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Revisiting Capital-Skill Complementarity, Inequality, and Labor Share*

Lee Ohanian[†] Musa Orak[‡] Shihan Shen[§]

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Abstract

This paper revisits capital-skill complementarity and inequality, as in Krusell, Ohanian, Rios-Rull and Violante (KORV, 2000). Using their methodology, we study how well the KORV model accounts for more recent data, including the large changes in the labor's share of income that were not present in KORV. We study both labor share of gross income (as in KORV), and income net of depreciation. We also use nonfarm business sector output as an alternative measure of production to real GDP. We find strong evidence for continued capital-skill complementarity in the most recent data, and we also find that the model continues to closely account for the skill premium. The model captures the average level of labor share, though it overpredicts its level by 2-4 percentage points at the end of the period.

Keywords: Capital-skill complementarity, elasticity of substitution, inequality, labor share, skill premium, technological change.

JEL Codes: E13, E25, J23, J3, J68.

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[†]University of California, Los Angeles, Department of Economics, 8283 Bunche Hall, Box 951477, Los Angeles, CA, 90095-1477. E-mail: ohanian@econ.ucla.edu.

[‡]Board of Governors of the Federal Reserve System, 20th St. and Constitution Ave. NW, Washington, D.C. 20551. E-mail: musa.orak@frb.gov.

[§]University of California, Los Angeles, Department of Economics, 8283 Bunche Hall, Box 951477, Los Angeles, CA, 90095-1477. E-mail: sshen92@g.ucla.edu.

1 Introduction

This paper studies capital-skill complementarity as developed by Krusell et al. (2000), hereafter referred to as KORV. There are two important and related reasons to revisit this hypothesis. One is that KORV analyze data from 1963–1992, which is well before recent concerns about rising inequality. Another is because information, communications, and other advanced technologies that form the conceptual basis for the KORV production function have advanced enormously since 1992.[1] To put this in perspective, we note that in 1992, the internet was largely unknown; only one out of four homes had a personal computer; the most popular business software was Lotus 1-2-3, and smart phones, online commerce; and portable document formatting (PDF) had not yet arrived. To the extent that these and related technological advances complement skilled labor more than unskilled labor, we would expect that the KORV hypothesis would continue to be quantitatively important in the post-1992 data.

We update the KORV dataset up to 2019. We estimate the parameters of the model, including the substitution elasticity parameters, using their same two-stage simulated pseudo maximum likelihood estimation (SPMLE) technique, in which parameters are chosen to minimize the distance between data and model moments involving the labor's share of income, the ratio of labor income paid to skilled workers to that of unskilled workers, and an ex-ante rate of return equality (arbitrage) between different types of capital goods. As in KORV, the wage premium is implied by estimated parameters and data.

This analysis allows us to address several questions about inequality and the capital-skill complementarity hypothesis. Will the KORV model closely account for the skill premium in post-1992 data? Will the parameter estimates be similar to the original estimates? If not, how will they change, and why? Along which dimensions will the model perform better, or worse? How will the large post-1992 changes in the labor's share of gross income affect the analysis?

[1] The growth rate of relative price of equipment capital, a proxy for the inverse of equipment-specific technological progress, has averaged negative 6.6 percent per year after 1992, compared to negative 4.3 percent observed during 1963–1992.

Regarding labor share, we analyze the model using both the labor share of gross income, which is the measure that has declined, and the labor share of income net of depreciation, which has not declined as much, and which is now being analyzed widely within the literature. KORV only considered gross labor share since there were no large changes in depreciation during the years they studied, and thus there was no need to consider both.

Our main finding is that the KORV model continues to fit the data quite well, with high substitutability between unskilled labor and capital and relative complementarity between skilled labor and capital.

The size of the relative complementarity between skilled labor and capital is modestly smaller than in KORV. This difference is driven largely by the post-1992 movements in the labor's share, as the estimated parameters from the original KORV period imply a significant increase in the labor's share of income outside of the original data period. Neither gross nor net labor share exhibits such a rise in observed data. The estimation thus chooses a somewhat smaller, though still highly significant, complementarity between skilled labor and equipment capital to attenuate this increase: 0.76 when gross labor share is used, and 0.72 for net labor share, compared with 0.67 in KORV (gross labor share).

