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Revisiting capital-skill complementarity, inequality, and labor share [☆]

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ABSTRACT

This paper analyzes the quantitative contribution of capital-skill complementarity in accounting for rising wage inequality, as in Krusell, Ohanian, Rios-Rull, and Violante (KORV, 2000). We study how well the KORV framework accounts for more recent data, including the large changes in labor's share of income that occurred after the KORV estimation period ended. We also study how using information and communications technology (ICT) capital as the complementary capital stock affects the model's implications for inequality and overall model fit. We find significant evidence for continued capital-skill complementarity across all model permutations we analyze. Despite nearly 30 years of additional data, we find very little change to the original KORV estimates of substitution elasticities when the total stock of capital equipment is used as the complementary capital stock. We find much more capital-skill complementarity when ICT capital is used. The KORV framework continues to closely account for rising wage inequality through 2019, though it misses the three percentage points decline in labor's share of income that has occurred since 2000.

1. Introduction

Krusell et al. (2000) (KORV, henceforth) found that empirically plausible differences in substitution elasticities between skilled labor and capital equipment, and unskilled labor and capital equipment, coupled with rapid growth in the stock of quality-adjusted capital equipment, can largely account for changes in the U.S. skill premium from 1963 to 1992. Krusell et al. (2000) thus provided a theory of skill-biased technological change, showed how to measure that change, and quantified its importance in understanding wage inequality.

KORV's production technology and substitution elasticity estimates continue to be used by other researchers studying inequality and related labor market topics, and the conclusions of Krusell et al. (2000) regarding the importance of capital-skill complementarity continue to be cited in the literature. However, there have been a number of important changes since

☆ Previously titled as "Capital-Skill Complementarity, Inequality, and Labor's Share of Income, 1963-2013" (Ohanian and Orak, 2016). We thank Loukas Karabarbounis, two referees, and Gianluca Violante for very helpful comments. The views in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or of any other person associated with the Federal Reserve System.

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1992 that may affect the estimated elasticities of KORV and the quantitative importance of capital-skill complementarity in accounting for wage inequality.

One key change is that information, communications, and other advanced technologies that in part motivated the conceptual basis for the KORV production function, have advanced enormously since 1992.[1] To put some of these changes in perspective, we note that in 1992, the last year of the KORV estimation period, Lotus 1-2-3 was one of the most popular and sophisticated business software programs, and smart phones, online commerce, cloud computing, 3-D printing, and the portable document formatting technology (PDF), among many other technologies used today had not yet arrived.

Another important change is that labor's share of income, which is a moment condition in the Krusell et al. (2000) estimation, and which was quite stable in their 1963-1992 estimation period, has declined significantly since 1992.

Yet another change is that depreciation rates have increased and have become more volatile since 1992. Depreciation not only affects the accumulation of capital stocks, but also affects one of the moment conditions in the Krusell et al. (2000) estimation, which in turn may affect the estimated elasticities.

This paper studies the KORV framework in light of these changes. To our knowledge, this paper provides the most comprehensive assessment of this framework's empirical performance, with a focus on its ability to account for the skill premium and labor's share of income.

We update the KORV dataset through 2019, estimate the model parameters, and analyze the model fit and its implications for the skill premium.

To address changes in depreciation rates since 1992, we conduct the analysis with both time-varying and constant depreciation rates. To address the decline in the labor share, we use labor income measured using gross output and using output net of depreciation, as well as using income from the non-farm business sector. To address the remarkable technological advances in some forms of capital equipment, we specify the complementary capital stock to skilled labor as Information-Communications-Technology (ICT) capital, as well as use the KORV baseline specification of total equipment capital.

As in Krusell et al. (2000), the model's skill premium is not part of the model's estimation, but rather is an outcome of the estimated parameters and data. We find that the estimated elasticities of Krusell et al. (2000) have changed little since 1992; and are robust to changes in depreciation measurement,measurement of labor share, and the type of capital that is most complementary to skilled labor. We find that KORV framework continues to account for much of the U.S. skill premium through 2019.

However, the model's fit for the labor share deteriorates when more recent data are applied in the analysis. This arises because capital-skill complementarity, combined with even faster capital-biased technological change measured in recent data, tends to increase the model's labor share by driving up the productivity of skilled labor.

We therefore frame the three modifications to Krusell et al. (2000) that we study - ICT capital as the complementary capital stock, different measures of labor's share of income, and changes in capital depreciation rates - as potential avenues for understanding the model's labor share deviation. We also use generalized method of moments (GMM) as an alternative estimation method to KORV's full-information likelihood-based method to assess whether KORV's estimator is affecting the model's ability to account for the labor share.

We find that changing the concept of capital-skill complementarity from equipment capital, as in Krusell et al. (2000), to ICT capital captures much of the skill premium over the entire period and modestly improves the model's fit of the labor share, accounting for about half of the drop in labor's share between the early 1960s and 2019. However, the model does not capture the much more recent declines in labor's share that occurred in the last 15 years.

The rest of the paper proceeds as follows. Section 2 summarizes related literature. Section 3 summarizes the data and its construction. Section 4 presents the theoretical model, and Section 5 presents the quantitative analysis. Section 6 presents a summary and conclusion.

2. Related literature

Our paper contributes to several strands of literature with Krusell et al. (2000), whose elasticity estimates have been used widely, being the most obvious one. Polgreen and Silos (2008) analyzed the KORV study using data through 2004, and found that capital-skill complementarity is robust to alternative approaches to constructing the real stock of capital equipment. An earlier version of this research (Ohanian and Orak (2016)), which has evolved into this paper, re-estimated the KORV framework and studied its fit through 2013, finding continued evidence of capital-skill complementarity. It also noted the deviation of KORV framework in accounting for the labor share after 1992. Building off of our 2016 analysis, this paper focuses on how the KORV framework can confront the post-1992 decline in labor's share, using alternative definitions of output, depreciation, labor's share, estimation techniques, and the conceptual measure of the complementarity capital stock.

Maliar et al. (2020) and Maliar et al. (2022) re-estimated the KORV model and studied its fit with data through 2017, also confirming capital-skill complementarity. They used their estimates to predict the future evolution of wage inequality. They

[1] The growth rate of the relative price of equipment capital, a proxy for the inverse of equipment-specific technological progress, has averaged negative 6.4 percent per year after 1992, compared to negative 4.2 percent observed during 1963–1992.

forecast that the skill premium will continue to grow up to 2037, albeit at a slower rate. However, unlike this paper, their paper does not focus on addressing the decline in labor's share within the KORV framework. Additionally, their estimation generates model rates of return to capital investment that are much too high, ranging between 30 to 50 percent over the full period (see Maliar et al. (2022), Figure 4). These returns are much higher than observed returns to capital investment over this period (see, for example Marx et al. (2019) and Jordà et al. (2019)), and are also much higher than the average model-generated returns in Krusell et al. (2000) (around 4 percent) and in this paper (ranging between 8 to 12 percent in the baseline estimation).[2] The size of investment returns has important implications for the skill premium because such excessively high returns would be expected empirically to lead to much more investment, which in turn would significantly widen the skill premium through capital-skill complementarity.

One factor that is contributing to substantially higher returns in their paper is that they estimate a higher value for the parameter governing the income share of structures capital in the model, nearly 0.2, compared to our estimate of 0.11, which is similar to the estimate in Krusell et al. (2000), and to the income share of structures capital in Greenwood et al. (1997). However, this difference alone cannot account for the very high returns their model generates, and we are unaware of other differences in their analysis that would deliver such high returns.

The paper also relates to the literature on factor income shares. Labor's share of gross income in the United States has been declining in recent years (see, for instance, Karabarbounis and Neiman (2014b) and Armenter (2015)). Karabarbounis and Neiman (2014b) study changes in the labor share across a panel dataset including 56 countries, and analyze this dataset using a model in which rapid productivity growth in capital goods, which in turn decreases the relative price of capital goods, incentivizes producers to substitute away from labor input into capital input within a production technology in which labor and capital are more substitutable than Cobb-Douglas. This substitution away from labor to capital decreases labor's share of income. Quantitatively they find that the observed long-run decline in investment goods prices accounts for about half of the change in labor share, even after allowing for other mechanisms, including changes in monopoly rents and changes in the skill composition of workers. Other factors studied within this literature include, trade and offshoring (Elsby et al. (2013)), foreign direct investment in inflows and mechanization (Guerriero and Sen (2012)), structural change and heterogeneity (Alvarez-Cuadrado et al. (2015)), a global productivity slowdown (Grossman et al. (2018)), and increasing concentration within industries (Dorn et al. (2017)). This paper connects the declining labor share to technological change, including Orak (2017), who links the decline in labor's share to technological change and the resulting shift in the occupational composition of the workforce; vom Lehn (2018), who explains the decline with replacement of workers engaged in routine (repetitive) occupations (job polarization); Eden and Gaggl (2018), who attribute half of the decline to the rise in the income share of ICT capital, using a framework distinguishing between ICT and non-ICT capital; and Eden and Gaggl (2019), who show that more than one quarter of the global decline in the labor share can be explained by a change in capital composition that works through automation. Analyzing the KORV framework after 1992 allows the model to confront these observations and analyze their quantitative importance in estimating the production function parameters.

There are also several studies suggesting that the decline in labor's share is less significant once some factors, such as a significant rise in housing capital (Rognlie (2015)); capitalization of intellectual property products (Koh et al. (2015)); a substantial rise in equity-based compensation (Eisfeldt et al. (2022)); and depreciation and taxes (Bridgman (2018)), are netted out.[3] Sherk (2016) argues that the decline in labor's share reflects how increased depreciation of capital and the income of the self-employed are accounted for. Given these issues regarding gross and net income, we construct a measure of net labor share to use in the analysis, which is indeed more stable than the gross labor share.[4]

3. Data

We construct capital stocks and labor inputs between 1963 and 2019 along the lines of Krusell et al. (2000). We collected equipment (including intellectual property products) and structures investment series from the National Income and Product Accounts (NIPA) and used the perpetual inventory method to construct capital stocks following the formula below:

$$Final\ inventory = Beginning\ inventory * (1 - Depreciation\ rate) + investment.$$

We obtain structures investment from NIPA Table 5.2.5, then use the implicit GDP price deflator to generate real investment levels for each year.[5] The quarterly data are transformed into an annual series via simple averaging.

As Krusell et al. (2000) point out, many economists (see, for example, Gordon (1990)) argue that, despite the BEA's best efforts, NIPA substantially understates the increases in quality of durable goods over time, including capital equipment, which in turn overstates the rate of price inflation among these goods. We follow Krusell et al. (2000) and use the deflator

2 Marx et al. (2019) report that return on U.S. productive capital has increased from 6 percent in 1980s to around 10 percent in late 1990s, before falling back to around 8 percent by 2010. Jordà et al. (2019) find the post-1980 real return on U.S. risky assets to be near 7 percent.

3 Note that Karabarbounis and Neiman (2014a) also analyze the labor share of gross income and of income net of depreciation, but they conclude that there is a declining trend in both labor share series on a global scale. However, Bridgman (2018) and our study focus solely on U.S. data.

4 KORV's measure of the gross labor share already excluded self-employment.

5 U.S. Bureau of Economic Analysis, Gross Domestic Product: Implicit Price Deflator [GDPDEF], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/GDPDEF.

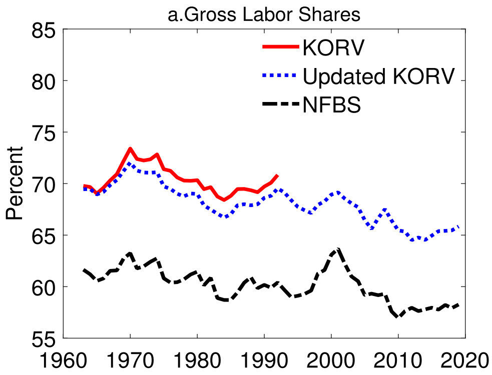


Fig. 3.1. Labor shares. (For interpretation of the colors in the figure(s), the reader is referred to the web version of this article.)

of the equipment investment series provided by DiCecio (2009), which are constructed following the procedure pioneered by Gordon (1990) and Cummins and Violante (2002).[6,7]

When constructing the capital stock series, we use time-varying depreciation rates, which we calculate from the NIPA tables by dividing the current cost capital consumption series by current cost capital stock series. This choice is motivated by the fact that the depreciation rates of equipment capital have risen significantly since the original KORV study (see Fig. 3.3), particularly during the technological boom period of late 1990s and early 2000s. Thus, time-varying depreciation rates may give a more accurate measure of the actual capital stock in any particular year than using an average rate. Alternatively, we use constant depreciation rates as in KORV, but calculate the average values using the most recent data.

3.1. Labor inputs and wage rates

As in Krusell et al. (2000), we specify skilled and unskilled labor based on educational attainment. The data are drawn mainly from the Current Population Survey (CPS) March Supplement, now called the Annual Social and Economic (ASEC) Supplement, integrated by IPUMS (Flood et al. (2015)) for the years 1963 through 2019. We use all of the person-level data, excluding those who are younger than 16 or older than 70, unpaid family workers, and those working in the military (together with other institutionalized population) to maintain comparability with earlier studies, including Katz and Murphy (1992) and Krusell et al. (2000). Although we drop the self-employed from our wage sample, we include them when constructing labor input series. We also drop the observations of those who report working less than 40 weeks or 35 hours a week or both from the wage sample as it is standard in the related literature. Finally, we exclude individuals with allocated income, those with hourly wages below half of the minimum federal wage rate, and those whose weekly pay was less than $62 in 1980 dollars to remove outliers and misreporting. A detailed description of the construction of labor input and hourly wages is in the Appendix A.1.

3.2. Labor share

We construct our labor share series using the BEA NIPA tables. To facilitate comparison with Krusell et al. (2000), we begin by using their definition of labor share, which is constructed in a manner similar to what Cooley and Prescott (1995) describe. As such, we define labor share as the ratio of labor income (wages, salaries, and benefits) to the sum of labor income plus capital income (depreciation, corporate profits, net interest, and rental income of persons). This is our benchmark definition and is called the “KORV definition.” As an alternative, we also use the nonfarm business sector (NFBS) labor share, which is the most commonly used definition in the labor share literature. The data construction is in Appendix A.2, and we also report some of the findings with this alternative definition in Appendix C. As shown in the top left panel of Fig. 3.1, although the (gross) labor share was nearly flat in KORV’s data, it has been trending down since that time. Apart from level differences, both the KORV and NFBS labor shares show this pattern, though the decline is less pronounced for the NFBS labor share.

While the declining labor share has been considered one of the most striking and puzzling features of the recent U.S. economy, some claim that the decline reflects increased depreciation of capital (see, for example, Sherk (2016)). To analyze how netting out depreciation affects our findings, we construct an alternative measure of labor share that subtracts depreciation from gross income, which we then use to construct the labor share of net income. As seen in the right panel of Fig. 3.1, these net measures of labor share do not exhibit a significant trend decline, though they are very volatile.

[6] DiCecio, Riccardo, Equipment Deflator [EDEF], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/EDEF.

[7] Fig. C.1 in the Appendix C compares the NIPA equipment price series with that of DiCecio (2009).

