC) effect shows that if $\sigma > \rho$ then positive growth in the quantity and/or quality of new capital equipment will in turn increase the marginal productivity of skilled workers faster than

[3] Similar to KORV, we will abstract from the relative efficiency effect which captures the growth rate of skilled labor efficiency with respect to unskilled labor efficiency. Since $g_{\psi_{ut}} = g_{\psi_{st}} = 0$, we have $g_{s_t} = g_{h_{st}}$ and $g_{u_t} = g_{h_{ut}}$. This assumption is consistent with our estimation results.

that of unskilled workers. Thus, under the CSC effect, an increase in the stock and quality of new capital equipment leads to an increase in skill premium. The relative quantity (RQ) effect captures the higher growth in the hours worked by skilled workers relative to those of unskilled workers will lower the growth of skill premium provided that $\sigma < 1$. Finally, the relative efficiency (RE) effect depends on the sign of the substitution parameter, σ. With $\sigma > 0$, then the elasticity of substitution between the two types of labor is greater than 1, implying that they are substitutes in production. In such case, when the growth rate of efficiency of skilled labor is higher than that of unskilled labor, the skill premium will rise. Similar to KORV, we abstract from the relative efficiency effect.

Once we adopt a more agnostic approach and allow all parameters of the production function to change over time, skill premium cannot be solely accounted for by the three channels described earlier. For example, under this "augmented" KORV specification, allowing for ρ to be time dependent adds a fourth channel, which specifies how the growth rate of the skill premium depends on the growth rate of ρ_t, defined as g_{ρ_t}. We isolate this channel as the "time-varying complementarity" (TVC) effect in the full decomposition as follows:

$$
\begin{aligned}
g_{\pi_t} \simeq\ & \underbrace{\lambda(\sigma-\rho_t)\left(\frac{k_{et}}{s_t}\right)^{\rho_t}(g_{k_{et}}-g_{h_{st}}-g_{\psi_{st}})}_{\text{Capital-skill complementarity (CSC) effect}} + \overbrace{(1-\sigma)(g_{h_{ut}}-g_{h_{st}})}^{\text{Relative quantity (RQ) effect}} + \underbrace{\sigma\left(g_{\psi_{st}}-g_{\psi_{ut}}\right)}_{\text{Relative efficiency (RE) effect}} \\
& + \underbrace{\left[\lambda\left(\frac{k_{et}}{s_t}\right)^{\rho_t}\left\{\ln\left(\frac{k_{et}}{s_t}\right)(\sigma-\rho_t)-\frac{\sigma}{\rho_t}\right\}+\lambda\frac{\sigma}{\rho_t}\right]g_{\rho_t}}_{\text{Time-varying complementarity (TVC) effect}} \qquad (8)
\end{aligned}
$$

The parameter ρ_t governs the elasticity of substitution between capital equipment and skilled labor that plays a role in the capital-skill complementarity (in levels) as well as in this new time-varying complementarity channel (in both levels and growth rates). If the profile of ρ follows a time-dependent upward trajectory, then not only would this weaken the existing capital-skill complementarity effect, but also its growth rate—g_{ρ_t}—would have a separate effect on the profile of the skill premium growth.

3 The econometric model

We estimate the parameters of the model using the same econometric methods as in KORV, the simulated pseudo maximum likelihood (SPMLE) procedure.[4]

To estimate our model, we use three structural equations: labor share of income, a wage bill ratio and a non-arbitrage condition.

$$\frac{W_{st}h_{st} + W_{ut}h_{ut}}{Y_t} = lsh_t(\psi_t, X_t; \phi), \tag{9}$$

$$\frac{W_{st}h_{st}}{W_{ut}h_{ut}} = wr_t(\psi_t, X_t; \phi), \tag{10}$$

$$(1 - \delta_{st}) + A_{t+1}G_{k_s}(\psi_{t+1}, X_{t+1}; \phi) = \mathbb{E}_t\left(\frac{q_t}{q_{t+1}}\right)(1 - \delta_{et}) + q_tA_{t+1}G_{k_e}(\psi_{t+1}, X_{t+1}; \phi) \tag{11}$$

Where equation (9) corresponds to the labor income share. The right hand side of the equation is the labor income share derived from profit maximizing conditions

[4] See Laroque and Salanie (1989) and KORV for details.

from the model. The left hand is its counterpart from the data. Equation (10) is the wage bill ratio. The right hand side in this equation is the wage bill of skilled to unskilled workers generated by the model, the left hand side is the counterpart from the data. Equation (11) specifies the non-arbitrage condition, which implies that the expected rate of return on capital structures equals the expected rate of return on investment in capital equipment.[5]

Labor efficiency is given by the vector $\psi_t = [\psi_{ut}, \psi_{st}]$, defining $\varphi_t \equiv log(\psi_t) = \varphi_0 + \gamma_\varphi t + \omega_t$. The parameter vector γ_φ is the growth rate of labor efficiency, and the term ω_t is a multivariate normal innovation with zero mean and variance-covariance matrix ϖ.[6] The exogenous inputs are given by $X_t \equiv \{k_{st}, k_{et}, h_{ut}, h_{st}, W_{ut}, W_{st}, y_t\}$ and the parameter set to be estimated is $\phi_t \equiv \{\alpha_t, \sigma_t, \rho_t, \mu_t, \lambda_t, \delta_{st}, \delta_{et}, \varphi_0, \gamma_\varphi, \varpi, \zeta_E^2\}$.

Given the relatively small sample size it is appropriate to reduce the dimension of the parameters set to be estimated. We do this by calibrating some of the parameters in advance of the estimation. We construct annual depreciation rates for capital equipment and capital structures using the BEA data.[7] Labor efficiency process is defined as in KORV, with $\varpi = I\eta_h^2$ and set $\eta_h^2 = 0.043$.[8] The benchmark specification of labor efficiency has no trend; the initial level of skilled labor

[5] We follow KORV and assume that $\mathbb{E}_t\left(\frac{q_t}{q_{t+1}}\right) = \frac{q_t}{q_{t+1}} + \varepsilon_q$, where the term ε_q is an error term for the expectation operator, where $\varepsilon_q \sim N(0, \zeta_E^2)$.

[6] Assuming a trend stationary process, as in Katz and Murphy (1992) and KORV, among others, for each type of labor input.

[7] The constructed depreciation rates vary over time; using average depreciation rates ($\bar{\delta_e} = 0.133$, $\bar{\delta_s} = 0.032$) or those reported by Greenwood et al. (1997), $\delta_s = 0.05$ and $\delta_e = 0.125$, has a very minor effect on the estimation results. Results with alternative measures of depreciation rates are available upon request.

[8] As estimated in KORV the values imply no correlation between innovations to skilled and unskilled labor efficiencies.

efficiency is normalized, $\varphi_{S,0} = 6$; we follow KORV and impose $\zeta_E^2 = 0.02$. The remaining parameters are jointly estimated. Details about the estimation method are reported in Appendix A.