We find even a bit stronger complementarity with net labor share, suggesting the decline in gross labor share reflects a compositional shift of the capital stock towards more rapidly depreciating equipment. The model with (KORV's definition of) net labor share outperforms the baseline model with gross labor share as it has a bit better fit of the skill premium, it is more consistent with the observed rates of return on equipment capital, and it can correctly capture the long-term stability of (net) labor share.

As a robustness check, we estimate the model using nonfarm business sector gross and net labor shares. A strong capital-skill complementarity between skilled labor and equipment capital prevails in this case too, and the model's fit of data improves slightly relative to the baseline case with KORV's definition of gross labor share, particularly for the skill premium.

This paper proceeds as follows. Section 2 presents a brief summary of the related literature. Section 3 presents a short description of data construction and a data summary. Section 4 presents the theoretical model, and Section 5 presents the quantitative analysis.

Section 6 concludes.

2 Related Literature

Our paper contributes to several strands of literature. Krusell et al. (2000), whose elasticity estimates have been used widely, is the most obvious. Previously, Polgreen and Silos (2008) revisited the KORV study, and, using data through 2004, they found that capital-skill complementarity is extremely robust to the price series used. In a more recent study, Maliar et al. (2020) re-estimated the KORV model with data through 2017. They also found that the capital-skill complementarity framework remains remarkably successful in explaining the U.S. data, particularly the skill premium. Despite the similarities in findings, our estimation gives a closer match to the original KORV results and a closer fit of the U.S. data. In particular, our estimates of ex-post rates of return are in line with standard measures of these returns, while those estimated by Maliar et al. (2020) are too high, averaging around 35–40 percent. We also assess the sensitivity of our results to various definitions of the labor share, particularly differentiating between gross and net (of depreciation) labor shares, and analyzing both real GDP and real nonfarm private business output.

The paper also relates to the literature on factor income shares. The 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)). Explanations of the declining trend include trade and offshoring (Elsby et al. (2013)), foreign direct investment in inflows and mechanization (Guerriero (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)). Our paper relates to those that connect the declining labor share to technological change, including Orak (2017), who links the decline in the labor's share to technological change and the resulting shift in occupational composition of the workforce; Eden and Gaggl (2018), who attribute half of the decline to the rise in the income share of information and communications technology (ICT) capital, using a framework distinguishing between ICT and non-ICT capital; 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; and vom Lehn (2018), who explains the decline with replacement of workers engaged in routine (repetitive) occupations (job polarization). Analyzing the KORV model 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 the labor's share is not significant once some factors, such as the housing sector (Rognlie (2015)), capitalization of intellectual property products (Koh et al. (2015)), and depreciation and taxes (Bridgman (2014)), are netted out.[2] Sherk (2016) argues that the decline in the 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.[3] Using net labor share leads to a higher estimated complementarity between skilled labor and equipment capital and a modestly better fit for the data, while producing a labor share more consistent with its data counterpart in terms of its long-run stability.

3 Data

We focus on U.S. time series of capital and labor between 1963 and 2019.

3.1 Capital Data

We collected the equipment (including intellectual property products) and structures investment series from National Income and Product Accounts (NIPA) and we used the perpetual

[2]Note that Karabarbounis and Neiman (2014a) 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 (2014) and our study focus solely on U.S. data.

[3]KORV's measure of the gross labor share already excluded self-employment.

inventory method 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 price deflator of GDP retrieved from FRED to generate real investment levels for each year.[4] The quarterly data are transformed into an annual series via simple averaging.

As Krusell et al. (2000) point out, NIPA data on capital equipment stock tends to overstate price changes because it does not adequately account for increases in quality over time. Therefore, we need a quality-adjusted equipment capital price series to deflate the investment in nonresidential equipment capital and intellectual property products when deriving the equipment capital stock series. We take the consumption deflator provided by DiCecio (2009) and multiply it with the relative price of equipment, also drawn from DiCecio (2009) to obtain the deflator of equipment investment, which are constructed following the procedure pioneered by Cummins and Violante (2002).[5][6]

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. Alternatively, we also use constant depreciation rates as in KORV, but recalibrate those using the most recent data.