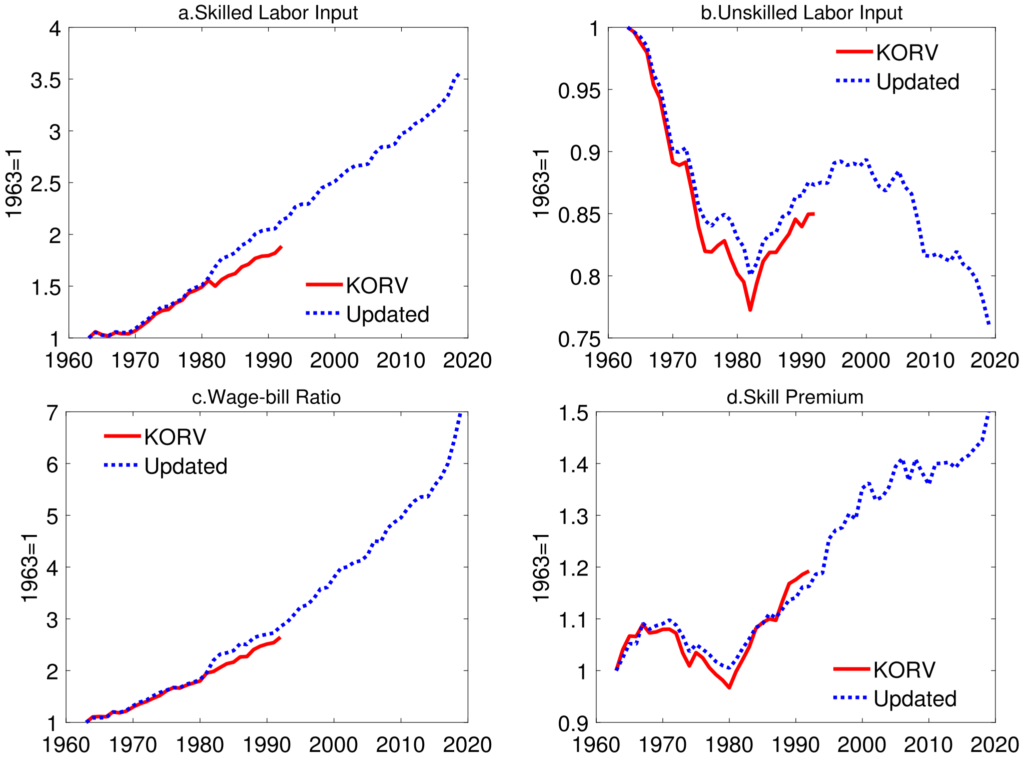


Fig. 3.2. Comparison of the original KORV data with updated labor data.

3.3. Summary of the data

Fig. 3.2 presents the evolution of the labor data from 1963 through 2019, along with a comparison to the original KORV data. Skilled labor input (panel a) has been continuously rising since the early 1970s, while unskilled labor input (panel b) declined by almost 25 percent over the 1963-2019 period. These patterns are largely in line with what KORV documented for the 1963-1992 period, though there is a level shift in skilled labor input (reflecting data revisions) beginning in 1982 relative to KORV.[8] The wage-bill ratio, which is the ratio of the labor income of skilled labor to that of unskilled labor, has continued to increase (panel c). More specifically, we construct the wage-bill ratio as the ratio of the product of average wage and total hours of the skilled labor (as constructed in Appendix A) to that of the unskilled. Finally, income inequality has continued to widen since KORV's study, with the skill premium rising from a normalized level of about 1.2 in 1992 (the final year of KORV) to about 1.5 in 2019 (panel d).

Fig. 3.3 presents the evolution of the capital stock data over the 1963-2019 period, with a comparison to the original KORV data when applicable. Consider first panel a, which shows the growth rate of the relative price of equipment capital, which in the model is equal to the inverse of the equipment-specific technology parameter. The decline in the relative price of equipment capital accelerated during the late 1990s and early 2000s, which is commonly cited as the "IT Boom" period. Since 1992, the growth rate of the relative price of equipment capital has averaged about negative 6.4 percent per year, compared with the negative 4.2 percent observed during the period of the original Krusell et al. (2000) study. This indicates faster technological progress in equipment after 1992, which coincides with a rising depreciation rate (panel b) and an acceleration of the increase in the stock of equipment capital (panel c). By 2019, the stock of equipment capital is more than eighty times larger than its 1963 level, whereas the stock of structures is only about 4.7 times larger in 2019 than in 1963 (panel d).

4. Model

4.1. Model environment

We use the same theoretical framework as Krusell et al. (2000). There are four factors of production: structures (k_{st}) and equipment (k_{eq}) capital; and skilled (s) and unskilled (u) labor inputs. These inputs are combined using a nested CES

8 Other studies replicating KORV data, including Polgreen and Silos (2008) and Maliar et al. (2020), have documented a similar level shift.

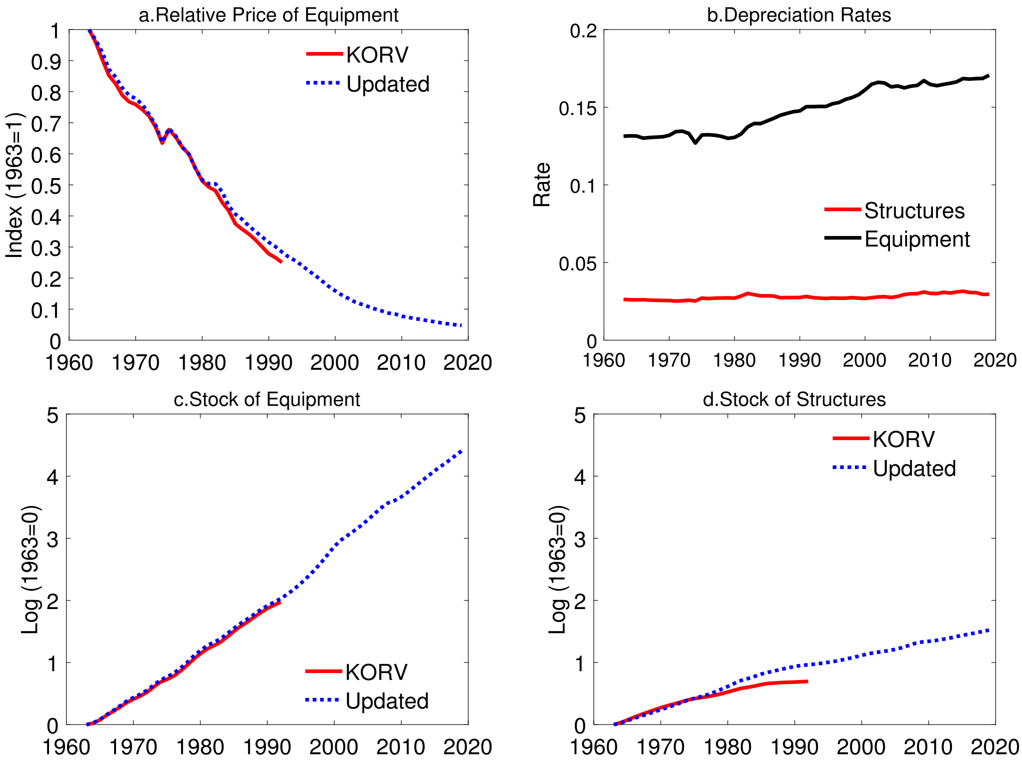


Fig. 3.3. Comparison of original KORV data with the updated capital data.

aggregate production function that allows different substitution elasticities between unskilled labor input and the composite output of equipment capital and skilled labor input, and between equipment capital and skilled labor input.

There are three final goods in the economy: consumption (c), investment in structures capital (i_{st}), and investment in equipment capital (i_{eq}). Consumption and structures capital are produced using the same constant returns to scale technology, and prices of both are normalized to one, as is standard in the literature. Of note, the growth rates of prices of consumption and structures are almost perfectly correlated in the data, as shown in Fig. C.2 in the Appendix C.

There is equipment-specific technological change in which one unit of the final good that is invested in equipment produces q_t units of equipment capital, where q_t is equipment-specific productivity.

Perfect competition guarantees that

$$p_{eq,t} = \frac{1}{q_t}, \tag{4.1}$$

where $p_{eq,t}$ is the relative price of equipment capital, and its inverse is used as the proxy for equipment-specific technological progress.

Given competition and constant returns to scale, the aggregate resource constraint for this economy is as follows:

$$Y_t = c_t + i_{st,t} + \frac{i_{eq,t}}{q_t} = A_t G\left(k_{st,t}, k_{eq,t}, h_{u,t}, h_{s,t}, \delta_{eq,t}, \delta_{st,t}; \Upsilon\right), \tag{4.2}$$

where Y is the final good, h_u, and h_s are raw unskilled and skilled labor units, respectively. A denotes neutral technological change. Finally, Υ is the set of model parameters, which is detailed below.

4.2. Production technology

Following Krusell et al. (2000), we use the CES aggregate production function below:[9]

$$G\left(k_{st,t}, k_{eq,t}, h_{u,t}, h_{s,t}, \delta_{eq,t}, \delta_{st,t}; \Upsilon\right) = k_{st,t}^{\alpha}\left(\mu u_t^{\sigma} + (1-\mu)\left[\lambda k_{eq,t}^{\rho} + (1-\lambda)s_t^{\rho}\right]^{\frac{\sigma}{\rho}}\right)^{\frac{1-\alpha}{\sigma}}. \tag{4.3}$$

[9] Krusell et al. (2000) argue that an alternative nesting that would restrict the elasticity of substitution between unskilled labor and equipment capital to be the same as that between skilled labor and equipment capital is not consistent with data. Orak (2017) reports a similar finding.

In equation (4.3), u_t and s_t, efficiency hours for the respective skill groups, are defined as follows:

$$u_t = e^{\varphi_{u,t}} h_{u,t} \tag{4.4}$$

$$s_t = e^{\varphi_{s,t}} h_{s,t}. \tag{4.5}$$

The model has the following set of parameters to be estimated: $\Upsilon \in \{\sigma, \rho, \alpha, \mu, \lambda \varphi_u, \varphi_s\}$. Here, μ and λ are parameters governing the factor shares. The parameter α is the income share of structures capital. φ_u and φ_s are the efficiencies of unskilled and skilled labor, respectively. The parameters σ and ρ govern the elasticities of substitution between equipment capital and the two types of labor input. Following Krusell et al. (2000), the elasticity of substitution between equipment capital and skilled labor input is $\frac{1}{1-\rho}$. The elasticity of substitution between unskilled labor input and the CES composite of equipment capital and skilled labor is $\frac{1}{1-\sigma}$. Holding other factors constant, the elasticity of substitution between unskilled labor and equipment is also $\frac{1}{1-\sigma}$.[10]

Krusell et al. (2000) show that capital-skill complementarity requires $\sigma > \rho$ (equivalently, $\frac{1}{1-\sigma} > \frac{1}{1-\rho}$). This implies that equipment-specific technological progress increases the relative demand for skilled labor input, and depresses the relative demand for unskilled labor.

4.3. The model skill premium

Given perfect competition, the firm's problem is:

$$\Pi_t = Y_t - r_{st,t} k_{st,t} - r_{eq,t} k_{eq,t} - w_{u,t} h_{u,t} - w_{s,t} h_{s,t}, \tag{4.6}$$

where $r_{st,t}$ and $r_{eq,t}$ are the rental rates of structures and equipment capital, respectively. Similarly, $w_{u,t}$ and $w_{s,t}$ denote the wage rates of unskilled and skilled labor at time t.

The skill premium at time t is:

$$\pi_t = \frac{w_{s_t}}{w_{u,t}} = \frac{MPL_{s,t}}{MPL_{u,t}} = \frac{A_t G_{s,t}}{A_t G_{u,t}},$$

where $MPL_{s,t}$ and $MPL_{u,t}$ are marginal products of skilled and unskilled labor inputs, respectively.

As presented in Krusell et al. (2000), the skill premium in this model is as follows:

$$\pi_t = \frac{(1-\mu)(1-\lambda)}{\mu} \left[\lambda \left(\frac{k_{eq,t}}{s_t} \right)^{\rho} + (1-\lambda) \right]^{\frac{\sigma-\rho}{\rho}} \left(\frac{h_{u,t}}{h_{s,t}} \right)^{1-\sigma} \left(\frac{\varphi_{s,t}}{\varphi_{u,t}} \right)^{\sigma}. \tag{4.7}$$

When equation (4.7) is log-linearized and differentiated with respect to time, one obtains:

$$g_{\pi_t} \approx \overbrace{(1-\sigma)(g_{h_{u,t}} - g_{h_{s,t}})}^{\text{relative quantity effect}} + \overbrace{\sigma (g_{\varphi_{s,t}} - g_{\varphi_{u,t}})}^{\text{relative efficiency effect}} \overbrace{+ (\sigma - \rho)\lambda \left(\frac{k_{eq,t}}{s_t} \right)^{\rho} (g_{k_{eq,t}} - g_{h_{s,t}} - g_{\varphi_{s,t}})}^{\text{capital-skill complementarity effect}}, \tag{4.8}$$

where $g_{j,t}$ denotes growth rate of variable j at time t.

As shown in equation (4.8), Krusell et al. (2000) decompose the growth in the skill premium into three components. The first component, the *relative quantity effect*, shows that when $\sigma < 1$, faster growth in skilled labor supply reduces the skill premium. The *relative efficiency effect* depends on the sign of σ. When $\sigma > 0$ ($\sigma < 0$), relatively faster growth of skilled labor efficiency drives the skill premium higher (lower). Finally, when there is *capital-skill complementarity effect*, meaning that $\sigma - \rho > 0$, faster growth in equipment capital relative to the supply of skilled labor input increases the skill premium. This effect would get smaller (larger) over time if $\rho < 0$ ($\rho > 0$).

5. Quantitative analyses

5.1. Estimation strategy

We estimate the model from 1963 through 2019 and we also estimate the model in sub-samples so we can compare the results to those from Krusell et al. (2000), who estimated the model from 1963 to 1992. As in Krusell et al. (2000), our

[10] Note that the KORV substitution elasticity definition assumes that all other factors are held constant. There are alternative definitions of the substitution elasticity between two factors in a production function that has more than three or more factors, including the Allen and Moroshima elasticities. Polgreen and Silos (2008) report that capital-skill complementarity also holds in the KORV framework for the Allen and Morishima elasticities, though the magnitudes are different. However, these distinctions in defining the substitution elasticity do not play a role in understanding the impact of capital deepening on wage inequality in the model. As we note immediately below, this depends on whether the value of $\sigma > \rho$.

baseline framework uses equipment capital as the capital stock that is complementary with skilled labor. As an alternative, we estimate the model using Information and Communication capital (ICT) as the complementary capital stock. We examine the model using this alternative measure of capital given the very rapid technological advances in this category of capital goods (e.g. computer hardware, software, telecommunications devices, etc.).

As noted above, we use the same empirical methodology as Krusell et al. (2000). This includes a two-stage simulated pseudo maximum likelihood estimation (SPMLE) procedure to estimate most of the model parameters. Appendix B describes this in detail. Since we later will find that the KORV framework will be challenged in capturing labor's share of income, we also estimate the parameters with generalized method of moments (GMM) methodology, which is more widely used than SPMLE and does not require the full likelihood of the model. Details are described in Appendix B.

For the SPMLE methodology, there are two stochastic elements to close the model and ensure that the likelihood is non-singular. This involves introducing stochastic components into the two labor inputs. Following Krusell et al. (2000), we specify the stochastic process as:

$$\varphi_t = \varphi_0 + \omega_t, \tag{5.1}$$

where φ_t is a 2×1 vector of the log of labor efficiencies for skilled and unskilled labor at time t, φ_0 is a 2×1 vector of constants that correspond to the average levels of efficiencies (efficiency levels in the absence of efficiency shocks), and ω_t is a 2×1 vector of labor efficiency shocks, which are assumed to have a multivariate normal distribution with zero mean and covariance matrix $\Omega = \begin{bmatrix} \eta_\omega^2 & 0 \\ 0 & \eta_\omega^2 \end{bmatrix}$, where η_ω^2 is the common variance of efficiency shocks. Note that, for comparability, we rule out trend growth for labor efficiencies as in Krusell et al. (2000).