The estimation of the time dependent model is performed in two steps. First, to allow for time varying parameters, we estimate the model using a rolling window of 30 year-period starting from 1963 to 2016. The first period is 1963–1992, same as in KORV, the last period is 1987–2016; we obtain series of all estimated parameters for each 30-year rolling window. Second, we perform an estimation where parameters that exhibit a trend in the first step are redefined to allow to be time dependent. The new set of parameters is then estimated using data for the entire period, 1963–2016.

4 Data

We estimate the model building on methods outlined in KORV. We construct data series for wages, capital and labor inputs for the 1963–2017 period, adding 25 years to the series in the original paper (1963–1992). Labor market inputs and wages variables are constructed using the CPS data; data on capital structures and equipment are from the National Income and Product Account tables.

4.1 Labor data

Labor market variables constructed using the 1963–2017 Current Population Survey (CPS), March Annual Demographic Supplements. All variables are constructed using suitable weights to achieve representativeness of the population. To construct annual hours worked we use information on weeks worked per year and hours worked per week. Hourly wage rates are calculated using last year annual income divided by annual hours. Annual income and hours refer to last year; therefore, the actual sample period is 1961–2016. Wage rates are in 1999 dollars (deflated by the CPI). To identify the individual skill type, we construct a schooling variable by converting information on the highest grade completed into years of schooling. Schooling information is not available in 1962 and we exclude this year from the analysis. We define workers as skilled if they have completed college education (16 or more years of schooling). Appendix B describes the labor inputs data construction in detail.

Figure 1 presents the labor market series. The left panel shows the ratio of total skilled to unskilled hours worked; between 1961–2016 this ratio increased from 0.25 to 0.93. The right panel reports the skill premium, which is increasing over time. Figure 1 also compares our constructed labor market series to those reported in KORV and shows a close fit.

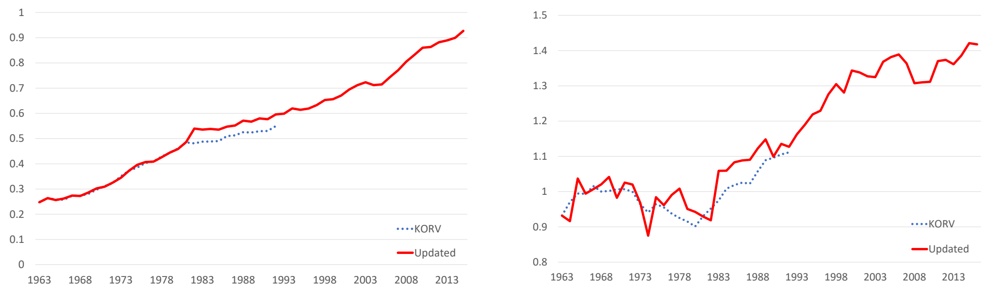
4.2 Capital data

To obtain the annual series for capital, we use the data on real private fixed investment in capital structures and equipment. Capital investment data are reported by the U.S. Bureau of Economic Analysis (BEA), we collect data on nonresidential investment in structures (K_s), and equipment and intellectual property products (K_e), this data are from Table 5.2.5, (Table 5.2.5: Gross and Net Domestic Invest-

Figure 1: Hours worked and skill premium

A) Labor input ratio, skilled/unskilled hours

B) Skill premium



Note: The left panel displays the skilled to unskilled hours worked ratio. The right panel displays the skill premium. For comparison, both panels include the original KORV series.

ment by Major Type). Capital price indexes are from the BEA Table 5.5.4 (Table 5.5.4: Price Indexes for Private Fixed Investment by Type).

To obtain quality adjusted capital equipment series, we construct a relative price index using nondurable consumption goods and nonhousing services price index divided by a quality-adjusted price of equipment and software. To measure the changes in efficiency of capital equipment over time, we follow Cummins and Violante (2002) methodology to extend Gordon (2007) series. We use data on 22 types of capital inputs price indexes and aggregate them using the Tornqvist procedure. Using the long time series (1947–1983) of Gordon's quality-adjusted and NIPA price indexes, for each type of capital input we project Gordon's quality-adjusted price index on time trend, cyclical indicator, and current and lagged values of the NIPA price indexes. Using the coefficient estimates, we extrapolate the quality-adjusted price level for each type of capital for 1984–2017. BEA provides a constant-quality price index for the information processing equipment and software category, we use this capital input category without modification.

The stock of capital structures and stock of capital equipment are constructed using capital accumulation equations; we apply the perpetual inventory model and follow specifications described in equations (3) and (4). To construct the capital stock series, we use time varying depreciation rates estimated from the NIPA tables.[9]

We follow Greenwood et al. (1997), Acemoglu (2002), Cummins and Violante (2002), and Fisher (2006) among others, to interpret the relative price index of capital equipment as an inverse measure of technological change. A declining index indicates an increasing state of technology. Figure 2 reports the constructed series of capital structures, capital equipment and the relative price index. The figure also includes KORV original data for comparison purposes.

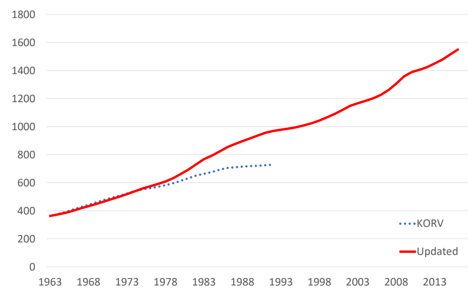
5 Results

We first estimate the original KORV model using data for 1963 to 2016, i.e., the "full sample", assuming that the parameters set $\phi \equiv \{\alpha, \sigma, \rho, \mu, \lambda, \varphi_{u0}\}$ is constant over time. Second, we perform the same estimation for each of the 30-year

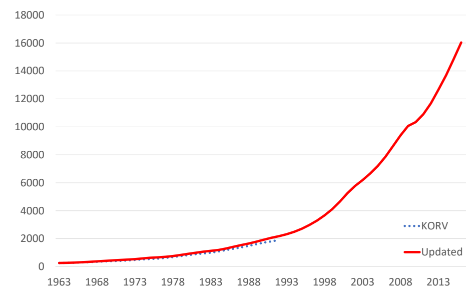
[9]We construct depreciation rates using annual implied depreciation rates reported at the industry level. To construct aggregate depreciation rates, we calculate annual weighted averages using relevant industry annual capital stock data as weights. Implied rates of depreciation of private nonresidential fixed assets are available here: `https://apps.bea.gov/national/FA2004/Details/xls/DetailNonres_rate.xlsx`, data on fixed-cost net capital stock of private nonresidential fixed assets are available here: `https://apps.bea.gov/national/FA2004/Details/xls/detailnonres_stk2.xlsx`. The files last opened on 07/19/2021.