3.2 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-

[4]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.

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

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

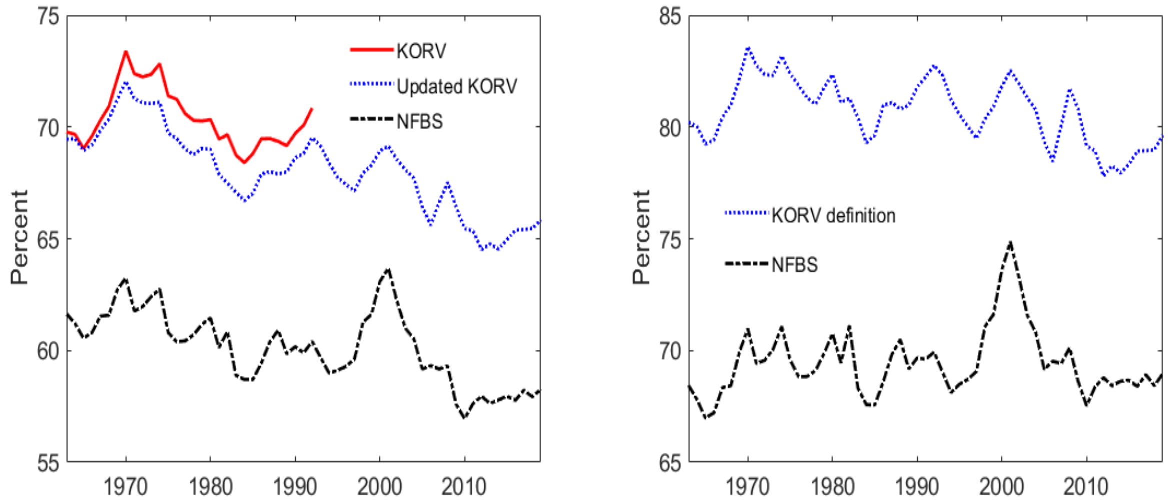
level data, excluding those who are younger than 16 or older than 70, unpaid family workers, and those working in the military. Although we also drop the self-employed from our wage sample, we include them when constructing labor input series. We also drop the observations of those who report working less than 40 weeks or 35 hours a week or both. 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.

3.3 Labor Share

We construct our labor share series using the BEA NIPA tables. To facilitate comparison with Krusell et al. (2000), we use 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 left panel of Figure 3.1, although the (gross) labor share was nearly flat in KORV's data, it has been trending down since then (though our data have some level differences, possibly driven by data revisions). Apart from level differences, both KORV and NFBS series 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 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 use to construct the labor share of net income. As seen in the

Figure 3.1: Labor shares
(left panel: gross labor shares; right panel: net labor shares)