The relative price of equipment capital is the second stochastic element. This price affects the rate of return to investment in equipment capital. Krusell et al. (2000) motivated this condition by hypothesizing a risk neutral investor, for whom arbitrage would equate the ex-ante expected returns on the two investments. Krusell et al. (2000) called this a "No Arbitrage" condition, and it is given as follows:

$$\underbrace{q_t A_{t+1} G_{eq,t+1} + (1-\delta_{eq,t+1}) E\left(\frac{q_t}{q_{t+1}}\right)}_{\text{ex-ante expected return on equipment capital}} = \underbrace{A_{t+1} G_{st,t+1} + (1-\delta_{st,t+1})}_{\text{ex-ante expected return on structures}}, \tag{5.2}$$

where $G_{eq,t+1}$ and $G_{st,t+1}$ are derivatives of function $G\left(k_{st,t}, k_{eq,t}, h_{u,t}, h_{s,t}, \delta_{eq,t}, \delta_{st,t}; \Upsilon\right)$ with respect to equipment and structures capital stocks at time $t+1$, respectively, and $\delta_{st,t}$ and $\delta_{eq,t}$ are the corresponding depreciation rates at time t. The first term on the left-hand side is the marginal product of equipment investment, and the second term is undepreciated equipment capital, adjusted by the expected change in its market price. The right-hand side terms are analogues for capital structures.

Equation (5.2) is one of the three equations used in the estimation. Krusell et al. (2000) developed this equation based on the idea of a risk neutral investor choosing between investing at the margin in equipment or structures, where both types of capital have the same tax treatment, and $(1-\delta_{eq,t+1})E\left(\frac{q_t}{q_{t+1}}\right) = (1-\delta_{eq,t+1})\frac{q_t}{q_{t+1}} + \epsilon_t$ with ϵ_t is assumed to be normally distributed with mean zero and variance η_ϵ^2. As such, we use the following form of equation (5.2) in the estimation:

$$0 = q_t A_{t+1} G_{eq,t+1} + (1-\delta_{eq,t+1}) E\left(\frac{q_t}{q_{t+1}}\right) - A_{t+1} G_{st,t+1} - (1-\delta_{st,t+1}) + \epsilon_t. \tag{5.3}$$

The other two equations used in the estimation are as follows:

$$\frac{w_{s,t} h_{s,t}}{w_{u,t} h_{u,t}} = wbr_t(X_t, \varphi_{u,t}, \varphi_{s,t}; \Upsilon) \tag{5.4}$$

$$\frac{w_{s,t} h_{s,t} + w_{u,t} h_{u,t}}{Y_t} = lshare_t(X_t, \varphi_{u,t}, \varphi_{s,t}; \Upsilon), \tag{5.5}$$

where the wbr_t is the wage-bill ratio and $lshare_t$ is the labor share at time t, both of which are obtained from model-implied marginal products of the skilled and unskilled labor inputs ($w_{s,t}$ and $w_{u,t}$, respectively). Each of these marginal products is a function of observable factor inputs $X_t = \left\{k_{st,t}, k_{eq,t}, h_{u,t}, h_{s,t}, \delta_{eq,t}, \delta_{st,t}\right\}$, unobservable labor efficiencies $\varphi_{u,t}$ and $\varphi_{s,t}$, and a set of parameters $\Upsilon = \{\sigma, \rho, \alpha, \mu, \lambda, \varphi_{u0}, \varphi_{s0}, \eta_\epsilon, \eta_\omega\}$.

The system is a nonlinear state space model with three observation equations $Z_t = f(X_t, \varphi_{u,t}, \varphi_{u,t}, \varepsilon_t; \Upsilon)$, and two state equations $\varphi_t = \varphi_0 + \omega_t$ (one for skilled and one for unskilled labor efficiency). Here, Z is a 3×1 vector of observables corresponding to equations (5.3) to (5.5). The right-hand sides of the equations are the model counterparts of the corresponding series implied by marginal products of inputs, observables, and estimated parameters and efficiencies.[11]

[11] The left-hand sides are: a vector of zeros for the no-arbitrage condition, the ratio of the product of average wage and hour of the skilled labor to that of the unskilled for the wage-bill ratio, and labor shares as constructed from the NIPA tables.

As in Krusell et al. (2000), we calibrate some of the parameters. Depreciation rates are obtained from the NIPA capital stock and capital consumption tables. Unlike Krusell et al. (2000), we use time varying depreciation rates in our benchmark analysis, as means and volatilities of these depreciation rates have increased since the Krusell et al. (2000) estimation period.

The depreciation rate of structural capital averages 0.0278, while the depreciation rate of equipment capital averages 0.1483 over the 1963-2019 period, beginning with 0.1311 in 1963 and rising up to 0.1706 in 2019. For simplicity, we assume the future depreciation rates in the case of time-varying depreciation are known. We will compare the results from time-varying depreciation to those with fixed depreciation below.

To calibrate η_ϵ, we estimate an ARIMA model for the growth rate of the relative price of equipment capital: $\hat{q}_t = \frac{q_{t-1}}{q_t}$. The estimated ARIMA model is $\hat{q}_t = 2.12 - 0.001t - 0.48\hat{q}_{t-1} + 0.58\epsilon_{t-1} + \epsilon_t$ with an estimated standard deviation of white-noise disturbance (σ_ϵ) of $= 0.0233$. As Krusell et al. (2000) do, η_ϵ is then calibrated as $(1 - \bar{\delta}_{eq})$ times σ_ϵ, where $\bar{\delta}_{eq}$ is the mean of the equipment capital depreciation rate. Using this calibration method, we set η_ϵ to $= 0.020$.[12]

Furthermore, because μ, λ, φ_{u0}, and φ_{s0} are scaling parameters, we normalize φ_{s0} as Krusell et al. (2000) do, setting it equal to 2.

The remaining parameters are estimated using the two-stage SPMLE method of Krusell et al. (2000), which is discussed in more detail in Appendix B. In the first stage, to allow for the possible dependence of labor input on shocks, we follow Krusell et al. (2000) and regress the labor inputs on the set of instruments they used: current and lagged stocks of both types of capital, the lagged relative equipment capital price, a time trend, and the lagged value of the index of leading business cycle indicators of the Conference Board. The fitted (instrumented) values are then used in the SPMLE stage.

As in KORV, we choose the value of η_ω that minimizes the joint sum of squared deviations between the skill premium and its model counterpart and between the ex-post returns on structures and equipment investments. Note that we do not view this parameter as having specific economic interest within the scope of this analysis; rather it is introduced to ensure a non-singular likelihood.[13]

The Krusell et al. (2000) estimation is complex, which in part is due to a number of latent exogenous variables within the likelihood function. We therefore also estimate the parameters using GMM, which does not use the full likelihood of the model.

To implement GMM, we use the same instruments as those used in the SPMLE estimation described above. We estimated the production function parameters α, σ, μ, ρ, and λ; and efficiency level of unskilled labor φ_u using the three moment conditions consisting of the wage-bill ratio, the labor share, and the no-arbitrage condition. As with SPMLE, we normalize φ_s at 2. Details of the GMM estimation are discussed in Appendix B.

5.2. Findings

This subsection presents the estimated parameters and model fit for the full 1963-2019 period as well as 1963-1992, the period analyzed by Krusell et al. (2000). Given recent changes in labor share and the large literature which has studied this change, we also estimate the model using two alternatives to Krusell et al. (2000), who use the standard measure of labor share of gross output. The alternatives are the share of labor income net of depreciation (as discussed in Bridgman (2018)) and nonfarm business sector (NFBS) labor income share, based on both gross output and output net of depreciation.

Because the findings are very similar to our baseline results when we use non-farm business sector output rather than real output of the business sector, we report parameter estimates and model fits for this case only in the Appendix (see Tables C.1 and C.2 and Figs. C.4, C.5 and C.6).[14] Although the parameter estimates change slightly in this case, capital-skill complementarity remains sizable and significant, as in the baseline case, which uses KORV's definition of the labor share.[15] When the nonfarm business sector labor share is used in the estimation, the model fit improves slightly for the skill premium and for the ex-ante no-arbitrage condition, though ex-post rates are somewhat larger than their empirical counterparts. In terms of the labor share, using the nonfarm business sector labor share brings no improvement (see Table 5.5).

Our baseline estimation involves time-varying depreciation rates to ensure consistency of data construction and model assumptions. However, because almost all macroeconomic models assume constant depreciation rates, we also estimated the baseline model using constant depreciation rates to check applicability of our results to general equilibrium models with standard assumptions for depreciation rates. The findings, which are reported in Appendix C (see Table C.3 and Fig. C.7),

12 When we estimate the ARIMA model for the 1963–1992 period, we obtain: $\hat{q}_t = 2.85 - 0.001t + 0.55\hat{q}_{t-1} - \epsilon_{t-1} + \epsilon_t$ with $\sigma_\epsilon = 0.0243$. By the same calibration strategy, we obtain $\eta_\epsilon = 0.021$ for this period.

13 As the working paper version of Krusell et al. (2000) (Krusell et al. (1997)) notes, if η_ω is estimated jointly with the rest of the parameters, the algorithm chooses a large value as it helps fit the difference between the two rates of return to capital in the mid-1970s when the relative price of equipment is extremely volatile and exhibits a very large spike in 1975. A very high value of η_ω, however, worsens the fit of the skill premium.

14 When using the nonfarm business sector labor share in estimation, we drop farm, households and government sectors when constructing wage and labor input data. The resulting skill premium series are highly correlated for both cases, reflecting the fact that the excluded sectors account for a small part of business sector output. We also subtracted farm sector investment when constructing corresponding capital inputs, which already excluded government capital as in Krusell et al. (2000).

15 The only parameter that is considerably different from the baseline case is α, which is the income share of structures capital. This difference is driven by the level difference between KORV and NFBS labor shares.

Table 5.1
Parameter estimates for the 1963-1992 period with original KORV data.

Model	Methodology	σ	ρ	α	η_ω
I. KORV (2000)	SPMLE	0.401	−0.495	0.117	0.043
		(0.234)	(0.048)	(0.007)	(0.003)
II. KORV Replication	SPMLE	0.411	−0.505	0.108	0.043
		(0.014)	(0.055)	(0.003)	(0.005)
III. KORV Replication	GMM	0.471	−0.396	0.117	–
		(0.021)	(0.043)	(0.002)	–

Note: The values in parentheses are standard errors.

Table 5.2
Parameter estimates with updated data.

Labor Share	Period	Methodology	σ	ρ	α	η_ω
KORV Gross	1963-1992	SPMLE	0.438	−0.520	0.105	0.083
			(0.020)	(0.043)	(0.002)	(0.007)
		GMM	0.467	−0.478	0.106	–
			(0.018)	(0.035)	(0.002)	–
	1963-2019	SPMLE	0.431	−0.309	0.109	0.085
			(0.013)	(0.026)	(0.002)	(0.005)
		GMM	0.461	−0.298	0.112	–
			(0.007)	(0.013)	(0.002)	–
KORV Net	1963-1992	SPMLE	0.412	−0.606	0.098	0.111
			(0.024)	(0.047)	(0.002)	(0.015)
		GMM	0.428	−0.592	0.098	–
			(0.022)	(0.041)	(0.002)	–
	1963-2019	SPMLE	0.422	−0.381	0.097	0.090
			(0.016)	(0.031)	(0.002)	(0.006)
		GMM	0.460	−0.339	0.098	–
			(0.008)	(0.014)	(0.002)	–

Note: The values in parentheses are standard errors.

are very similar to the baseline findings, suggesting that time-varying depreciation rates assumption are not impacting the results.

5.2.1. Baseline results with KORV's definition of gross labor share

Table 5.1 presents the estimated parameters for 1963 through 1992, which is the original time period analyzed by KORV, and using the original KORV data.

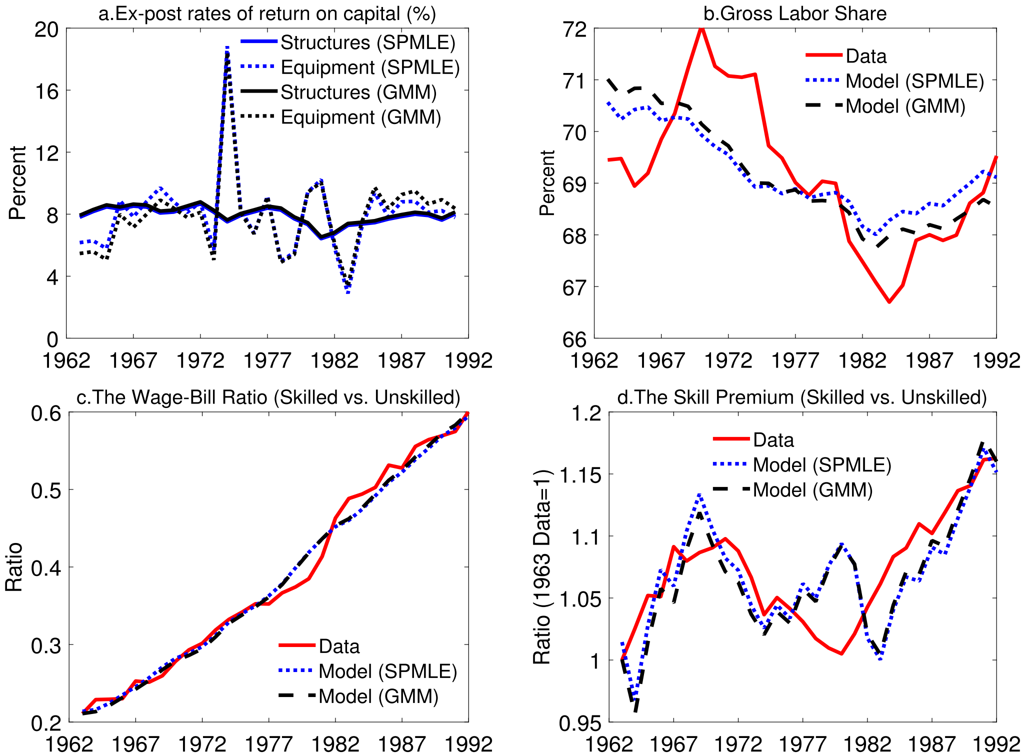
Row I reports the estimates of KORV and row II is our replication using the original KORV data and their SPMLE methodology. Fig. C.3, which is presented in the Appendix, should be compared with figures 5 through 8 in Krusell et al. (2000), as it shows the model fit with the same data and estimation methodology.

The SPMLE estimated parameters and the model's fit are both nearly identical to KORV, confirming that any changes in our results in the following discussion will be data-driven. GMM estimates are presented in row III, and are also similar to the SPMLE estimates. GMM confirms significant capital-skill complementarity, though indicating somewhat larger substitution elasticities between equipment capital and skilled labor and between their composite output and unskilled labor compared with the original and replicated KORV elasticities (rows I and II).