Figure 2: Capital series

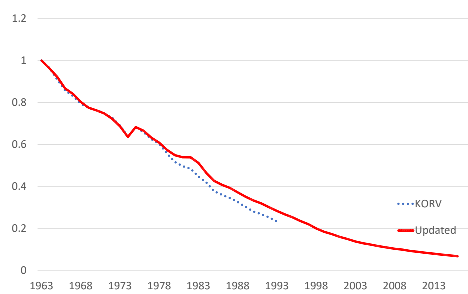
A) Capital structures



B) Capital Equipment



C) Relative price index



Note: Panels A and B display series for capital structures and capital equipment (including intellectual property), respectively. Panel C displays the relative price index of capital equipment. All panels include the original KORV series for comparison.

period rolling-windows within the full sample. The first rolling window (1963–1992) covers exactly the same time period as in KORV, while the last rolling window (1987–2016) covers the most recent three decades. For this estimation, we assume that the parameters can change over time but are constant within the window period; i.e., $\phi_\tau \equiv \{\alpha_\tau, \sigma_\tau, \rho_\tau, \mu_\tau, \lambda_\tau, \varphi_{u0_\tau}\}$, where τ refers to the relevant rolling window; Third, after establishing which parameters exhibit time trends, we estimate the augmented KORV model redefining the relevant parameters to be time dependent. Lastly, we perform a decomposition exercise to assess the roles of capital-skill complementarity channel, changing complementary structure and relative supply effect channels on the evolution of skill premium and labor share.

5.1 Full sample results

Table 1 reports selected estimates for the full, 1963–2016, period, along with KORV, Polgreen and Silos (2008) and our replication results for the 1963–1992 period.[10] Our estimates for the original 1963–1992 period are close to those reported in KORV and well within the range of estimates reported in Polgreen and Silos (2008). Estimations for the extended period show little change in σ but a substantially higher ρ; capital-skill complementarity assumption still holds since $\sigma > \rho$; α does not vary much across studies or periods.[11]

Table 1: Selected Estimates

	Sample Period	Elasticity Parameters		
		σ	ρ	α
Castex, Cho and Dechter	1963–2016	0.486	-0.208	0.110
KORV (2000)	1963–1992	0.401	-0.495	0.117
Polgreen and Silos (2008)	1963–1992	$0.50 \sim 0.88$	$-0.66 \sim -0.16$	0.110
Castex, Cho and Dechter (KORV data)	1963–1992	0.379	-0.403	0.117
Castex, Cho and Dechter (own data)	1963–1992	0.479	-0.408	0.110

Figure 3 shows the model generated time series. The estimated model matches

[10]The full set of parameter estimates and standard errors is reported in column (1) of Table C.1 in Appendix C.

[11]Polgreen and Silos (2008) obtain α from KORV and do not estimate it.

data well along the three target dimensions. Panel A shows that the model generally captures the profile of labor income share in the data, except for the more recent periods where the decline in labor share picks up at a faster pace in the data. Panel B shows the the wage bill ratio between skilled and unskilled workers as predicted by the model, which consistently fits the data for the entire period. Panel C shows the rates of return for each type of capital, the rates are consistent with the non-arbitrage condition in equation (11). Panel D shows that the skill premium implied by the model fits the data well. Consistent with the original KORV results, the model predicts an increase in the skill premium in the 1960s, a decline in the 1970s, and the subsequent rise during the 1980s and early 1990s. The model also captures well the rising trend in the skill premium which continues throughout the last two decades at a a slower pace.

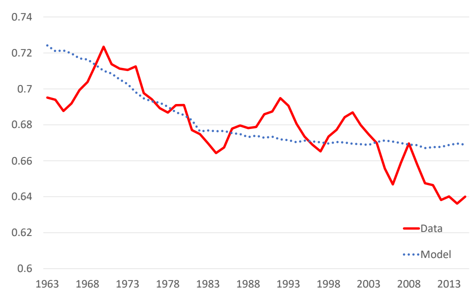
5.2 KORV in rolling windows

In this section, we analyze the changes in the estimated KORV parameters over time by performing an estimation for each of the 30-year period rolling windows within the full sample period. The first period of our rolling window (1963–1992) matches the period documented in KORV, while the last period (1987–2016) mostly captures the period not documented in KORV. Figure 4 plots the estimated parameter values of σ and ρ for each rolling window.[12] Table 1 reports

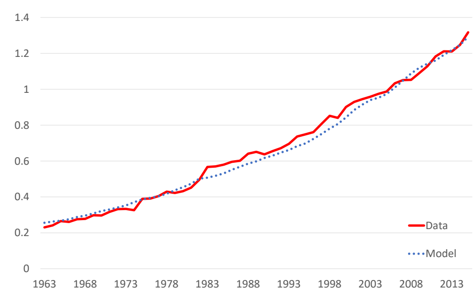
[12]The full set of parameter estimates is available in Table C.2 in the Appendix. With exception of ρ, model parameters exhibit stability over time.

Figure 3: Model Targets and Skill Premium – Model vs. Data (1963–2016), Benchmark Model

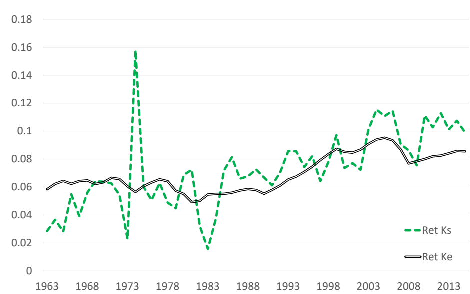
A) Labor income share



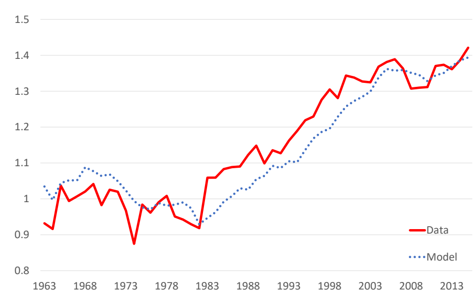
B) Wage bill ratio



C) Non-arbitrage condition



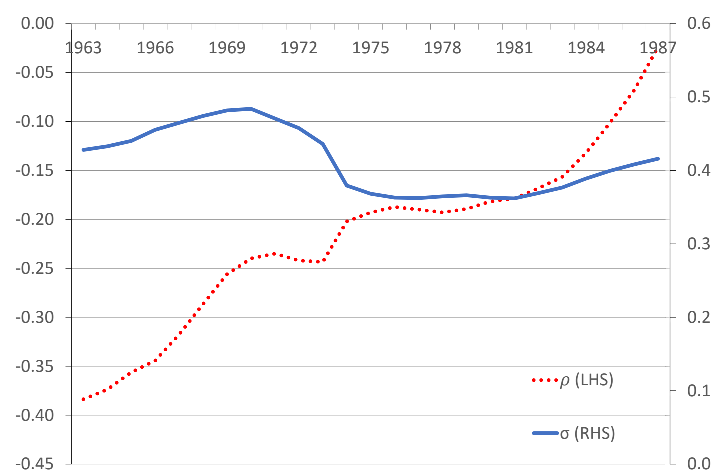
D) Skill premium



Note: Fitted series and data for the 1963–2016 sample. Panels A-C report the series for the three estimated equations; Panel D reports results for the skill premium.

estimation results for σ and ρ for the sample period 1963–1992, the estimates are 0.428 and -0.384, respectively, closely match those in KORV. Remarkably, we document a gradual shift in the parameter that governs the substitution between equipment capital and skilled labor, ρ, such that in the final rolling window that covers years between 1987–2016, the parameter estimates of σ and ρ are 0.416 and -0.024, respectively.