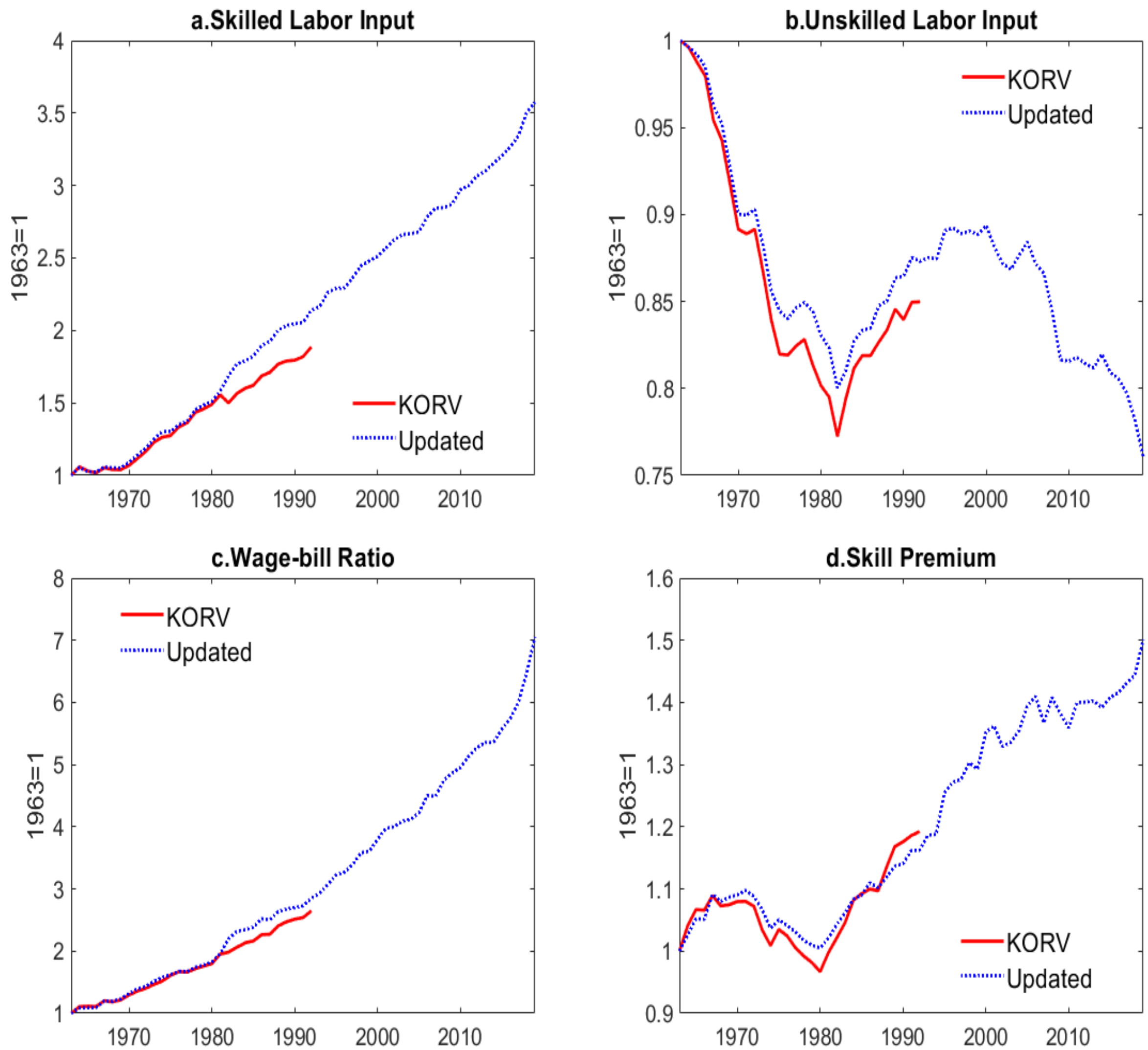
right panel of Figure 3.1, these net measures of labor share do not exhibit a significant trend decline, though they are volatile.

3.4 Summary of the Data

Figure 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 revision) beginning from 1982 in our update relative to KORV. Of note, other studies replicating KORV data, including Polgreen and Silos (2008) and Maliar et al. (2020), have documented a similar level shift. The wage-bill ratio, which is the ratio of income share of skilled labor to that of unskilled labor, has continued to increase (panel c). 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).