Table 5.2 presents the parameter estimates when we use our revised and updated data in estimation for both 1963-1992 and 1963-2019 periods, for KORV's definition of both gross and net labor shares, and with the two estimation methodologies. In all cases, SPMLE and GMM parameter estimates and model fits are very similar. First consider the results for original period of KORV's study with KORV's definition of the gross labor share and SPMLE estimation. In this case, ρ, the parameter governing the elasticity of substitution between equipment capital and skilled labor input, and α, the share of structures capital in production, are little changed from the original KORV results and from our replication with original KORV data in Table 5.1.

Our estimate of σ, the parameter governing the elasticity of substitution between equipment capital and unskilled labor input, is only slightly different with the revised data. KORV's estimated elasticity was 1.67, compared to our estimate of 1.70 using their original data (row II of Table 5.1), and 1.77 with revised data, indicating even more substitutability between equipment and unskilled labor in the revised data. The estimated parameters change only slightly with GMM, and the degree of capital-skill complementarity is largely unchanged.

Fig. 5.1 presents the model's fit for 1963 through 1992 using the revised data with both SPMLE and GMM estimation and with KORV's definition of gross labor share. Panels a through d shows that the model predictions are broadly in line with the data for both SPMLE and GMM. Panel d shows that the model captures the rise in the skill premium in the late 1960s, the decline until the 1980s, except for an increase in the early 1980s, and the large rise thereafter. Regarding the



Note: These charts are produced using the observed factor inputs and the parameters estimated using data for 1963-1992. KORV's definition of gross labor share is used in the estimation. While panel a runs through 1991, the rest of the panels plot the data and the model fit for the entire 1963-1992 period.

Fig. 5.1. Model fit for the 1963-1992 period with updated data.

labor share, the model generates a labor share that is too smooth (see panel b), but the model captures a sizable component of long-run changes in labor share, predicting a decline until the early 1980s and a slight increase afterwards. Both the data and the model have the same average labor share of 69.2 percent.

The elasticity parameters estimated by Krusell et al. (2000) have been used extensively in the inequality literature. To evaluate the empirical fit of the model after 1992, we kept these parameters constant from row II in Table 5.1, which are obtained using original KORV data, but projected the model through 2019, extending the original KORV data with the growth rates of variables since 1992. Fig. 5.2 shows these results with SPMLE estimation.[16] As seen in panels c and d, the model does remarkably well regarding the wage-bill ratio and the skill premium until recently. Consider the skill premium, as shown in panel d. Although the parameters are obtained with data until 1992, the model predicts the rise in the skill premium until the early 2000s, as well as the slowdown in its growth rate until around 2014. However, the model with the original KORV parameter estimates fails to capture the increase in the skill premium in the past few years.

The KORV framework does not capture the ongoing decline in the (gross) labor share. In contrast, it predicts a counterfactual rise of the labor's share up to about 78 percent by 2019, from an average value of 69.2 percent. Similarly, the model tends to miss equating the ex-ante expected rates of returns of structures and equipment capital after the 1990s.

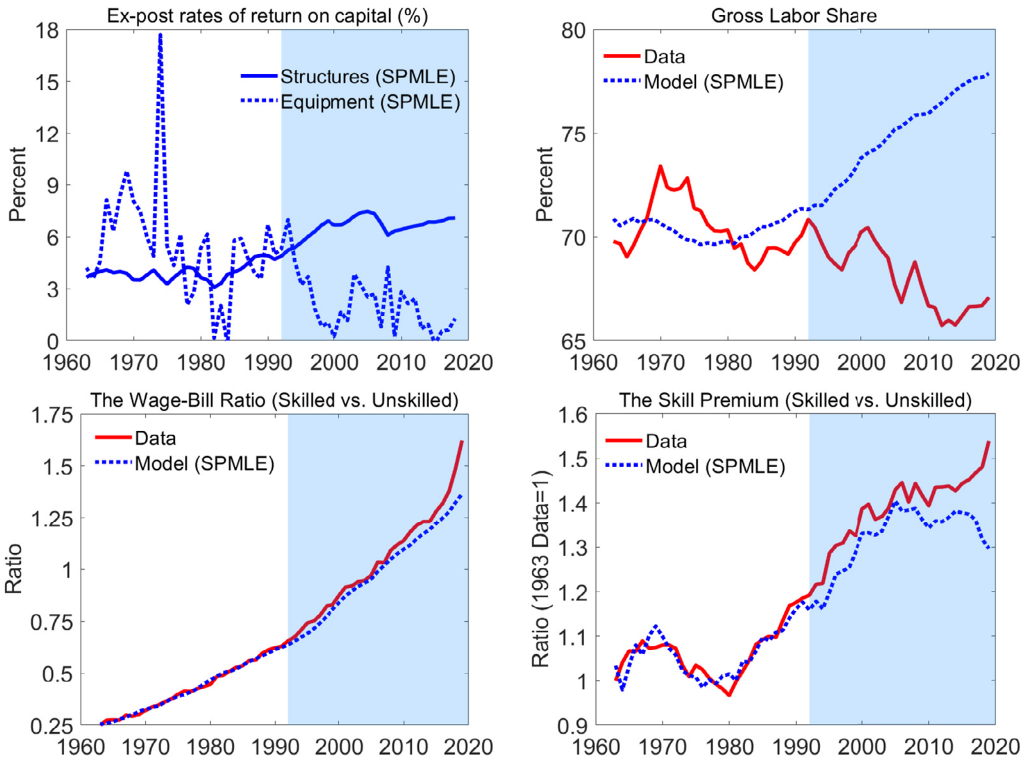
To understand why the original KORV parameters predict a large rise in the labor share, we conduct several counterfactuals, which are presented in Fig. 5.3.

Consider first the green dotted line, which is generated by keeping the skilled and unskilled labor inputs constant at their 1992 levels. The figure shows that keeping these inputs fixed generates an even larger increase in the labor share, as keeping these inputs fixed increases the scarcity of labor as a factor of production.

Consider next the blue and black lines, which are generated by keeping the growth rate of equipment capital during the post-1992 period at its average rate over the 1963-1992 period, and by keeping the stock of equipment capital fixed at its 1992 level, respectively. These counterfactuals show that the model's failure to track the labor share results from the enormous rise in the stock of equipment capital.

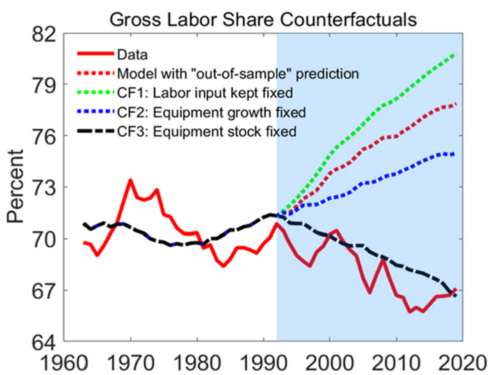
Given the large post-1992 changes in the data, it is natural to re-estimate the model and these key elasticities with data through 2019. Table 5.2 reports the parameters estimated from 1963 through 2019 for our baseline case with KORV's definition of gross labor share for the two estimation methodology we used.

[16] Because the model fits are very similar for two methodologies, we do not report the GMM fits in this figure.



Note: These charts are produced using the observed factor inputs and the parameters estimated with the original KORV data until 1992 and with the SPMLE methodology. KORV's definition of gross labor share is used in the estimation. The blue area represents the out of sample prediction. While panel a runs through 2018, the rest of the panels plot the data and the model fit for the entire 1963-2019 period.

Fig. 5.2. Model out of sample predictions for the 1993-2019 period with original KORV data until 1992.



Note: The chart is produced using parameters estimated using the original KORV data until 1992 with the SPMLE methodology. The blue area represents the out-of-sample dates. The solid line is the original KORV data up to 1992, and we then extend it afterwards. The red dashed line is produced using the observed factor inputs. In counterfactual 1, we keep skilled and unskilled labor inputs constant at their 1992 levels. In counterfactual 2, we keep the growth rate of equipment capital during the post-1992 period at its average rate over the 1963-1992 period. Counterfactual 3 keeps the stock of equipment capital fixed at its 1992 level.

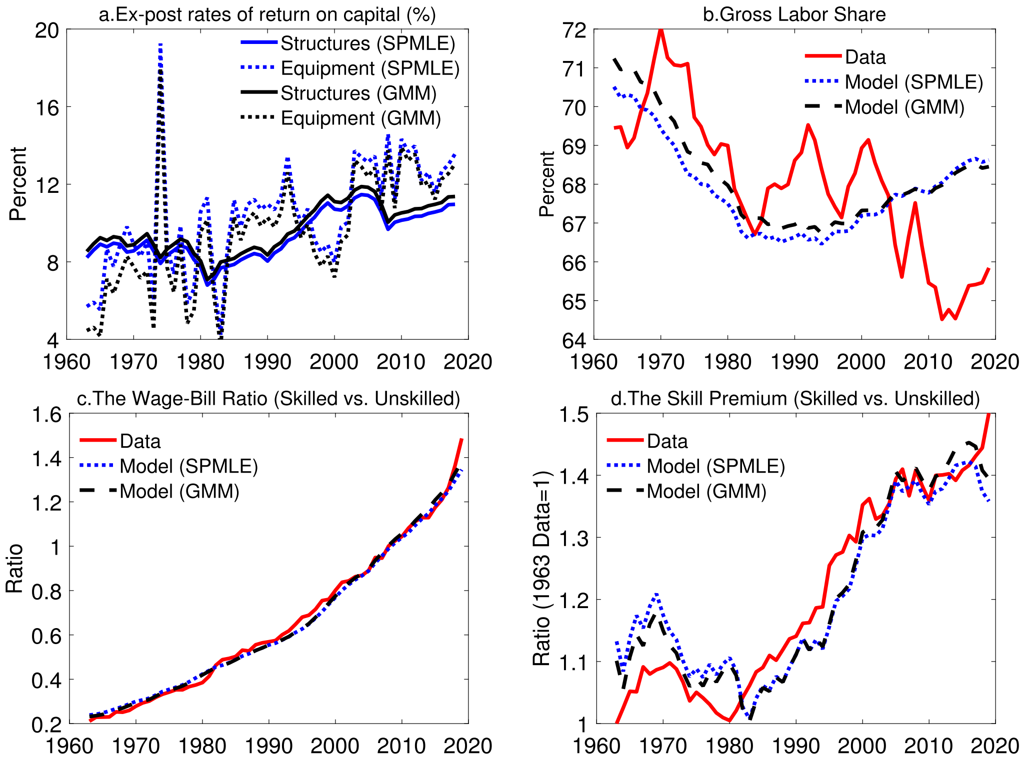
Fig. 5.3. Gross labor share counterfactuals.

As seen in Table 5.2, the parameters σ and α do not change significantly from those estimated by Krusell et al. (2000) and our estimates for the 1963-1992 period (see first row of Table 5.1 and first two rows of Table 5.2, respectively). However, the estimated value of ρ, the parameter governing the elasticity of substitution between equipment capital and the skilled labor input shows somewhat less complementarity than in Krusell et al. (2000) when estimated through 2019, with an estimated value of -0.309 and -0.299 with the SPMLE and GMM methodologies, respectively, compared with -0.517 and -0.477, when estimated using revised data from 1963 through 1992.

From a technological perspective, the finding that equipment capital and skilled labor became somewhat less complementary since the early 1990s may reflect the notion that equipment-specific technology is now replacing some jobs

Table 5.3
Estimated elasticities of substitution (using SPMLE methodology).

	I. KORV (2000) (1963-1992)	II. Updated (1963-1992)	III. Updated (1963-2019)
$\frac{1}{1-\sigma}$	1.67	1.77	1.76
$\frac{1}{1-\rho}$	0.67	0.66	0.76



Note: These charts are produced using the observed factor inputs and the parameters estimated employing data for the 1963-2019 period. KORV's definition of gross labor share is used in the estimation. While panel a runs through 2018, the rest of the panels plot the data and the model fit for the entire 1963-2019 period.

Fig. 5.4. Model fit for the 1963-2019 period.

involving skilled labor. For example, artificial intelligence and machine learning are now being used as a substitute for skilled labor in some industries.

From a goodness-of-fit perspective, the optimization algorithm chooses a somewhat lower complementarity between skilled labor and equipment capital to attenuate the model's prediction of a higher labor's share of income, as a very high complementarity increases skilled labor's productivity and thus labor's share.

Nonetheless, there is still significant capital-skill complementarity when the model is estimated through 2019, with an estimated elasticity between unskilled labor and equipment of 1.77, and an estimated elasticity of 0.76 between skilled labor and capital equipment with SPMLE methodology. The difference in these two elasticities is very similar to the difference reported in KORV. Table 5.3 compares our elasticity estimates with SPMLE methodology reported in Table 5.2 with those of Krusell et al. (2000) (row I of Table 5.1).

Fig. 5.4 presents the model's fit for 1963 to 2019 with the two estimation procedures and with KORV's definition of gross labor share. Compared to using parameters estimated for the original KORV period (Fig. 5.2), the model estimated through 2019 gives a much better fit of the labor share (panel b) as the counterfactual rise in the labor share is attenuated. Although the model misses the volatility of labor's share, particularly the fall since the early 2000s, the average labor share in the model and data are both about 68 percent.

The model estimated over 1963-2019 also improves the fit of the no-arbitrage condition, as ex-post rates of return move together for both types of capital (see panel a), though the model's predicted ex-post rates of return are a bit higher than what empirical studies suggest. To compare, Marx et al. (2019) report that return on U.S. productive capital increased from

6 percent in 1980s to around 10 percent in late 1990s, before falling back to around 8 percent by 2010. In contrast, our model predicts a return on capital just above 10 percent since early 2000s.

The model continues to capture the large changes in the skill premium, which include the rise until the early 1970s, the fall until the early 1980s, and the rise thereafter, together with a slowdown in the rise since the early 2000s up until recently. This indicates that the KORV framework, and the hypothesis of capital-skill complementarity more broadly, remains quantitatively important from 1963 through 2019, a period with remarkable growth in the relative supplies of skilled and unskilled workers and a period featuring enormous technological change.

The results with constant depreciation rates are almost unchanged from the baseline estimation (see Table C.3), suggesting that our assumption on depreciation rates has no substantive effect on our findings. This can also be clearly seen in Fig. C.7, which shows that the resulting model fit is nearly identical when either time-varying or constant depreciation rates are used in the construction of capital stock series and in the estimation.

5.2.2. Estimation with net labor share

This section discusses estimation results when the labor share is measured using income net of depreciation. As discussed earlier, gross labor share shows around a 5 percentage points decrease (our baseline), while net labor share does not have any obvious trend change, given higher deprecation.

When using net labor share, we change the labor share equation as:

$$\widetilde{lshare}_t = \frac{A_t G_{s,t} h_{s,t} + A_t G_{u,t} h_{u,t}}{A_t G_t - p_{eq,t}\delta_{eq,t}k_{eq,t} - \delta_{st,t}k_{st,t}}, \tag{5.6}$$

while the wage-bill-ratio equation and the no-arbitrage condition remain unchanged.

The lower block of Table 5.2 reports the parameter estimates with KORV's definition of net labor share for both periods we study. Similar to our baseline parameter estimates, capital-skill complementarity remains quantitatively important and significant with this definition of the labor share. The parameter ρ is estimated to be slightly more complementary with equipment for the entire period of the study when the net labor share is targeted. With the SPMLE estimation for the 1963-2019 period, we obtain -0.381 compared to -0.309 (gross labor share) for ρ, which represents a lower elasticity of substitution between skilled labor and equipment capital, 0.72 compared to 0.76 estimated with gross labor share.