Figure 4: Elasticity of substitution - Rolling window



Note: The figure displays rolling windows estimates for σ (right hand side) and ρ (left hand side); each window includes 30 years, such that the reporting year corresponds to the first year in the window.

The increasing trend in ρ leads to the decline in the difference between the two elasticity parameters, $\sigma - \rho$, a measure used in KORV to gauge the degree of capital-skill complementarity, which decreases from 0.812 in the 1963–1992 period to 0.440 in the last rolling window covering 1987–2016.

To further analyze the decline in the degree of capital-skill complementarity, we convert the parameter values into elasticities, as shown in Table 2.[13] First, the elasticity of substitution between capital equipment (or skilled labor) and unskilled labor, reflected in the term $\frac{1}{1-\sigma}$, fluctuates between 1.57 and 1.94, which is well within the range reported by KORV and Polgreen and Silos (2008). On the other hand, the elasticity of substitution between capital and skilled labor exhibits an increasing trend over time. For the first period of rolling window, our estimated value of $\frac{1}{1-\rho}$ is 0.72, which is quite close to that reported in KORV. However, the estimated elasticity gradually rises close to unit elasticity as more recent periods are incorporated. In fact, for most of the later rolling-window periods, the elasticity of substitution between capital equipment and skilled labor exceeds its range suggested in Polgreen and Silos (2008). These results suggest that the declining degree of capital-skill complementarity is mostly explained by the increasing degree of substitutability between capital equipment and skilled labor.

Table 2: Estimated Substitution Elasticities: Labor and Equipment Capital

	Sample Period	Unskilled Labor: $\frac{1}{1-\sigma}$	Skilled Labor: $\frac{1}{1-\rho}$
Castex, Cho and Dechter	rolling windows	$1.567 \sim 1.938$	$0.723 \sim 0.977$
KORV (2000)	1963–1992	1.669	0.669
Polgreen and Silos (2008)	1963–1992	$2.000 \sim 8.333$	$0.602 \sim 0.862$
Castex, Cho and Dechter (KORV data)	1963–1992	1.610	0.713

[13] For comparability we also report elasticities estimated using the original KORV data as shown in the last row of Table 2.

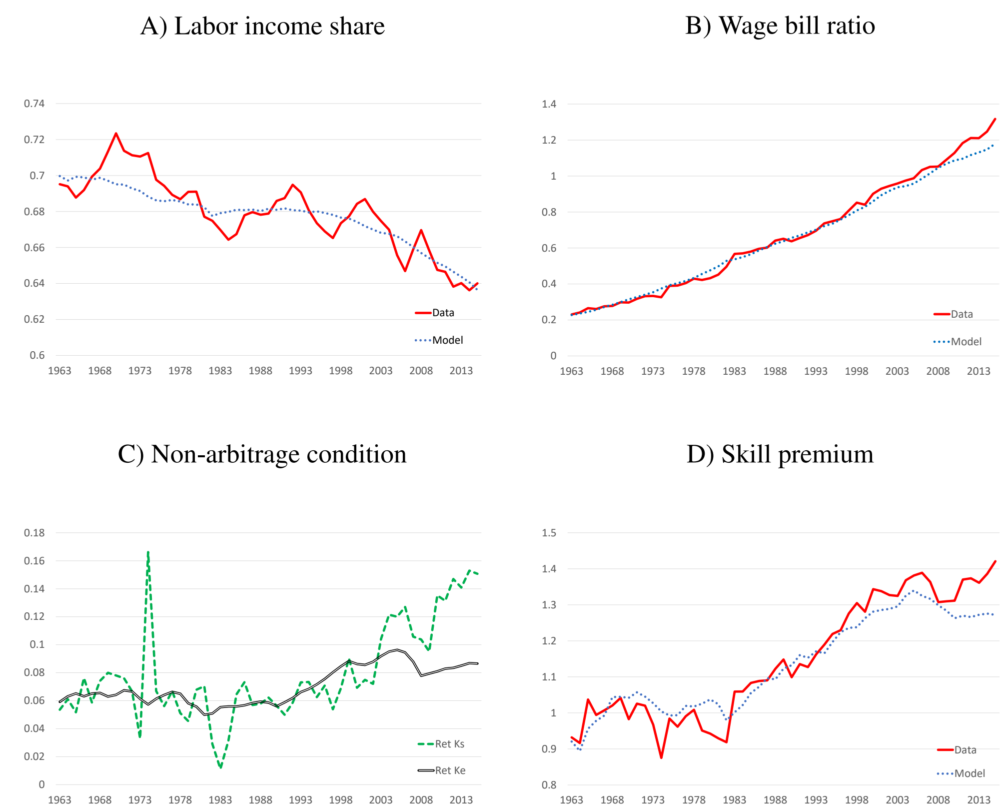
5.3 KORV with time-varying capital-skill complementarity

In Section 5.2 we document a decline in the degree of capital-skill complementarity due to an increase in ρ, or the elasticity of substitution between capital equipment and skilled labor, over time. Guided by these findings, we modify the benchmark KORV model by allowing the ρ parameter to be time dependent. In this "augmented" KORV specification, we re-estimate the parameters of the model using the full sample and allow for the elasticity of substitution between capital equipment and skilled labor to be time dependent $\rho_t = \rho_0 + \gamma_\rho t$, where t denotes time and γ_ρ captures the linear growth trend in the elasticity.

Our estimate of ρ_0 and γ_ρ are -0.380 and 0.008, respectively. The remaining estimated parameters are consistent with our benchmark estimates and exhibit minor changes.The difference between σ and ρ_t is positive for the entire period which indicates that the augmented KORV specification are qualitatively consistent with the capital-skill complementarity. However, its value decreases over time from 0.842 to 0.426, or a decline in 49 percent.

Panels A, B, C in Figure 5 present the estimated equations of the augmented KORV model; Panel D presents the skill premium in the data and that predicted by the augmented KORV model. All series generated by the model are consistent with the data. What is particularly striking is that our augmented KORV model with declining capital-skill complementarity can produce the downward trend in the aggregate labor share, closely fitting the pattern observed in the data.

Figure 5: Model Targets and Skill Premium – Model vs. Data (1963–2016), Augmented Model



Note: Fitted series and data for the 1963–2016 sample. Panels A-C report the series for the three estimated equations; Panel D reports results for the skill premium.

5.4 Skill premium decomposition

Using the estimated model parameters, we perform a decomposition experiment, building on Lindquist (2005), to examine which channels explain the changes in skill premium.[14] For the full sample and rolling window results presented in

[14] As the CSC and RQ effects have opposite effects on the skill premium, Lindquist (2005) takes absolute values to account for the overall changes in the skill premium.

Section 5.1 and 5.2, we use equation (7) to decompose the changes in the skill premium into capital-skill complementarity (CSC) and relative quantity (RQ) effects.[15]

As follows from equation (7), each of the CSC and RQ effects depends on the growth rate of different factors of production, and we can further assess to what extent each factor input can account for changes in the skill premium. Assuming $\sigma > \rho$, the growth in skilled labor (g_{s_t}) has a negative effect on the skill premium through both CSC and RQ effects, while the growth in capital equipment ($g_{k_{et}}$) and unskilled labor (g_{u_t}) have a positive effect on the skill premium through CSC and RQ effect, respectively. Within the CSC effect, we examine the role of capital equipment by setting the growth rate of skilled labor to zero; we examine the role of skilled labor by muting the growth rate of capital equipment to be zero. Similarly, we separately decompose the RQ effect when the skilled (or unskilled) labor is the only operative by setting the growth of the other labor type to zero.