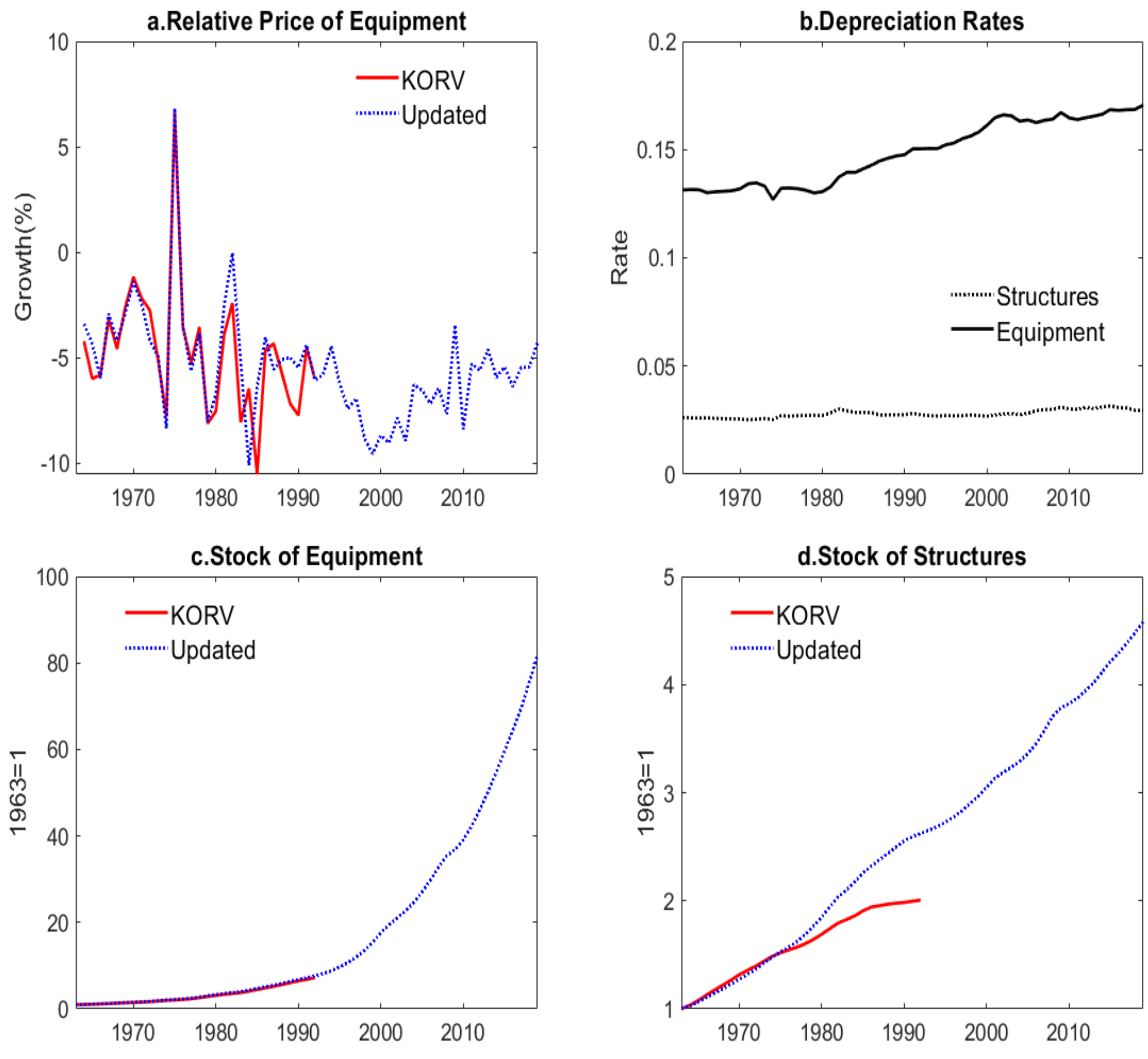
Figure 3.3 presents the evolution of the capital data over the 1963-2019 period, together

Figure 3.2: Comparison of original KORV data and updated labor data



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, the (inverse) proxy for technological progress. 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 then, the growth rate of relative price of equipment capital has averaged about negative 6.6 percent per year, compared with the negative 4.3 percent observed during the period of 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). Even so, our stock of structures has a more rapid growth pace relative to original KORV data, including during the period of the original KORV study, reflecting data revisions.

Figure 3.3: Comparison of original KORV data and updated capital data



4 Model

4.1 Model Environment

We use the same theoretical model 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 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 1. 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, which is used as the (inverse) proxy for technological progress.