Fig. 5.5 presents the model fit with net labor share for the 1963–2019 period with the two estimation methodologies we used. The model fit for the skill premium and wage-bill ratio improves slightly, especially for the latter period relative to our baseline case with gross labor share (see Table 5.5). More importantly, the model is consistent with the observed lower rate of return on equipment capital over the past two decades. Without the challenge of having to fit the persistent negative trend in gross labor's share, the model captures the relative stability of (net) labor's share, with an average net labor share of 80.5 percent, compared with 80.7 percent in data. That being said, using the net labor share as one of the targets instead of using the gross labor share worsens the fit of the gross labor share. This point is depicted in Fig. C.8 in Appendix C, which plots the model fits for the gross labor share when either the net labor share or the gross labor share is used in the estimation. As seen in the figure, the model generates a counterfactual rise in the gross labor share when the net labor share is targeted, consistent with the fact that substitution parameters are closer to original KORV parameters in this case.

5.2.3. Summary of elasticity estimates across alternative labor share definitions

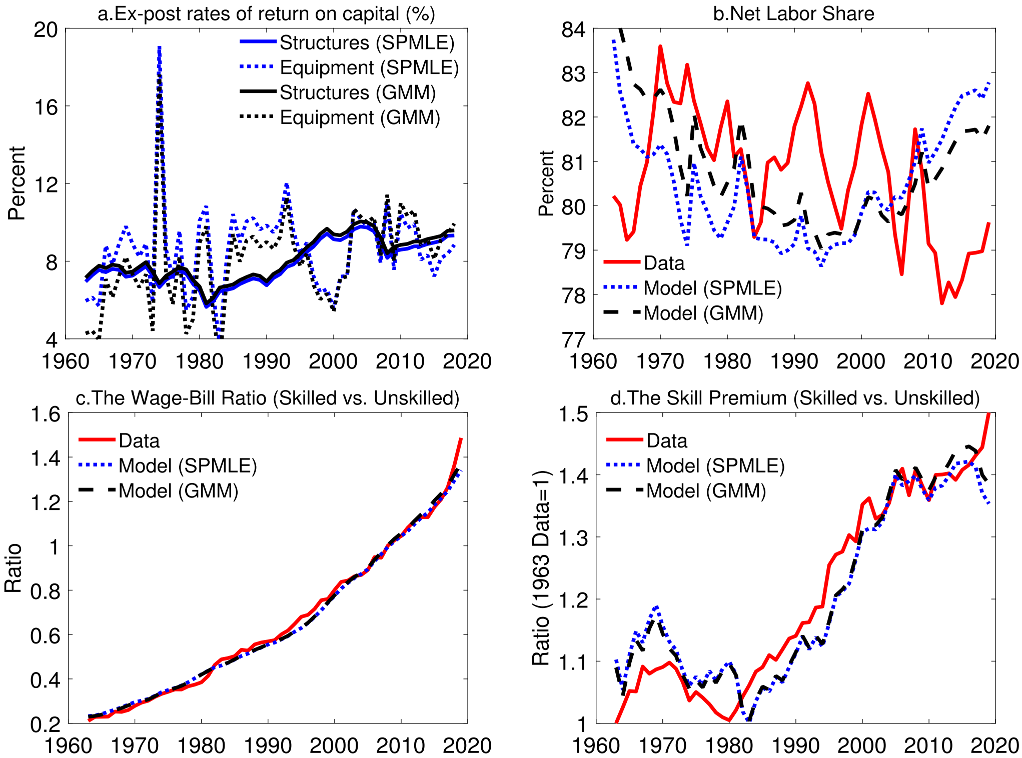
The different cases studied in this paper confirmed that capital-skill complementarity remains important. While the estimated substitution elasticities between equipment and unskilled and skilled labor are both somewhat higher than in KORV, the difference between the two elasticities is very similar to that in KORV. We averaged the elasticity estimates we obtained using the four different labor share types and two estimation methodologies for the two periods we studied. As seen in Table 5.4, on average, our elasticity estimates are almost unchanged from what Krusell et al. (2000) report for the 1963-1992 period: 1.67 for the elasticity between unskilled labor and the composite of equipment and skilled labor, and 0.65 for the elasticity between skilled labor and equipment. When the 1963-2019 period is considered, a modestly larger pair of elasticities–1.70 and 0.75, respectively–are estimated in order to address the secular decline in the labor share.

5.2.4. Comparison of model fits across alternative labor share definitions

To analyze the model fits for the skill premium and labor shares, we compare normalized root mean squared errors (NRMSEs) for both gross and net income for both the KORV and nonfarm business income definitions. Table 5.5 reports NRMSEs for both the 1963-1992 and the 1963-2019 periods using the SPMLE methodology in estimation.

Regarding the skill premium, all labor share definitions perform similarly well for the 1963-2019 period, while we see a non-negligible improvement in the fit when we use KORV's net labor share definition as well as two types of NFBS labor shares. Regarding the labor share, estimation with KORV's gross labor share (our baseline) slightly outperforms all other versions for both periods once the RMSEs are corrected (normalized) to account for different levels of labor share definitions.

Overall, the findings are quantitatively similar, with no specific case appearing to be superior to the others in all aspects.



Note: These charts are produced using the observable factor inputs and the parameters estimated employing data for the 1963-2019 period. KORV's definition of labor share, net of depreciation, is used in estimation. While panel a runs through 2018, the rest of the panels plot the data and the model fit for the entire 1963-2019 period.

Fig. 5.5. Model fit for the 1963-2019 period (with KORV's definition of net labor share).

Table 5.4
Averaged elasticity estimates.

	Period	$\frac{1}{1-\sigma}$	$\frac{1}{1-\rho}$
Krusell et al. (2000)	1963–1992	1.67	0.67
Updated estimate	1963–1992	1.67	0.65
Updated estimate	1963–2019	1.70	0.75

Note: Updated estimates are average of eight different estimates obtained using four labor share types: KORV's definition of gross and net labor shares and NFBS gross and net labor shares; and two estimation methodologies: SPMLE and GMM.

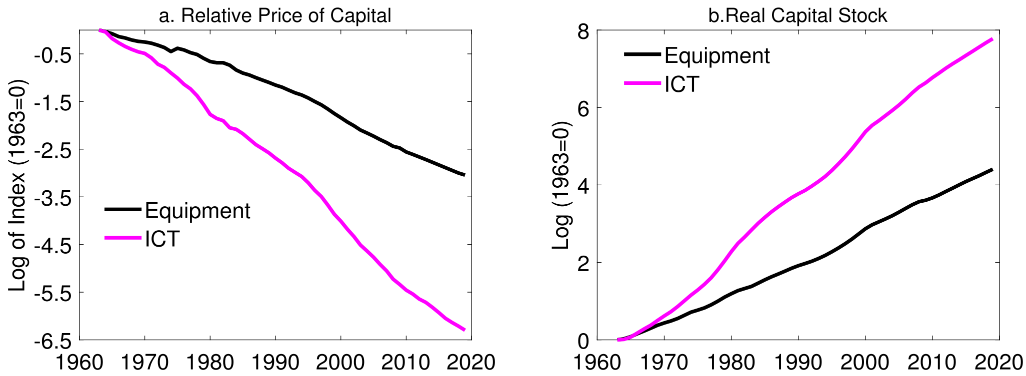
Table 5.5
Normalized RMSEs for the skill premium and the labor share.

	Skill Premium		Labor Share	
	1963–1992	1963–2019	1963–1992	1963–2019
KORV Gross	**0.033**	0.051	**0.015**	**0.028**
KORV Net	0.035	0.044	0.018	**0.028**
NFBS Gross	**0.033**	0.044	0.016	0.032
NFBS Net	0.035	**0.042**	0.020	0.033

Note: RMSE stands for root mean squared error.
Normalized RMSE is the RMSE divided by the mean value of the variable during the relevant period.
Bold entries represent the smallest value in each column.

5.2.5. Estimation with information and communication technologies capital

This section analyzes the implications of changing the complementary capital stock from total equipment capital to ICT capital. We use the quality-adjusted ICT price deflator of DiCecio (2009) to construct real ICT investment, and we apply the perpetual inventory method to construct the annual ICT capital stock. Non-ICT capital equipment is added to the stock of capital structures.



Source: Authors' calculations from the BEA's NIPA tables and ICT and equipment capital investment price deflators of DiCecio (2009).

Fig. 5.6. Equipment vs ICT Capital.

Table 5.6
Comparison of estimates of parameters governing elasticities (with KORV's definition of gross labor share).

Capital	Methodology	σ	ρ
Equipment	SPMLE	0.431	−0.309
		(0.013)	(0.026)
	GMM	0.461	−0.298
		(0.007)	(0.013)
ICT	SPMLE	0.603	−0.077
		(0.050)	(0.008)
	GMM	0.669	−0.109
		(0.007)	(0.009)

Note: The values in parentheses are standard errors.

Extending the KORV framework along this dimension allows us not only to evaluate whether the model labor share will be closer to the data, but also focuses the analysis on a concept of a complementary capital stock that has exhibited the fastest technological change.

Panel a of Fig. 5.6 shows the very rapid drop in the relative price of ICT capital compared to total capital equipment (including ICT capital), while panel b shows the corresponding very rapid rise in the real stock of ICT capital compared to the stock of total equipment. These differences reflect faster technological change in ICT capital compared to total equipment.

We estimate the model using both SPMLE as in Krusell et al. (2000) and GMM. The results for the elasticity parameters, along with the results with equipment capital (our baseline) are presented in Table 5.6.

The parameter estimates show strong capital-skill complementarity using ICT capital as the complementary capital stock. We find an elasticity of substitution of 2.52 between unskilled labor and the composite output of ICT capital and skilled labor and an elasticity of substitution of 0.93 between ICT capital and skilled labor using the SPMLE methodology. Corresponding GMM elasticity estimates are 3.01 and 0.90, respectively.

The larger unskilled labor elasticity compared to the baseline model with total equipment suggests that ICT capital is significantly more substitutable with unskilled labor than is the total stock of equipment.

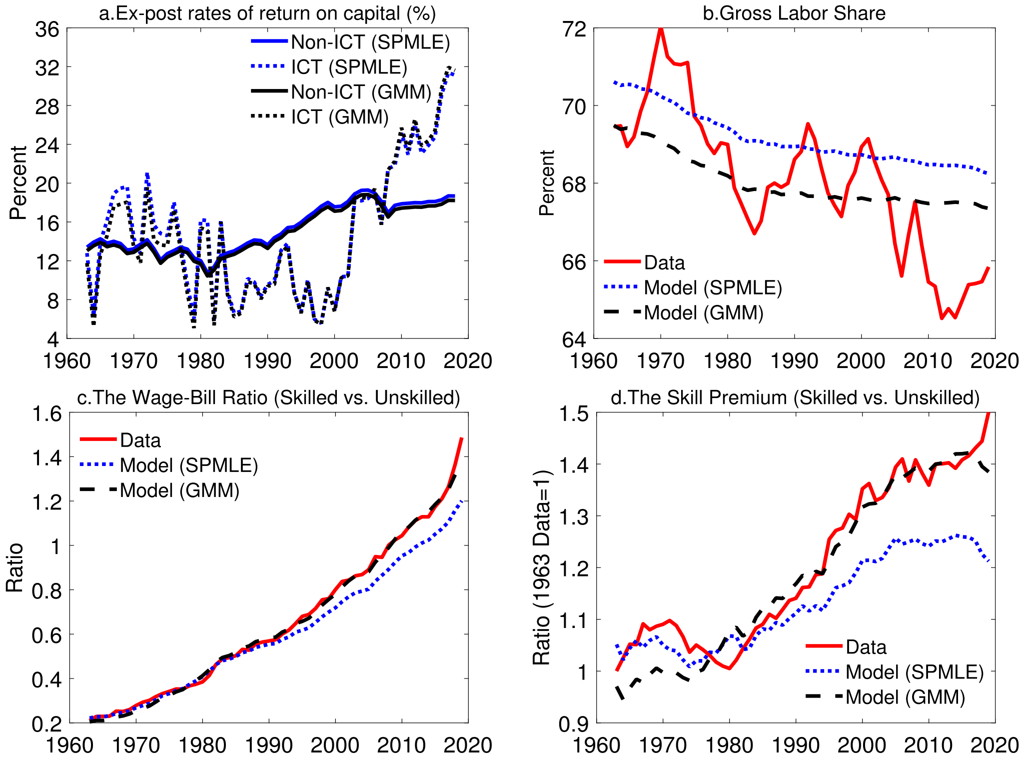
This finding connects with the closely related literature on the skill content of jobs introduced in Autor et al. (2003), and further developed in Autor (2015), and related studies of automation replacing routine jobs, including Acemoglu and Restrepo (2018), Acemoglu and Restrepo (2019), Eden and Gaggl (2018), and Eden and Gaggl (2019). In particular, unskilled workers primarily occupy the routine jobs that are being replaced by automation, which in turn reflects rapid innovations in ICT capital.

Based on these related literatures, it is natural to expect a higher substitution elasticity. This analysis thus provides a quantitative estimate for how much higher this elasticity is.

The differences in the substitution elasticities between SPMLE and GMM have implications for the overall model fit and the skill premium, which are presented in Fig. 5.7.

Using ICT capital moderately improves the fit for the model labor share relative to using the total stock of equipment.[17] Both the SPMLE and GMM estimates (see panel b of Fig. 5.7) show about a three percentage point decline in labor share over the full period of analysis (1963-2019) using ICT capital. However, neither estimation method produces a significant

[17] See Fig. C.9 in the Appendix for a comparison of model fits for KORV's gross labor share when either equipment or ICT capital is used as complementary capital.



Note: These charts are produced using the observable factor inputs and the parameters estimated employing data for the 1963-2019 period. KORV's definition of gross labor share and ICT capital are used in estimation. While panel a runs through 2018, the rest of the panels plot the data and the model fit for the entire 1963-2019 period.

Fig. 5.7. Model fit for the 1963-2019 period (with ICT capital and KORV's definition of gross labor share).

labor share decline after 1992, a period in which the actual labor share declines by about five percentage points. This finding is consistent with the results in Eden and Gaggl (2018), who use a different classification of labor input (routine and non-routine tasks), and a different price deflator and investment series for the construction of the ICT capital stock to study the welfare effects of automation (growth of ICT capital) and find also that the increasing use of ICT has been responsible for about half of the decline in the labor income share.[18] Our findings are also similar to Eden and Gaggl (2018) in that both analyses suggest that capital-biased technological change in conjunction with empirically plausible substitution possibilities across factors do not fully account for the change in labor share.

The two estimation methods fit the no-arbitrage condition equally well, though neither captures the large increases in the marginal product of capital equipment that occur after 2010. The GMM parameter estimates fit the skilled-unskilled wage bill ratio very closely over the full period, while the SPMLE parameter estimates generate a wage bill ratio that grows more slowly than the actual wage bill ratio after around 2000.

In contrast to all the other cases considered, the model skill premium differs between the two estimation methods. Panel d of Fig. 5.7 shows the model skill premium for both estimation methods. The model skill premium estimated with GMM tracks the actual skill premium quite closely over the entire period, including capturing the slowdown in the growth of the skill premium between 2002 and 2016, a period in which the normalized skill premium remains at around 40 percent above its 1963 level. The SPMLE model skill premium does not track the data as closely, particularly the increases that occur after 2005.

The more accurate model skill premium produced using GMM reflects a larger degree of capital skill complementarity compared to SPMLE. Both methods estimate a skilled labor - ICT capital elasticity of around 0.9, but the estimated elasticity between unskilled labor and the composite output of ICT capital and skilled labor is about 3 for GMM, and about 2.5 for SPMLE.