Finally, for the augmented KORV specification results presented in Section 5.3, we use equation (8), which includes the additional time-varying complementarity (TVC) effect. We then highlight the role of time-varying elasticities of substitution between capital equipment and skilled labor on both skill premium and labor share profiles.

[15] Similar to KORV, we abstract from the relative efficiency (RE) effect which captures the growth rate of skilled labor efficiency with respect to unskilled labor efficiency, since $g_{\psi_{ut}} = g_{\psi_{st}} = 0$, $g_{s_t} = g_{h_{st}}$ and $g_{u_t} = g_{h_{ut}}$.

5.4.1 Full sample and rolling windows decomposition

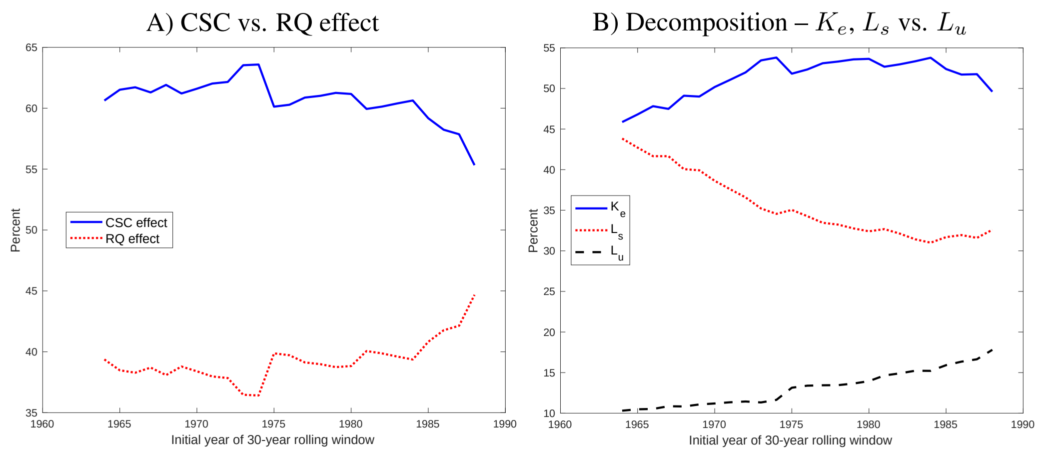
We first decompose the changes in skill premium into CSC and RQ effects for our full sample results, and the results are presented in the last column of Table 3. Around 61 percent of the changes in the skill premium between 1963–2016 can be attributed to the capital-skill complementarity (CSC) channel; the remaining 39 percent are explained by the relative quantity (RQ) channel. Further, the decomposition shows that the major driving force behind the CSC effect is capital deepening, or the growth in the capital equipment, which accounts for almost half of the overall changes in skill premium. Within the RQ effect, it is mainly the changes in skilled labor that drive the skill premium patterns. Finally, the bottom row in Table 3 summarizes the effects of each factor input. Between 1963 and 2016, approximately half of the changes in the skill premium was due to capital deepening, whereas the remainder is attributed to relative changes in the labor force. Changes in the supply of skilled labor explain around 39 percent of the changes in the skill premium, with two thirds of this coming through the RQ channel.

Table 3: Decomposition of Changes in the Model Skill Premium, Original KORV Model, 1963–2016

	L_s	L_u	K_e	Total
CSC effect	12.3%		48.7%	61.0%
RQ effect	26.4%	12.53		39.0%
Total	38.8%	12.5%	48.7%	100%

Next, we perform the decomposition exercise using the rolling window estimates; the results are in Figure 6. The left panel summarizes the contribution of the CSC effect, which ranges between 61 and 64 percent in the earlier windows. Over time, the importance of the CSC gradually declines and reaches 55 percent in the final rolling window. This weakening of the CSC effect is explained by the growth in the supply of skilled labor; it is not due to a slowdown in capital deepening, as shown on the right panel of the figure where the share of capital equipment shows an increasing trend over time.

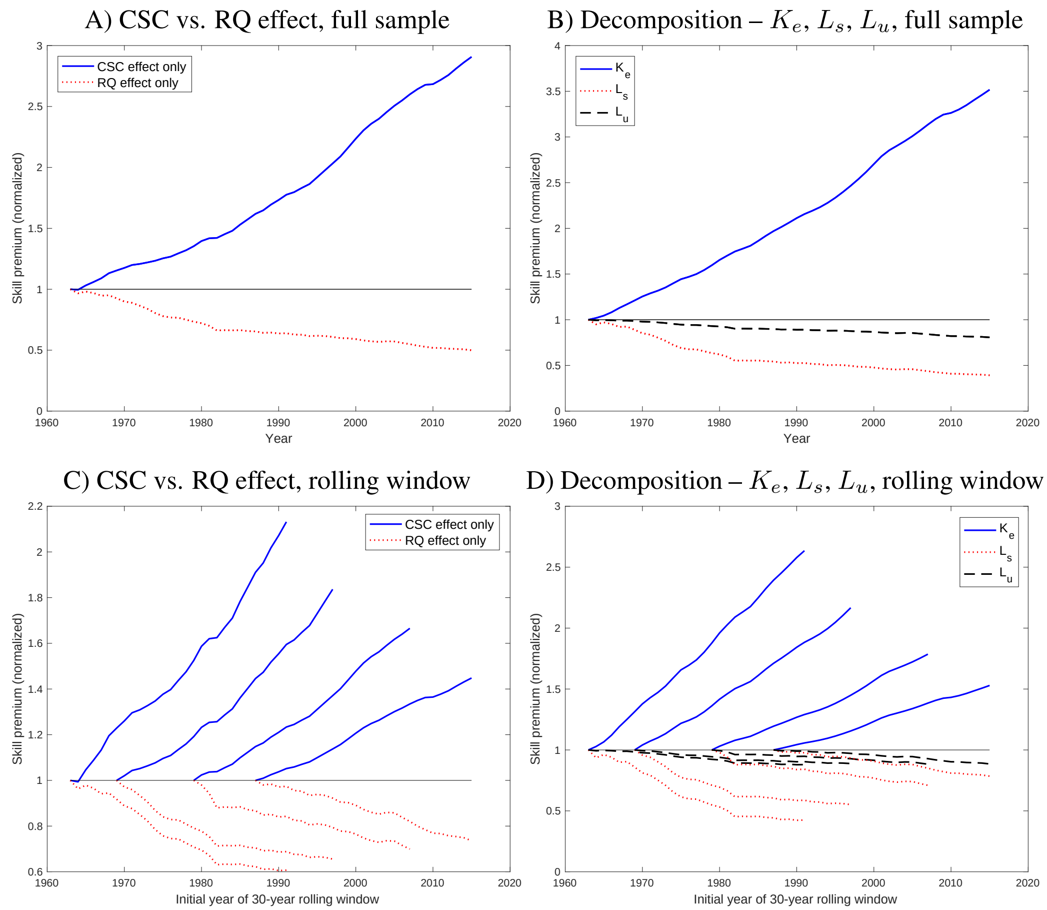
Figure 6: Rolling Window Decomposition of Changes in the Skill Premium



Note: The figures display the decomposition of skill premium changes into CSC and RQ effects (left) and individual factors of production (right) for each of the 30-year rolling window.