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

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

where Y_t is the final good, h_u, and h_s are raw unskilled and skilled labor units, respectively. Similarly, φ_u and φ_s are efficiencies of these labor types. A_t 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:

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

The elasticity of substitution between unskilled labor input and equipment capital is the same as the substitution elasticity between unskilled and skilled labor inputs.[7] In equation (4.3), u_t and s_t, efficiency hours for the respective skill group, are defined as follows:

$$u_t = e^{\varphi_{u,t}} h_{u,t} \quad (4.4)$$

$$s_t = e^{\varphi_{s,t}} h_{s,t}. \quad (4.5)$$

The model has the following set of parameters to be estimated: $\Upsilon \in \{\sigma, \rho, \alpha, \mu, \lambda\}$. Here, μ and λ are parameters governing the factor shares. The parameter α is the income share of structures capital. The parameters σ and ρ are the key parameters as they govern the elasticities of substitution between equipment capital and the two types of labor input. Following Krusell et al. (2000), we define the elasticity of substitution between unskilled labor input and the composite product of equipment capital and skilled labor as $\frac{1}{1-\sigma}$, and the elasticity of substitution between equipment capital and skilled labor input as $\frac{1}{1-\rho}$.[8]

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, while the relative demand for unskilled labor would fall.

4.3 The Model Skill Premium

Given perfect competition, the firm's problem is

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

[7] 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.

[8] Note that this definition assumes that all other factors are constant. Polgreen and Silos (2008) report that capital-skill complementarity prevails even when the Allen and Morishima elasticities of substitution are used instead, though at significantly varying magnitudes.

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:

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

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 we log-linearize equation (4.7) and differentiate with respect to time, we obtain

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

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 $\sigma < 1$, relatively 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, 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, compared with from 1963 through 1992 in Krusell et al. (2000). We use the same empirical methodology as Krusell et al. (2000). This includes a two-stage SPMLE procedure to estimate most of the model parameters. Appendix B describes this in detail.

There are two stochastic elements to close the model and ensure that the likelihood is well-defined. One element involves introducing stochastic components into the two labor inputs. Following Krusell et al. (2000), we specify the stochastic process as:

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

where φ_t is a 2×1 vector of the log of labor efficiencies for skilled and unskilled labor at time t, γ is a 2×1 vector of efficiency growth rates, φ_0 is a 2×1 vector of constants that correspond to the initial levels of efficiencies (and average efficiency levels in the absence of trend growth), and ω_t is a 2×1 vector of labor efficiency shocks, which have a multivariate normal distribution with zero mean and covariance matrix Ω. We set $\gamma = 0$ as Krusell et al. (2000) did.

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) hypothesized a risk neutral investor in which arbitrage equates the ex-ante expected returns on structures and equipment investments. This "no arbitrage" condition is given as

$$q_t A_{t+1} G_{eq,t+1} + (1 - \delta_{eq,t+1}) E\left(\frac{q_t}{q_{t+1}}\right) = A_{t+1} G_{st,t+1} + (1 - \delta_{st,t+1}), \tag{5.2}$$

where $G_{eq,t+1}$ and $G_{st,t+1}$ are derivatives of function $G\left(k_{st,t}, k_{eq,t}, h_{u,t}, h_{s,t}; \varphi_{u,t}, \varphi_{s,t}; \Upsilon\right)$ with respect to equipment and structural capitals 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 value. The right-hand side terms are analogues.

Equation (5.2) is one of the three equations used in the estimation. We adopt the assumptions of Krusell et al. (2000) regarding this equation: there is no risk premium, tax treatments for these two types of capital are the same, 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.

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

$$wbr_t(X_t, \varphi_{u,t}, \varphi_{s,t}; \Upsilon) = \frac{w_{s,t}h_{s,t}}{w_{u,t}h_{u,t}} \tag{5.3}$$

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

where the wbr_t is the wage-bill ratio and $lshare_t$ is the labor share, both of which are a function of observable factor inputs $X_t = \{k_{st,t}, k_{eq,t}, h_{u,t}, h_{s,t}\}$, unobservable labor efficiencies $\varphi_{u,t}$ and $\varphi_{s,t}$, and a set of parameters $\Upsilon = \{\sigma, \rho, \alpha, \mu, \lambda, \varphi_{u0}, \varphi_{s0}, \eta_\epsilon, \eta_\omega, \delta_{eq}, \delta_{st}\}$. This 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 5.2 to 5.4. The right-hand sides of the equations are the model counterparts.