[18] Eden and Gaggl (2018) construct nominal ICT investment series based on data from the World Information Technology and Services Alliance (WITSA) and the International Telecommunication Union (ITU) databases. They treat non-ICT investment as the residual between total capital investment and this ICT investment. Instead, we take "Information processing equipment investment" (line 10 from NIPA Table 5.3.5) as the nominal ICT investment and use the difference between total equipment investment (line 9 from NIPA Table 5.3.5) and "Information processing equipment investment" (line 10 from NIPA Table 5.3.5) as nominal non-ICT equipment investment. Additionally, Eden and Gaggl (2018) use an ICT price deflator estimated based on the BEA's fixed asset accounts, while we used the DiCecio (2009) deflator.

To understand the importance of these differences for the model skill premium, recall from equation (4.8) that the difference between the parameters governing elasticities (σ and ρ) is a key factor driving the skill premium. With GMM, the difference between σ and ρ is about 0.78, whereas this difference with SPMLE is about 0.68, which correspond to a difference between $\frac{1}{1-\sigma}$ and $\frac{1}{1-\rho}$ of 2.1 and 1.6, respectively.

These results raise the question of why the SPMLE and GMM estimates are different in this case, whereas they are very similar in all other cases. The primary distinction between the two estimation methods is that GMM does not need to estimate the variances of the latent labor efficiency processes, whereas these variances are needed to prevent singularity in the full-information SPMLE estimation method used originally in Krusell et al. (2000).

We found difficulty in achieving convergence with SPMLE without a very volatile labor efficiency shock process, one in which the standard deviation of labor efficiencies is nearly 30 percent per year. This strikes us as being implausibly large. We conjecture that this high volatility may be due to the fact that ICT capital grows so much more quickly than the stock of total equipment; real ICT capital rises by a factor of nearly 2,500 since 1963, while the total stock of equipment rises by about a factor of 83 over the same period.

Given that GMM provided reasonable results in all the other cases evaluated here, we focus on the GMM estimates for the case of ICT capital, which yield substitution elasticities of about 3 between unskilled labor and the composite output of ICT capital and skilled labor, and about 0.9 between skilled labor and capital, and leave the technical issues regarding SPMLE estimation for future research.

6. Conclusion

This paper analyzes the quantitative importance of capital-skill complementarity as a determinant of U.S. wage inequality, using data through 2019, compared with Krusell et al. (2000), which used data through 1992.

We first study the out-of-sample performance of the original Krusell et al. (2000) framework, which predicts a rise in the skill premium after 1992, but a counterfactual rise in labor's share of income. We then study how alternative measures of income, labor's share of income, depreciation, the conceptual definition of the complementary capital stock, and an alternative estimation method, affect the model's ability to jointly capture the skill premium and labor's share.

We find that capital-skill complementarity continues to be a quantitatively important determinant of U.S. wage inequality, despite the five percentage points decline in labor's share that has occurred after the Krusell et al. (2000) estimation period ended. In all of the estimation cases, the post-1992 decline in labor's share results in an estimated degree of complementarity between skilled labor and capital that is slightly lower than in Krusell et al. (2000), as well as a modestly higher estimated elasticity between unskilled labor and composite output of equipment and skilled labor. The reason for this is because slightly higher elasticities, ceteris paribus, reduce the marginal productivities compared to lower elasticities, and thus do not put as much upward pressure on the model's labor share. The largest departure we consider from Krusell et al. (2000) is replacing the total stock of equipment capital with information-communications-technology capital as the capital stock that is complementary with skilled labor. When estimated with GMM, the model captures the skill premium closely and produces a slowly declining labor share between 1963-1992. However, the model does not capture the drop in labor's share that occurs after 2000.

For economic models that posit the total stock of equipment as the complementary capital stock, we find that the KORV elasticity estimates change very little, from about 1.67 to about 1.70 for unskilled labor and equipment, and from about 0.67 to about 0.75 for skilled labor and equipment. For models that posit ICT capital as the complementary capital stock, we find the unskilled labor elasticity rises to about 3, which may reflect the process of routine jobs being replaced by automation, as analyzed in Autor (2015) and Acemoglu and Restrepo (2018). For the ICT case, the substitution elasticity between skilled labor and capital is about 0.9.

This study finds that capital-skill complementarity remains strong in U.S. data between 1963-2019, accounting for much of the change in wage inequality between highly skilled and less-skilled workers. However, the KORV framework does not yet capture the drop in labor's share that has occurred more recently. A task for future research is to focus on jointly accounting for the dynamics of wage inequality and the decline in labor's share within this framework.

Data availability

Data will be made available upon request.

Appendix A. Data description

A.1. Construction of labor inputs and wage rates

Our labor and wage series construction follow earlier studies, including Katz and Murphy (1992), Krusell et al. (2000), Autor et al. (2008) and Domeij and Ljungqvist (2019). We use all of the person-level data, excluding the agents who are younger than 16 or older than 70, unpaid family workers, those working in the military, who were not in the labor force in the previous year, and who did not report their education level. We included the self-employed when constructing labor inputs, even though we excluded them from our wage sample. This gave us a better match of original KORV data, but excluding or including the self-employed from the labor input construction did not have any significant effect on our findings. In our wage sample, we also dropped the observations reporting working less than 40 weeks or 35 hours a week or both. Following Domeij and Ljungqvist (2019), we also dropped individuals with allocated income, those with hourly wages below half of the minimum federal wage rate, and those whose weekly pay was less than \$62 in 1980 dollars from our wage sample.

For each person, we record their personal characteristics: age, sex, race; employment statistics: employment status (empstat), class of worker (classwly), weeks worked last year (wkswork1 and wkswork2), usual hours worked per week last year (uhrsworkly and shrsworky), income—total wage and salary income (incwage)—and CPS personal supplement weights: asecwt. Then, each person is assigned to one of 264 groups created by age, race, sex, and skill (education). Age is divided into 11 five-year groups: 16–20, 21–25, 26–30, 31–35, 36–40, 41–45, 46–50, 51–55, 56–60, 61–65, an 66–70. Race is divided into three: white, black, others; sex is divided into male and female, and education is divided into four groups: below high school, high school, some college, and college graduates and beyond.

Following Krusell et al. (2000), we did not do any correction for topcodes. Alternatively, we adjusted topcoded income variables using the "revised income top-codes files" published by the Census Bureau to swap top-coded values in 1976-2010 CPS files with these revised values. This procedure replaces the top-coded values with new values based on the Income Component Rank Proximity Swap method, which was introduced in 2011. With this method, we had the top-coding methodology consistent and comparable for most of the years in our sample. Because the main results remained unchanged in this alternative case, we reported only findings without corrections for topcodes, for the sake of comparability with Krusell et al. (2000).

For the CPS years after 1975, CPS has usual hours worked per week and weeks worked last year. Thus, calculating the annual hours for a person is straightforward: We simply multiply weeks worked last year by usual hours worked. Hence, for CPS years 1976 and after, total hours are:

$$hours_{i,t-1} = wkswork1_{i,t-1} \times uhrswork_{i,t-1},$$

where i is individual observation and t is the CPS year.

For earlier years, we need to do two adjustments. First, weeks worked are available only as intervals, and we need to approximate a scalar value for each interval. Fortunately, both the intervals and actual weeks are available for years after 1975. Therefore, we calculated the average weeks worked after year 1975 for each interval and replaced the earlier years with those values.

Second, we have to use the "hours worked last week" variable as a proxy to usual hours worked per week last year. However, there are many agents who were not employed the week before the survey or who were employed but not at work for some reason, despite reporting a positive income for the previous year. Rather than dropping those observations, we replaced the hours they worked per week with the average of the hours worked by the people in their group in that particular year. We also paid attention to whether the person was employed part time or full time when doing this replacement.

Hourly wage is calculated as

$$wage_{i,t-1} = \frac{incwage_{i,t-1}}{hours_{i,t-1}}$$

Later, observations with weeks worked less than 40 hours, weekly hours less than 35, hourly wage less than half the minimum wage, and weekly pay less than \$62 in 1980 dollars are dropped to smooth out the effect of outliers and misreporting. Following this, for each groups and year, we calculate group weights as $\mu_{g,t} = \sum_{i \in g} \mu_{i,t}$, where $i \in g$ is set of groups. Then, average hours and wage measures for each group and year are calculated as follows:

$$hours_{g,t-1} = \frac{\sum_{i \in g} \mu_{i,t} \times hours_{i,t-1}}{\mu_{g,t}}$$

$$wage_{g,t-1} = \frac{\sum_{i \in g} \mu_{i,t} \times wage_{i,t-1}}{\mu_{g,t}}.$$

To aggregate across groups into aggregate task groups, we follow Krusell et al. (2000) and use the group wages of 1980 as the weights. We have total hours

$$N_{t-1} = \sum_{g \in G} hours_{g,t-1} \times \mu_{g,t} \times wage_{g,80}$$

and the average hourly wage is

$$W_{t-1} = \frac{\sum_{g \in G} hours_{g,t-1} \times \mu_{g,t} \times wage_{g,80}}{N_{t-1}}.$$

A.2. Labor share

A.2.1. Gross labor share

As the baseline, we followed KORV's definition of labor share, which we constructed from the BEA National Income and Product Accounts (NIPA) Tables 1.10 and 1.17.5. To calculate the gross labor share, we first constructed the capital's income share following Cooley and Prescott (1995) as the ratio of the sum of unambiguous capital income (net interest and miscellaneous payments (domestic industries), rental income of persons with capital consumption adjustment, corporate profits with inventory valuation and capital consumption adjustments (domestic industries) and depreciation (consumption of fixed capital) to the difference between gross domestic income and proprietors' income. We then subtracted this ratio from 1 to obtain the gross labor share.

An alternative measure uses the nonfarm business sector labor share, defined as "total employee compensation in the nonfarm business sector excluding self-employment income" divided by "gross value added in the nonfarm business sector excluding self-employment income." It is constructed using NIPA Tables 1.3.5, 1.12, 1.13 and 6.2. To construct the numerator, we take "compensation of employees, domestic industries (NIPA Table 6.2, line 2)" and subtract the following items from it: farm compensation (Table 6.2, line 5), federal general government compensation (Table 6.2, line 88), state and local general government compensation (Table 6.2, line 93), compensation of households (Table 1.13, line 43), and compensation of institutions (Table 1.13, line 50). To obtain the denominator, we take "gross value added in the nonfarm business sector (Table 1.3.5, line 3)" and subtract "sole proprietors income in the nonfarm business sector (Table 1.12, line 11)" from it. The labor share still demonstrates about a 3 percentage points decline, a little less than about 5 percentage points seen when the KORV's measure of labor share is considered.

In short, when calculating the alternative labor share, we subtract farm and government compensations from both the numerator and denominator of the KORV's measure. Economically, the difference between KORV's definition and the alternative measure of labor share is the sectors: the former takes the whole economy while the latter focuses on the nonfarm business sectors.

A.2.2. Net labor share

Our first measure of net labor share is comparable to the first measure of gross labor share (the KORV version), only excluding consumption of fixed capital from the numerator and denominator when calculating the income share of capital. The alternative net labor share measure is the nonfarm business sector labor share net of depreciation. To build it, we only replace the "gross value added in the nonfarm business sector (Table 1.3.5, line 3)" with "net value added in the nonfarm business sector (Table 1.9.5, line 3)." We see a slight increase in this measure of labor share over years after taking into account the effect of depreciation. The surge around 2000 is largely attributed to an increase in employee compensations, and a stable series of value added.

Appendix B. Estimation techniques

B.1. Simulated pseudo-maximum likelihood estimation

The estimation process entirely follows Krusell et al. (2000). The process is a simulated two-stage pseudo-maximum likelihood estimation (SPMLE) method developed by White (1996). Here, we are providing a brief description borrowed from KORV. Further details can be found in the original paper, particularly in the working paper version.

In the first stage, we treat the skilled and unskilled labor input as endogenous, and project them onto a constant and a trend; current, and lagged stocks of capital equipment and structures; the lagged relative price of equipment; and the lagged value of the U.S. Commerce Department's composite index of business cycle indicators. Then in the second stage, we use the fitted values of skilled and unskilled labor input from the regression in stage 1 to estimate the model. We define the vector $\tilde{X}_t$ as consisting of the stocks of equipment and structures and of the instrumented values of skilled and unskilled labor input: $\tilde{X}_t = \left\{k_{st,t}, k_{eq,t}, \hat{h}_{s,t}, \hat{h}_{u,t}, \delta_{eq,t}, \delta_{st,t}\right\}$, where $\hat{h}_{s,t}$ and $\hat{h}_{u,t}$ stand for the fitted values for skilled and unskilled labor.

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

$$\begin{aligned} &\text{Step 1:} \quad \varphi_t^i = \varphi_0 + \gamma t + \omega_t^i \\ &\text{Step 2:} \quad Z_t^i = f\left(\tilde{X}_t, \psi_t^i, \varepsilon_t^i; \phi\right). \end{aligned} \tag{B.1}$$

In Step 1, a realization of ω_t is drawn from its distribution and used to construct a year t value for φ_t. In Step 2, this realization of φ_t, together with a draw of ε_t allows us to generate a realization of Z_t. By simulating the model, we obtain the first and second moments of Z_t:

$$\begin{aligned} &m_S\left(\tilde{X}_t; \phi\right) = \tfrac{1}{S}\textstyle\sum_{i=1}^{S} f\left(\tilde{X}_t, \psi_t^i, \varepsilon_t^i; \phi\right) \\ &V_S\left(\tilde{X}_t; \phi\right) = \tfrac{1}{S-1}\textstyle\sum_{i=1}^{S}\left(Z_t^i - m_S\left(\tilde{X}_t; \phi\right)\right)\left(Z_t^i - m_S\left(\tilde{X}_t; \phi\right)\right)'. \end{aligned} \tag{B.2}$$

On the basis of these moments constructed for each $t = 1...T$, we can write the second stage objective function as:

$$\ell^2\left(Z^T; \tilde{X}_t, \phi\right) = -\frac{1}{2T}\sum_{t=1}^{T}\left\{\left[Z_t - m_S\left(\tilde{X}_t;\phi\right)\right]'\left(V_S\left(\tilde{X}_t;\phi\right)\right)^{-1}\left[Z_t - m_S\left(\tilde{X}_t;\phi\right)\right] - \log\det\left(V_S\left(\tilde{X}_t;\phi\right)\right)\right\}. \tag{B.3}$$

The SPML estimator $\hat{\phi}_{ST}$ is defined as the maximizer of equation (B.3). Following Krusell et al. (2000), we compute the standard errors using Theorem (6.11) in White (1996).

Standard errors:

The computations of the exact asymptotic standard errors take into account the first-stage parameter uncertainty in the instrumental variable estimation. Define the set of potentially endogenous variables as X^T and the set of instruments as W^T in the first stage. Clearly, the projection in the first stage can be regarded as a special case of maximum likelihood estimation, and we denote the first-stage likelihood function as $\ell^1\left(X^T; W^T, \theta\right)$, where θ is the parameters of this first-stage likelihood function. The second-stage likelihood function is $\ell^2\left(Z^T; \tilde{X}^T\left(W^T, \theta^*\right), \phi\right)$, where $\tilde{X}^T\left(W^T, \theta^*\right)$ is the linear projection of X^T in the space of W^T, and the "*" parameters denote the pseudo-true values.