Figure 7 provides results of an alternative decomposition exercise where we show how the skill premium would have evolved if each of the effects were operating individually in the absence of the other factor changes. The figures also show the cumulative effects of each factor of production on the profile of skill premium. The upper figures, Panels A and B, display results for the full sample using

Figure 7: Cumulative decomposition of skill premium



Note: The upper panel figures display the cumulative profile of skill premium (normalized to 1 in 1963) when each of the CSC and RQ effects (left) or factor of production (right) is operative in the absence of others. The lower panel figures display the cumulative profile of skill premium (normalized to 1 in the initial year of the rolling window) when each of the CSC and RQ effects (left) or factor of production (right) are operative in the absence of others. For ease of illustration, only the following rolling-window results are displayed: 1963–1992, 1970–1999, 1980–2009, 1987–2016.

the original KORV model. Until the early 1980s, the RQ effect has significantly lowered the skill premium; in the later period the RQ effect becomes less important. The CSC effect, on the other hand, consistently drives the skill premium upward for the whole duration of the period. As for each factor of production, as shown on Panel B, growth in capital equipment alone would have lifted the skill premium by more than three-fold, whereas the individual changes in skilled and unskilled labor would have negatively impacted the skill premium.

We repeat this exercise for selected rolling windows estimates; the results are presented the lower panel of Figure 7. Comparing the cumulative effect of CSC (and capital equipment) across different rolling windows shows its diminishing effect over time, which is consistent with the estimates reported in previous sections. For the first 30-year rolling window, the CSC effect alone would have increased skill premium by more than 100 percent in that period, whereas in the last 30-year rolling window, this magnitude weakens to around 40 percent. The RQ effect significantly lowers the skill premium in the rolling window that includes the first two decades until the early 1980s, after which its effect declines.

5.4.2 Augmented KORV model decomposition

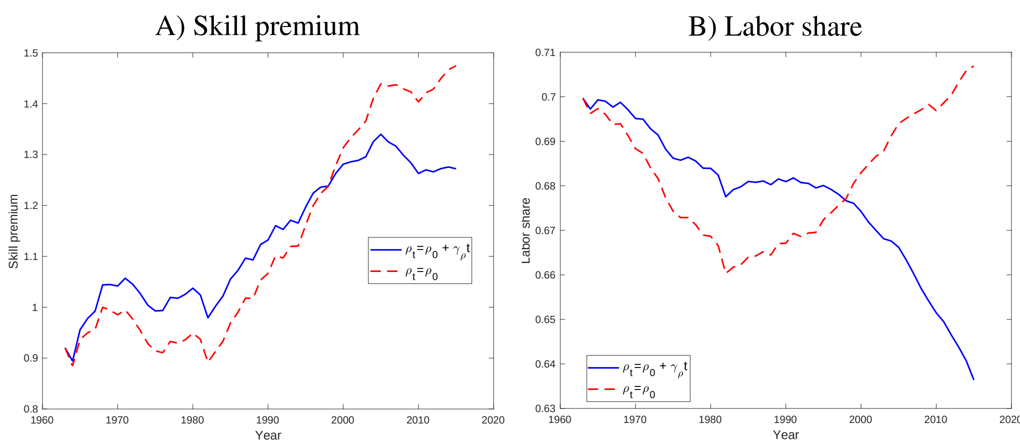
In the augmented KORV model specification, equation (8) includes an additional time-varying complementarity (TVC) channel where the profile of ρ_t plays a role in accounting for changes in the skill premium. Table 4 presents results of the decomposition exercise using the augmented model estimates. Around 12 percent of the change in the model skill premium can be attributed to the TVC effect. The inclusion of the TVC channel mainly lowers the magnitude of capital-skill complementarity which is reflected in the lower contribution of the CSC effect. Compared to the standard KORV model decomposition in Table 3, the share of the CSC effect falls from 61 to 53 percent whereas that of the RQ effect drops from 39 to 36 percent. Further, the decomposition confirms that the TVC channel reduces the CSC effect with a fall in the decomposition share of skilled labor and capital equipment in equal magnitudes.

Table 4: Decomposition of Changes in the Model Skill Premium, Augmented KORV Model, 1963–2016

	L_s	L_u	K_e	ρ	Total
CSC effect	8.9%		43.7%		52.6%
RQ effect	23.8%	12.0%			35.9%
TVC effect				11.5%	11.5%
Total	32.8%	12.0%	43.7%	11.5%	100%

An alternative way to document the role of the TVC effect is to generate a counterfactual profile of skill premium had the estimate of ρ_t remained constant at ρ_0 while all other variables are allowed to change. Following our results in Section 5.3, we also generate a similar counterfactual profile for the labor share, setting ρ_t to remain constant at ρ_0. In Figure 8, these counterfactual profiles of skill premium and labor share are plotted against the actual profiles generated by the augmented KORV model. Panel A shows the model predicted skill premium, in the absence of the TVC effect, the capital-skill complementarity effect generates a much steeper profile of the skill premium post-1980. Panel B reports results for the labor share, where setting the elasticity of substitution between equipment capital and skilled labor at its initial level produces a labor share that follows a V-shaped profile with the early declining pattern followed by an increase starting in the early 1980s. Therefore, without the TVC effect, the model not only fails to match the magnitude of changes in skill premium but also misses the main features of labor share profile.

Figure 8: The effect of TVC on skill premium and labor share



Note: The left panel depicts the skill premium profiles with time-dependent $\rho_t = \rho_0 + \gamma_\rho t$ and constant $\rho = \hat{\rho_0} = -0.380$. The right panel compares labor share profiles with time-dependent $\rho_t = \rho_0 + \gamma_\rho t$ and constant $\rho = \hat{\rho_0} = -0.380$.

6 Discussion

We extend the KORV framework allowing for a flexible technology structure and let data dictate the trends in parameters of the model. Only the parameter that governs substitution between capital equipment and skilled labor, ρ, exhibits a substantial increasing trend, whereas other parameters of the model are remarkably stable over time. As seen in Section 5.3, the increase in ρ implies a decline in the degree of capital-skill complementarity of 49% between 1963 and 2016.

Our augmented KORV model delivers a good match for the skill premium and labor share patterns; whereas the original KORV model can only produce the former. Our decomposition exercise shows that the capital-skill complementarity effect is the dominant channel to explain the changes in skill premium. Around 52.6 percent of the variation in the skill premium is attributed to the capital-skill complementarity channel; the time-varying complementarity and relative supply effect channels explain 11.5 and 35.9 percent of the evolution in skill premium, respectively.