As in Krusell et al. (2000), we calibrate some of the parameters. Depreciation rates are calibrated using the NIPA tables for the capital stock and capital consumption. Unlike Krusell et al. (2000), we use time varying depreciation rates in our benchmark analysis. We find that 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.

Following Krusell et al. (2000), we estimate an ARIMA model for the relative price of equipment capital to calibrate η_ϵ, where η_ϵ is set equal to $(1-\bar{\delta}_{eq})$ times the standard error of the residuals of the ARIMA model. The resulting regression is $\hat{q}_t = 2.12 - 0.001t - 0.48\hat{q}_{t-1} + 0.58\epsilon_{t-1} + \epsilon_t$ with $\hat{q}_t = \frac{q_{t-1}}{q_t}$ and $\sigma_\epsilon = 0.0233$.[9] This regression gives us $\eta_\epsilon = 0.020$. 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 factors that could potentially affect labor quality, which are the current and lagged stocks of both types of capital, lagged relative equipment capital price, a time trend, and the lagged value of leading business cycle indicator of the Conference Board. The fitted (instrumented) values are then used in the SPMLE stage.

As in KORV, we chose 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 structural and equipment investments. Note that we do not view this parameter as having economic interest, as it was introduced to ensure a well-behaved likelihood.[10]

5.2 Findings

This subsection presents the baseline results, which use KORV's definition of gross labor share for comparability and include the BEA's time-varying depreciation rates. As a robustness check, we also estimated the model using constant depreciation rates. The findings are very similar and thus are reported in Appendix C.

Table 5.1 presents the estimated parameters for 1963 through 1992, the original period of KORV, using both the original KORV data and revised data. Column I reports the estimates of KORV. Column II is our replication using the original KORV data. Figure C.1 in the Appendix, should be compared with figures 5 through 8 in Krusell et al. (2000), as it presents

[9]When we estimate the ARIMA model for the 1963-1992 period, we obtain the following regression: $\hat{q}_t = 2.85 - 0.001t + 0.55\hat{q}_{t-1} - \epsilon_{t-1} + \epsilon_t$ with $\sigma_\epsilon = 0.0243$, which gives us $\eta_\epsilon = 0.021$.

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

the model fit from this case. The estimated parameters and the model's fit are both very similar to KORV.

Table 5.1: Parameter estimates for the 1963–1992 period

	I. KORV(2000)	II. KORV Replication	III. Re-estimation with updated data
σ	0.401 (0.234)	0.412 (0.015)	0.436 (0.020)
ρ	−0.495 (0.048)	−0.505 (0.056)	−0.517 (0.043)
α	0.117 (0.007)	0.109 (0.003)	0.105 (0.002)
η_ω	0.043 (0.003)	0.043 (0.004)	0.083 (0.008)