Let ∇_θ and $\nabla_{\theta\theta}$ denote the first and second derivative with respect to θ. The Hessian matrix and information matrix are as follows:

$$H^* = \begin{bmatrix} \nabla_{\theta\theta}\ell^1(\theta^*,\phi^*) & \nabla_{\theta\phi}\ell^1(\theta^*,\phi^*) \\ \nabla_{\phi\theta}\ell^2(\theta^*,\phi^*) & \nabla_{\phi\phi}\ell^2(\theta^*,\phi^*) \end{bmatrix} = \begin{bmatrix} \nabla_{\theta\theta}\ell^1(\theta^*,\phi^*) & 0 \\ \nabla_{\phi\theta}\ell^2(\theta^*,\phi^*) & \nabla_{\phi\phi}\ell^2(\theta^*,\phi^*) \end{bmatrix} \tag{B.4}$$

$$I^* = \begin{bmatrix} \nabla_\theta\ell^1(\theta^*)\cdot\nabla'_\theta\ell^1(\theta^*) & \nabla_\theta\ell^1(\theta^*)\cdot\nabla'_\phi\ell^2(\theta^*,\phi^*) \\ \nabla_\phi\ell^2(\theta^*,\phi^*)\cdot\nabla'_\theta\ell^1(\theta^*) & \nabla_\phi\ell^2(\theta^*,\phi^*)\cdot\nabla'_\phi\ell^2(\theta^*,\phi^*) \end{bmatrix} \tag{B.5}$$

Theorem 6.11 in White (1996) establishes that the asymptotic variance-covariance matrix of $\hat{\phi}_T$ is $\mathrm{var}\left(\hat{\phi}_T\right) = H_{22}^{*-1}\left[I_{22}^* - H_{21}^{*\prime}H_{11}^{*-1}I_{12}^* - I_{21}^*H_{11}^{*-1}H_{21}^* + H_{21}^{*\prime}H_{11}^{*-1}I_{11}^*H_{11}^{*-1}H_{21}^*\right]H_{22}^{*-1}$. To compute the asymptotic variance of our simulation-based estimates of the parameters, we replace in the above expressions θ^* by $\hat{\theta}^T$ as well as ϕ^* and $\hat{\phi}_T$ by $\hat{\phi}_{ST}$.

B.2. Generalized method of moments

Denote Y_t as the annual sample data used for estimation, and $\theta = (\alpha, \sigma, \mu, \rho, \lambda, \varphi_u)$ as the parameters to estimate. To apply GMM, we use the same three moment conditions as in the SPMLE methodology: the wage-bill ratio, the labor share, and the no-arbitrage condition:

$$g(Y_t, \theta) = \begin{bmatrix} \frac{w_{s,t}h_{s,t}}{w_{u,t}h_{u,t}} - \mathrm{wbr}_t \\ \frac{w_{s,t}h_{s,t} + w_{u,t}h_{u,t}}{Y_t} - \mathrm{lshare}_t \\ q_t A_{t+1}G_{eq,t+1} + \left(1-\delta_{eq,t+1}\right)E\left(\frac{q_t}{q_{t+1}}\right) - A_{t+1}G_{st,t+1} - \left(1-\delta_{st,t+1}\right) \end{bmatrix}. \tag{B.6}$$

The goal of estimation is to find a set of parameters (θ_0) that satisfy:

$$m(\theta_0) \equiv \mathrm{E}\left[g\left(Y_t, \theta_0\right)\right] = 0, \tag{B.7}$$

where $m(\theta_0)$ is the value of the function $g(Y_t, \theta)$ evaluated at θ_0 and E is expected value. Then, we replace the theoretical expected value $E[\cdot]$ with its sample average:

$$\hat{m}(\theta) \equiv \frac{1}{T}\sum_{t=1}^{T} g\left(Y_t, \theta\right). \tag{B.8}$$

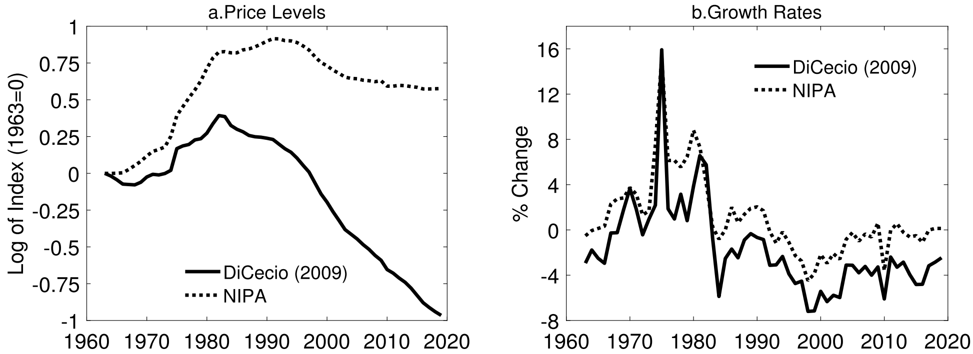
We then minimize the norm of this expression with respect to θ. Therefore, the GMM estimator can be written as:

$$\hat{\theta} = \arg\min_{\theta\in\Theta}\left(\frac{1}{T}\sum_{t=1}^{T} g\left(Y_t,\theta\right)\right)'\hat{W}\left(\frac{1}{T}\sum_{t=1}^{T} g\left(Y_t,\theta\right)\right), \tag{B.9}$$

where $\hat{W}$ is the weighting matrix computed based on the available data set.

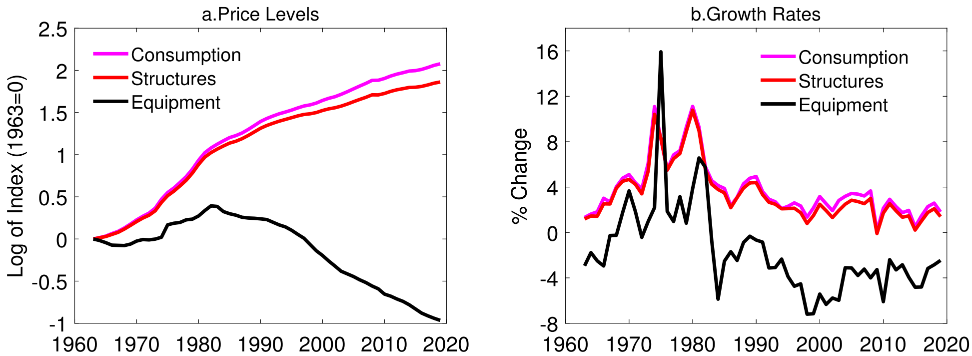
In the estimation, we use STATA's default two-state estimator with modified Newton–Raphson algorithm. We also use "unadjusted" weight matrix that assumes the moment equations are independent and identically distributed, and that errors are homoskedastic. As instruments, we use current and lagged stocks of equipment and structures, lagged relative price of equipment capital, a time trend, and the lagged value of the U.S. Commerce Department's composite index of business cycle indicators without a constant.

Appendix C. Additional figures and tables



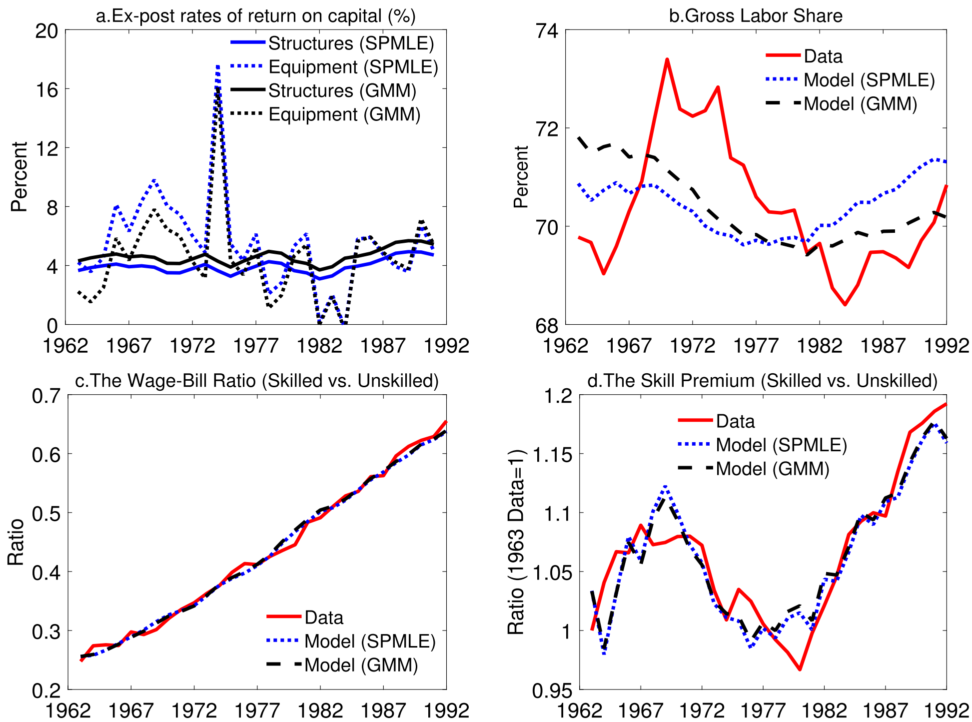
Source: Authors' calculations from the BEA's NIPA tables and from the investment prices series of DiCecio (2009).

Fig. C.1. Price of equipment capital.



Source: Authors' calculations from the BEA's NIPA tables and from the investment prices series of DiCecio (2009).

Fig. C.2. Prices of consumption, structures, and equipment capital.



Note: These charts are produced using the observable factor inputs and the parameters estimated employing the original KORV data, which covers the period between 1963 and 1992. While panel a runs through 1991, the rest of the panels plot the data and the model fit for the entire 1963–1992 period.

Fig. C.3. Replication with original KORV data.

Table C.1
Comparison of parameter estimates for the 1963-1992 period for alternative labor shares.

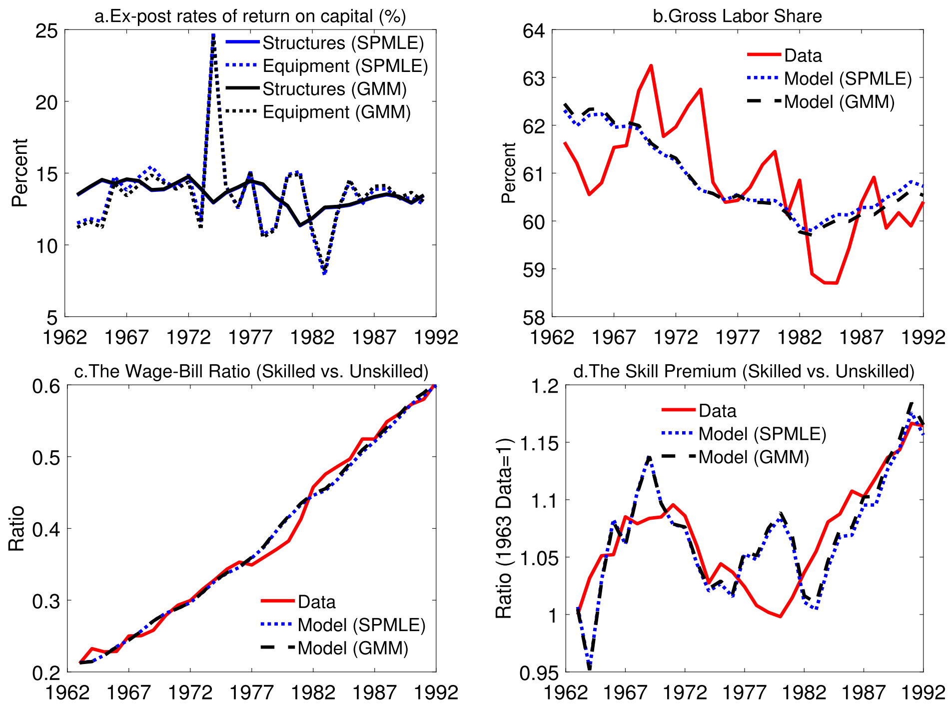
Methodology	Labor Share	σ	ρ	α	η_ω
I. SPMLE	KORV Gross	0.438 (0.020)	−0.520 (0.043)	0.105 (0.002)	0.083 (0.007)
II. GMM		0.467 (0.018)	−0.478 (0.035)	0.106 (0.002)	– –
III. SPMLE	KORV Net	0.412 (0.024)	−0.606 (0.048)	0.098 (0.002)	0.111 (0.015)
IV. GMM		0.428 (0.022)	−0.592 (0.041)	0.098 (0.002)	– –
V. SPMLE	NFBS Gross	0.380 (0.018)	−0.494 (0.040)	0.155 (0.002)	0.088 (0.012)
VI. GMM		0.390 (0.016)	−0.484 (0.027)	0.156 (0.002)	– –
VII. SPMLE	NFBS Net	0.346 (0.021)	−0.565 (0.042)	0.158 (0.002)	0.111 (0.019)
VIII. GMM		0.343 (0.020)	−0.582 (0.033)	0.158 (0.002)	– –

Note: The values in parentheses are standard errors.

Table C.2
Comparison of parameter estimates for the 1963-2019 period for alternative labor shares.

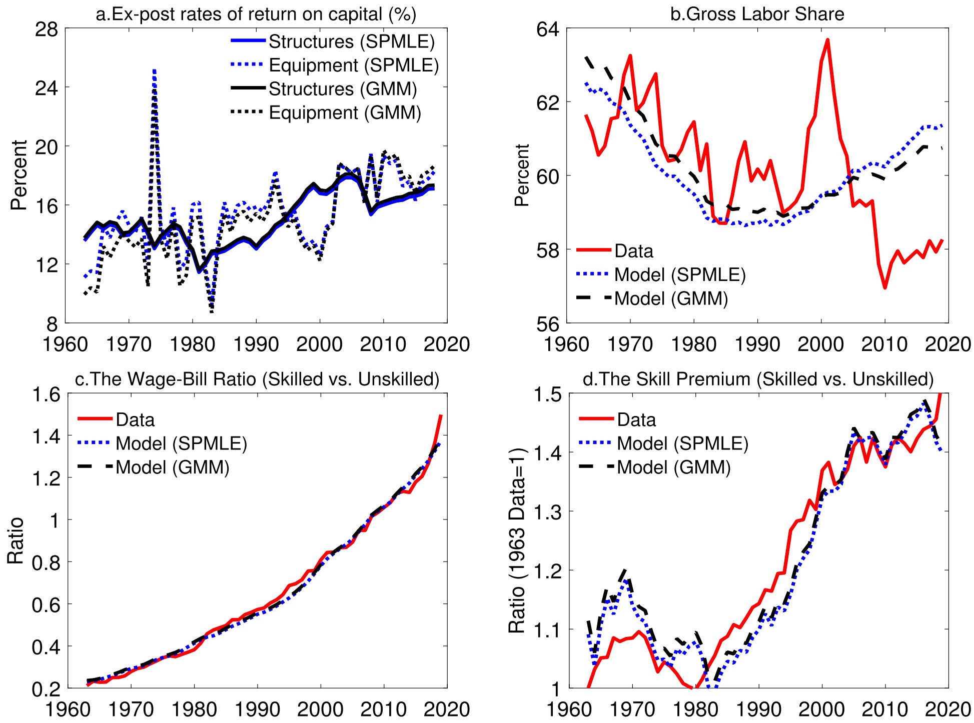
Methodology	Labor Share	σ	ρ	α	η_ω
I. SPMLE	KORV Gross	0.431 (0.013)	−0.309 (0.026)	0.109 (0.002)	0.085 (0.005)
II. GMM		0.461 (0.007)	−0.298 (0.013)	0.112 (0.002)	– –
III. SPMLE	KORV Net	0.422 (0.016)	−0.381 (0.032)	0.097 (0.002)	0.090 (0.006)
IV. GMM		0.460 (0.008)	−0.339 (0.014)	0.098 (0.002)	– –
V. SPMLE	NFBS Gross	0.381 (0.008)	−0.325 (0.019)	0.156 (0.002)	0.086 (0.005)
VI. GMM		0.395 (0.006)	−0.296 (0.011)	0.158 (0.002)	– –
VII. SPMLE	NFBS Net	0.356 (0.010)	−0.386 (0.020)	0.153 (0.002)	0.123 (0.007)
VIII. GMM		0.376 (0.006)	−0.335 (0.012)	0.153 (0.002)	– –

Note: The values in parentheses are standard errors.