The decline in capital-skill complementarity implies that a decrease in the price of capital equipment will lead to a smaller increase in the demand for skilled labor in the later years. The decline in capital-skill complementarity may reflect the adoption and routinization of new technologies, which leads to a decline in comparative advantage of the skilled workers, as conjectured in Katz (2000), among others. Model developed in Greenwood and Yorukoglu (1997) shows how a technological advancement is followed by a transitory increase in the demand for skilled labor that is needed to implement the new technologies; following the initial adoption of the new technology, the relative demand for skilled labor declines towards its original steady state level. Castro and Coen-Pirani (2008) argue that such mechanism could provide a theoretical explanation for the decline in capital-skill complementarity. They show that a one-off decline in capital-skill complementarity in the mid 1980s can explain the increase in volatility of skilled hours since mid 1980s.

The idea of capital maturity following the IT revolution is also adopted in Beaudry et al. (2016) who argue that in the early 2000s the demand for cognitive tasks or high educational skill underwent a reversal. This reversal lead to high-skilled workers moving down the occupational ladder and performing jobs traditionally done by lower-skilled workers and can explain the decline in labor market outcomes after 2000 more generally. Occupational transition of high-educated workers to jobs which require less education can explain the observed decline in capital-skill complementarity.

We show that both versions of the KORV model, with and without time-varying capital-skill complementarity, deliver a good fit for the skill premium, wage-bill ratio and are consistent with the observed rates of return on equipment capital. However, the KORV model without a declining trend in capital-skill complementarity cannot explain the decline in labor share, whereas a model with the trend can. Ohanian, Orak, and Shen (2021) and Maliar, Maliar, and Tsener (2020) estimate the KORV model for the extended time period with fixed parameters and show that it performs well in explaining the changes in skill-premium over time; however, neither study can explain the declining pattern in labor share.[16] The standard KORV model produces an increasing or constant labor share in the later period due to the decline in the price of equipment and the fixed complementarity between capital equipment and skilled labor.

We use the KORV framework to analyze the decline in labor share in the second half of the period. The decline in labor share is widely documented, start-

[16]We follow KORV specification and construct gross labor share; Ohanian, Orak, and Shen (2021) distinguish between gross and net labor share, where the latter is a ratio of labor income to total income minus capital depreciation. The gross labor share has been trending down since the 1990s; whereas there is no significant decline in the net labor share.

ing with studies by Elsby et al. (2013) and Karabarbounis and Neiman (2014). Karabarbounis and Neiman (2014) and Piketty and Zucman (2014) argue that if labor and capital are gross substitutes, such that the aggregate substitution elasticity between capital and labor is greater than one, the investment-specific technological change will lead to the decline of the labor share because firms will shift from labor to capital. In our specification, a sufficient condition would be that both elasticities of substitution are greater than one. Our empirical estimations show that this is not the case. The estimated parameters from the original KORV period imply an increase in the labor share of income in the more recent decades. The loss of income of the unskilled labor outweighs the gains of skilled labor when there is a decline in capital-skill complementarity in the later years. Similar conjectures are made in Balleer and Van Rens (2013), who posit that the aggregate elasticity of substitution between capital and skill may vary with the task composition of the workforce and argue that since 1990s, technological improvements in capital substituted skilled workers more than unskilled workers.

We show that the decline in complementarity between skilled labor and equipment capital can account for the decline in the labor share of income. The mechanisms outlined in Greenwood and Yorukoglu (1997) and Beaudry et al. (2016) can explain the observed decline in capital-skill complementarity. This mechanism also predicts a depressed price of labor across skill levels, consistent with the observed patterns of skill premium.[17]

[17] According to Beaudry et al. (2016), the downward demand shift for cognitive tasks after 2000 led to: decreased employment and labor prices in the cognitive sector; decreased employment and prices in the routine sector, increased employment and lower prices the manual sector; and overall

A number of recent studies examine the role of shift in occupational composition of the workforce on declining labor share. This stream of literature builds on the idea that digital technologies and globalization make it easy for employers to replace workers doing routine tasks. For example, Orak (2017), Eden and Gaggl (2018) and vom Lehn (2018), apply the KORV methodology and find that a large portion of the decline in labor share is due to the replacement of workers engaged in routine occupations. However, occupational shift is less likely to explain the decline in complementarity between skilled labor and equipment capital since skilled (college-educated) workers are less likely to occupy routine jobs (manual and cognitive). For example, Acemoglu and Autor (2011) show that routine cognitive tasks are used most intensively by high school and some-college workers but not by college or higher educated workers. Since in KORV and in our specification skilled workers are defined as those with 16 or more years of schooling, the decline in demand for routine tasks is less likely to explain the decrease in capital-skill complementarity.

7 Conclusions

Since Krusell, Ohanian, Ríos-Rull, and Violante (2000), the notion of capital-skill complementary has been firmly embedded into the macroeconomics literature. We revisit the validity of the capital-skill complementarity theory by including more recent decades that witnessed several major structural changes. Since

decreased employment rates as the least skilled leave the market.

KORV, there were significant changes in production processes, workplace environment and labor markets, which were accompanied by a continued increase in skilled labor, a slowdown in skill premium and a decline in labor share. The predictions of the original KORV model with capital-skill complementarity are broadly consistent with the rising skill premium patterns in recent decades, however, the model falls short of predicting the decline in labor share. We extend the model to allow for time-varying parameters; the capital-skill complementarity hypothesis holds throughout the period we consider; however, we find that the degree of complementarity between capital and skilled labor attenuates over time. The decline in capital-skill complementarity offers some possible explanations for the declining aggregate labor share phenomenon in the recent times.

The decline in capital-skill complementarity implies that a decrease in the price of capital equipment will lead to a smaller increase in the demand for skilled labor in the later years. The decline in capital-skill complementarity is consistent with the process of adoption and routinization of new technologies, which leads to a decline in comparative advantage of the skilled workers; it is also consistent with the documented reversal in demand for skilled workers (see, for example, Beaudry et al. (2016)).

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A Estimation method - SPMLE

We follow the estimation method used in Krusell, Ohanian, Ríos-Rull, and Violante (2000), developed by Laroque and Salanie (1989). The model is estimated using the simulated pseudo-maximum likelihood (PSMLE) method.[18]

We simulate the latent labor efficiency in the first step (2×1 vector). In the second step we combine the labor efficiency vector with the non linear function and estimate the likelihood function. The nonlinear latent variable model is as follows:

$$SE : \varphi_t = \varphi_0 + \gamma_\varphi t + \omega_t \tag{A.1}$$

$$ME : Z_t = f(X_t, \psi_t, \phi) \tag{A.2}$$

The state equation, SE, corresponds to the functional form and parameters of labor efficiency vector. The measure equations, ME, correspond to 3 structural equations described in equations (9) to (11), the labor share, wage bill ratio and the non arbitrage condition.

The first stage of the simulation requires to draw ω_t from its distribution and construct the time series for labor efficiency. We perform this simulation $S = 5000$ times. At the second step, we draw the error term from the non arbitrage condition, equation (11), and build the measurement equations, ME. We compute the first and second moments of the simulated distribution as follows:

[18]For details on performance of alternative estimation methods for nonlinear latent production function, see Ohanian, Violante, Krusell, and Ríos-Rull (2000).

$$m_S(X_t;\phi) = \frac{1}{S}\sum_{i=1}^{S} f(X_t, \psi_t^i, \varepsilon_t^i, \phi) \tag{A.3}$$

$$V_S(X_t;\phi) = \frac{1}{S-1}\sum_{i=1}^{S}(Z_t - f(X_t, \psi_t^i, \varepsilon_t^i, \phi))(Z_t - f(X_t, \psi_t^i, \varepsilon_t^i, \phi))' \tag{A.4}$$

The simulated pseudo likelihood as a function of the parameter space, ϕ, is:

$$l_S(Z^T, X^T;\phi) = \frac{1}{2T}\sum_{t=1}^{T}\{(Z_t - m_S(X_t;\phi))' V_s(X_t;\phi)^{-1}(Z_t - m_S(X_t;\phi)) + \log\det V_s(X_t;\phi) \tag{A.5}$$

The data used in our estimations is reported in the Section 4. Estimation results are displayed in the Section 5.

B Labor Data

To construct the wage and hours data for different experience/education groups we follow Krusell et al. (2000). The main source of the data is the Annual Social and Economic Supplement of the Current Population Survey (CPS) from 1962 to 2017. The raw CPS sample contains approximately 5.5 million observations, 50,000 to 160,000 observations per year. To construct the dataset, we use age, sex, race, education, weeks worked last year, hours worked last week, income from wage or salary last year, and the CPS sampling weights. We eliminate observations with missing weeks worked and exclude those with no income from salary or wages.

For each individual, the CPS reports income and weeks worked last year and hours worked last week. Prior to 1976, weeks worked last year are reported in 6 intervals, we impute the weeks worked last year based on weighted observations of individuals with similar characteristics in 1976–1985 within the weeks intervals. Hours worked last week are more likely to have missing entries. Similarly to Krusell et al. (2000) we impute missing values. Hourly wages are calculated using annual real income divided by annual hours. For imputation purposes, we divide the raw March CPS data into 264 groups, consisting of 11 age groups (5 years/group), 3 race groups (white, black and other), 2 gender groups and 4 education groups (less than high school, high school, some college and college or more). For each group we calculate the weighted average of weeks worked using data between 1976–1985, ignoring individuals with missing or zero weeks worked. Some individuals report working zero hours last week and strictly positive weeks last year. For these individuals we calculate weighted average of weeks worked last week within each age-race-gender-education group.

To construct the schooling variable, we convert information on the highest grade completed into years of schooling. Schooling information is not available in 1962 and we exclude this year from the analysis. We define a worker as skilled if he/she has 16 or more years of schooling. We construct hourly wages and labor inputs for each type of labor.

For each type of labor we construct the average wage and labor inputs. Labour inputs are constructed as sums of total annual hours of all individuals in the relevant skill group weighted using the CPS weights and the average wage of the relevant demographic group in 1980. Assuming that wage represents worker's marginal product, the latter weighting allows for productivity differences in labor inputs per hour across individuals.[19] To construct labor input we use the following formula,

$$L_{j,t} = \sum_{g \in G_j} l_{g,t} w_{g,1980} \mu_{g,t}, \tag{B.1}$$

where l are annual hours, w are wages, μ are CPS weights, j is an indicator of skill, t is time, and g is the demographic group. Wages are constructed as follows,

$$W_{j,t} = \frac{\sum_{g \in G_j} w_{g,t} l_{g,t} \mu_{g,t}}{L_{j,t}}. \tag{B.2}$$

Income and weeks worked data refer to last year therefore the actual sample period is 1961–2016. Wage rates are in 1999 dollars (deflated using the CPI).

C Estimates

Table C.1 displays the full set of parameter estimates including standard errors in parentheses for the original KORV and augmented KORV specifications in Section 5.1 and Section 5.3, respectively.

[19] Different productivity weights were considered, using 1980, 2000 and 2007 hourly wages. We also consider a measure of labor inputs where we abstract from productivity differences, i.e., setting this weight to 1. There were no substantial differences in the results. We chose the 1980 series to be consistent with Krusell et al. (2000).

Table C.1: Parameter estimates (1963–2016)

	(1) Original KORV	(2) Augmented KORV
σ	0.486	0.462
	(0.015)	(0.037)
α	0.110	0.111
	(0.001)	(0.001)
λ	0.430	0.414
	(0.003)	(0.003)
μ	0.352	0.384
	(0.038)	(0.178)
φ_u	6.202	5.927
	(2.443)	(14.164)
ρ	-0.208	–
	(0.092)	
ρ_0	–	-0.380
		(0.243)
γ_ρ	–	0.008
		(0.000)

Note: Column 1 displays the parameter estimates of the KORV model for the full sample period. Column 2 displays the parameters of the augmented model, when the elasticity of substitution between capital equipment and skilled labor is allowed to change over time. Standard errors in parenthesis.

Table C.2 displays the full set of parameter estimates for the rolling window results in Section 5.2.

Table C.2: Parameter estimates (Rolling window)

Period	σ	λ	ρ	μ	φ_u	α
1963 –1992	0.428	0.389	-0.384	0.352	6.435	0.110
1964 –1993	0.433	0.391	-0.374	0.325	6.688	0.108
1965 –1994	0.440	0.394	-0.356	0.385	6.048	0.107
1966 –1995	0.455	0.397	-0.344	0.318	6.657	0.107
1967 –1996	0.465	0.403	-0.318	0.375	6.063	0.106
1968 –1997	0.474	0.410	-0.286	0.361	6.165	0.107
1969 –1998	0.482	0.417	-0.256	0.348	6.243	0.106
1970 –1999	0.484	0.420	-0.240	0.371	6.018	0.106
1971 –2000	0.471	0.420	-0.235	0.373	6.021	0.106
1972 –2001	0.458	0.419	-0.242	0.380	5.969	0.105
1973 –2002	0.436	0.417	-0.243	0.368	6.115	0.105
1974 –2003	0.379	0.419	-0.202	0.373	6.162	0.105
1975 –2004	0.368	0.421	-0.193	0.378	6.111	0.105
1976 –2005	0.363	0.422	-0.187	0.368	6.227	0.105
1977 –2006	0.362	0.422	-0.190	0.396	5.893	0.105
1978 –2007	0.365	0.421	-0.193	0.388	5.970	0.105
1979 –2008	0.366	0.422	-0.189	0.389	5.945	0.105
1980 –2009	0.363	0.423	-0.182	0.349	6.407	0.106
1981 –2010	0.362	0.424	-0.179	0.383	5.991	0.106
1982 –2011	0.369	0.424	-0.168	0.356	6.297	0.107
1983 –2012	0.377	0.423	-0.157	0.344	6.418	0.108
1984 –2013	0.389	0.421	-0.132	0.360	6.207	0.109
1985 –2014	0.400	0.420	-0.101	0.359	6.194	0.111
1986 –2015	0.408	0.418	-0.068	0.355	6.211	0.114
1987 –2016	0.416	0.415	-0.024	0.400	5.737	0.116