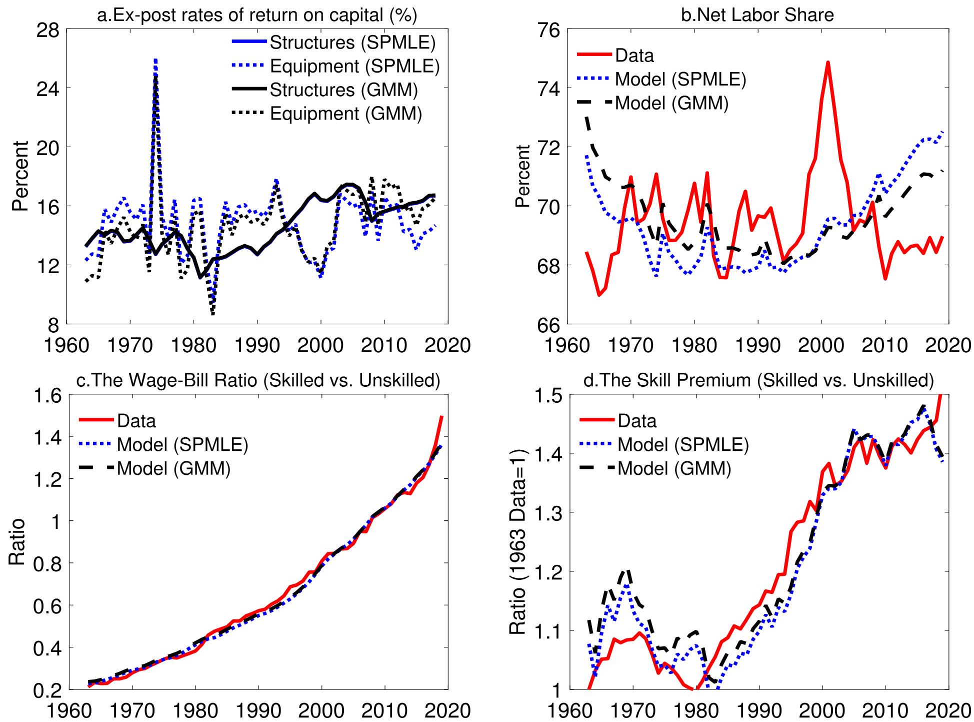
Note: These charts are produced using the observable factor inputs and the parameters estimated employing data for the 1963–1992 period. Nonfarm business sector gross labor share is used in estimation. While panel a runs through 1991, the rest of the panels plot the data and the model fit for the entire 1963–1992 period.

Fig. C.4. The model's fit for the 1963-1992 period (with nonfarm business sector gross labor share).



Note: These charts are produced using the observed factor inputs and the parameters estimated employing data for the 1963–2019 period. Nonfarm business sector gross labor is used. While panel a runs through 2018, the rest of the panels plot the data and the model fit for the entire 1963–2019 period.

Fig. C.5. The model's fit for the 1963-2019 period (with nonfarm business sector gross labor share).



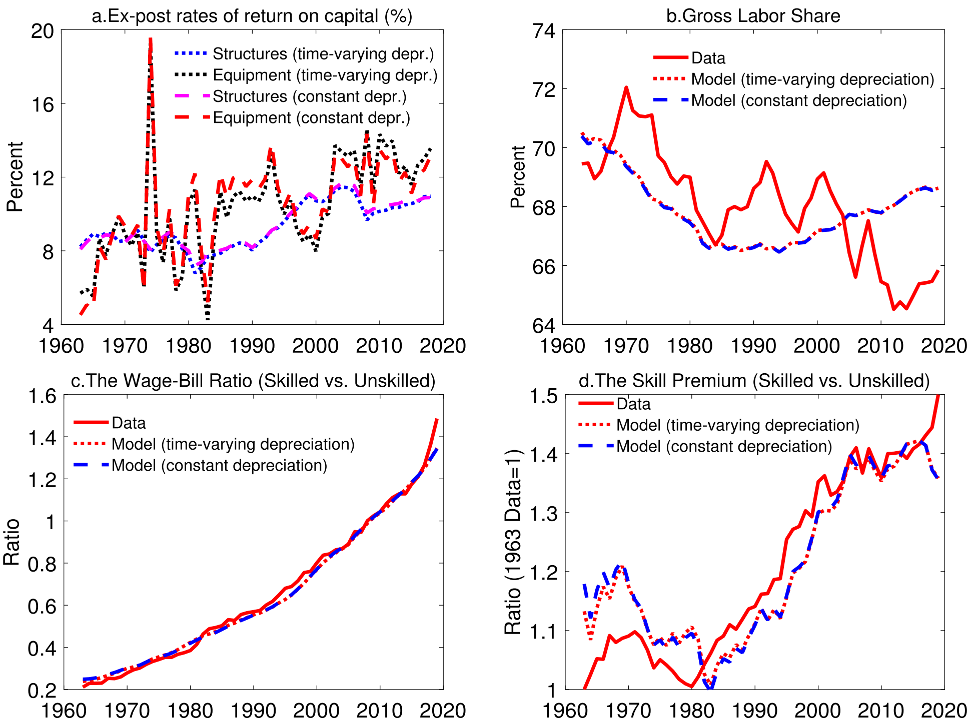
Note: These charts are produced using the observable factor inputs and the parameters estimated employing data for the 1963–2019 period. Nonfarm business sector labor share net of depreciation is used in estimation. While panel a runs through 2018, the rest of the panels plot the data and the model fit for the entire 1963–2019 period.

Fig. C.6. The model's fit for the 1963-2019 period (with nonfarm business sector net labor share).

Table C.3
Comparison of parameter estimates with constant depreciation rates (with KORV definition of gross labor share).

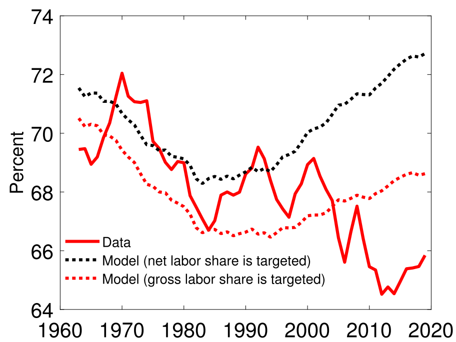
	1963-1992	1963-1992	1963-2019	1963-2019
	Time-varying	Constant	Time-varying	Constant
σ	0.438 (0.020)	0.435 (0.017)	0.431 (0.013)	0.418 (0.011)
ρ	−0.520 (0.043)	−0.534 (0.048)	−0.309 (0.026)	−0.293 (0.024)
α	0.105 (0.002)	0.106 (0.002)	0.109 (0.002)	0.109 (0.002)
η_ω	0.083 (0.007)	0.082 (0.026)	0.085 (0.005)	0.090 (0.005)

Note: The values in parentheses are standard errors.



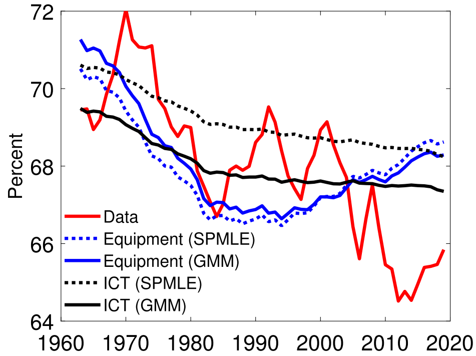
Note: These charts are produced using the observable factor inputs and the parameters estimated with the SPMLE methodology employing the original KORV data, which covers the period between 1963 and 2019. While panel a runs through 2018, the rest of the panels plot the data and the model fit for the entire 1963–2019 period.

Fig. C.7. Comparison of model fit with time-varying and constant depreciation rates (with KORV's definition of gross labor share).



Note: This chart is produced using the observable factor inputs and the parameters estimated employing data for the 1963–2019 period. The black dotted line is the implied gross labor share when KORV's definition of the net labor share is used in estimation. The red dotted line is the gross labor share when KORV's definition of gross labor share is used in estimation.

Fig. C.8. Model fits for KORV's gross labor share (using either net or gross labor shares as targets).



Note: This chart is produced using the observable factor inputs and the parameters estimated employing data for the 1963–2019 period. Blue lines are obtained when equipment capital is used as complementary capital, while black lines are obtained when ICT capital is used as complementary capital.

Fig. C.9. Model fits for KORV's gross labor share (using either equipment or ICT capital as complementary capital).

References

Acemoglu, D., Restrepo, P., 2018. The race between man and machine: implications of technology for growth, factor shares, and employment. American Economic Review 108, 1488–1542.
Acemoglu, D., Restrepo, P., 2019. Automation and new tasks: how technology displaces and reinstates labor. The Journal of Economic Perspectives 33, 3–30.
Alvarez-Cuadrado, F., Long, N., Poschke, M., 2015. Capital-Labor Substitution, Structural Change and the Labor Income Share. IZA Discussion Papers 8941. Institute for the Study of Labor (IZA).
Armenter, R., 2015. A bit of a miracle no more: the decline of the labor share. Business Review, 1–9.
Autor, D.H., 2015. Why are there still so many jobs? The history and future of workplace automation. The Journal of Economic Perspectives.
Autor, D.H., Levy, F., Murnane, R.J., 2003. The skill content of recent technological change: an empirical exploration. The Quarterly Journal of Economics 118, 1279–1333.
Autor, D.H., Katz, L.F., Kearney, M.S., 2008. Trends in U.S. wage inequality: revising the revisionists. Review of Economics and Statistics 90, 300–323.
Bridgman, B., 2018. Is labor's loss capital's gain? Gross versus net labor shares. Macroeconomic Dynamics 22, 2070–2087.
Cooley, T.F., Prescott, E.C., 1995. Frontiers of Business Cycle Research. Princeton University Press, pp. 1–38.
Cummins, J.G., Violante, G.L., 2002. Investment-specific technical change in the US (1947-2000): measurement and macroeconomic consequences. Review of Economic Dynamics 5, 243–284.
DiCecio, R., 2009. Sticky wages and sectoral labor comovement. Journal of Economic Dynamics and Control 33, 538–553.
Domeij, D., Ljungqvist, L., 2019. Public sector employment and the skill premium: Sweden versus the United States 1970–2012. Scandinavian Journal of Economics 121, 3–31.
Dorn, D., Katz, L.F., Patterson, C., Van Reenen, J., et al., 2017. Concentrating on the fall of the labor share. American Economic Review 107, 180–185.
Eden, M., Gaggl, P., 2018. On the welfare implications of automation. Review of Economic Dynamics 29, 15–43.
Eden, M., Gaggl, P., 2019. Capital Composition and the Declining Labor Share. Tech. Rep.
Eisfeldt, A.L., Falato, A., Xiaolan, M.Z., 2022. Human capitalists. In: NBER Macroeconomics Annual 2022, vol. 37. National Bureau of Economic Research, Inc. NBER Chapters.
Elsby, M., Hobijn, B., Sahin, A., 2013. The decline of the U.S. labor share. Brookings Papers on Economic Activity 47, 1–63.
Flood, S., King, M., Ruggles, S., Warren, J.R., 2015. Integrated public use microdata series, current population survey: version 4.0. [machine-readable database]. https://cps.ipums.org/cps/.
Gordon, R.J., 1990. The Measurement of Durable Goods Prices. NBER Books, No. gord90-1. National Bureau of Economic Research, Inc.
Greenwood, J., Hercowitz, Z., Krusell, P., 1997. Long-run implications of investment-specific technological change. American Economic Review 87, 342–362.
Grossman, G., Helpman, E., Oberfield, E., Sampson, T., 2018. The Productivity Slowdown and the Declining Labor Share. Tech. Rep.
Guerriero, M., Sen, K., 2012. What Determines the Share of Labour in National Income? A Cross-Country Analysis. IZA Discussion Papers 6643. Institute for the Study of Labor (IZA).
Jordà, Òscar, Knoll, K., Kuvshinov, D., Schularick, M., Taylor, A.M., 2019. The rate of return on everything, 1870–2015. The Quarterly Journal of Economics 134, 1225–1298.
Karabarbounis, L., Neiman, B., 2014a. Capital Depreciation and Labor Shares Around the World: Measurement and Implications. NBER Working Papers 20606. National Bureau of Economic Research, Inc.
Karabarbounis, L., Neiman, B., 2014b. The global decline of the labor share. The Quarterly Journal of Economics 129, 61–103.
Katz, L.F., Murphy, K.M., 1992. Changes in relative wages, 1963-1987: supply and demand factors. The Quarterly Journal of Economics 107, 35–78.
Koh, D., Santaeulalia-Llopis, R., Zheng, Y., 2015. Labor Share Decline and the Capitalization of Intellectual Property Products.
Krusell, P., Ohanian, L.E., Rios-Rull, J.-V., Violante, G.L., 1997. Capital-skill complementarity and inequality: a macroeconomic analysis. Tech. Rep.
Krusell, P., Ohanian, L.E., Rios-Rull, J.-V., Violante, G.L., 2000. Capital-skill complementarity and inequality: a macroeconomic analysis. Econometrica 68, 1029–1054.
Maliar, L., Maliar, S., Tsener, I., 2020. Capital-Skill Complementarity and Inequality: Twenty Years After. CEPR Discussion Papers 15228, C.E.P.R. Discussion Papers.
Maliar, L., Maliar, S., Tsener, I., 2022. Capital-skill complementarity and inequality: twenty years after. Economics Letters 220, 110844.
Marx, M., Mojon, B., Velde, F.R., 2019. Why have interest rates fallen far below the return on capital. BIS Working Papers 794. Bank for International Settlements.
Ohanian, L.E., Orak, M., 2016. Capital-Skill Complementarity, Inequality, and Labor's Share of Income, 1963-2013. Discussion Paper.
Orak, M., 2017. Capital-Task Complementarity and the Decline of the U.S. Labor Share of Income. International Finance Discussion Papers 1200. Board of Governors of the Federal Reserve System (U.S.).
Polgreen, L., Silos, P., 2008. Capital-skill complementarity and inequality: a sensitivity analysis. Review of Economic Dynamics 11, 302–313.

Rognlie, M., 2015. Deciphering the fall and rise in the net capital share: accumulation or scarcity? Brookings Papers on Economic Activity 46, 1–69.
Sherk, J., 2016. Labor's Share of Income Little Changed Since 1948. The Heritage Foundation Report.
vom Lehn, C., 2018. Understanding the decline in the U.S. labor share: evidence from occupational tasks. European Economic Review 108, 191–220.
White, H., 1996. Estimation, Inference and Specification Analysis, vol. 22. Cambridge University Press.