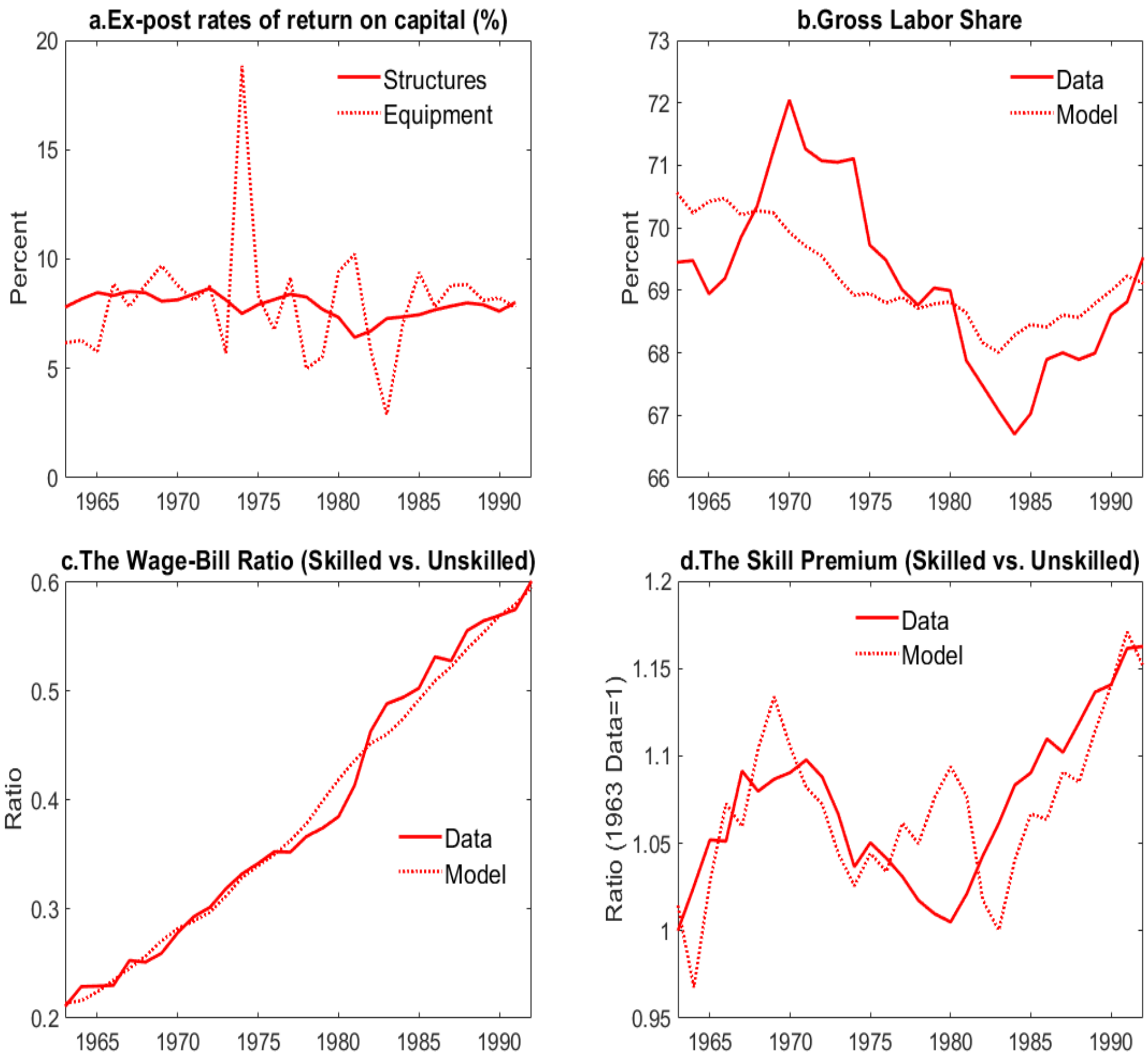
Note: The values in parentheses are standard errors.

As seen in Table 5.1, ρ, the parameter governing the elasticity of substitution between equipment capital and skilled labor input, and α, the share of structures capital in production, is about the same in all three cases. Our estimate of σ, the parameter governing the elasticity of substitution between equipment capital and skilled labor input, is slightly different with revised data from KORV and from our estimates using their original data. KORV's estimated elasticity was 1.67, compared to our estimate of 1.70 using their original data (case II), and 1.77 with revised data (case III).

Figure 5.1 presents the model's fit for 1963 through 1992 using the revised data (case III in table 5.1). Panels a through d shows that the model predictions are broadly in line with the data. Setting the shocks to labor efficiency to zero, 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 labor share, the model fails to capture the volatility observed in the data and instead predicts a fairly stable labor share (panel b). Despite this, the model captures a sizable component of its long-run trend, 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

Figure 5.1: The model's fit for the 1963–1992 period with updated data



Note: These charts are produced using the observed factor inputs and the parameters estimated using data for 1963-1992. The shock terms are set to zero when producing the charts. 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.

in the inequality literature. To determine their empirical fit after 1992, we kept these parameters constant from case II in Table 5.1 but projected the model through 2019, extending the original KORV data with the growth rates of variables since 1992. Figure 5.2 shows these results. 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 the mid 2010s. However, the model with the original KORV parameter estimates fails to capture the pickup in the skill premium in the past few years.

The model fails to capture the ongoing decline in the (gross) labor share, as 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 does not equate the ex-ante expected rates of returns of structural and equipment capital after the 1990s.

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

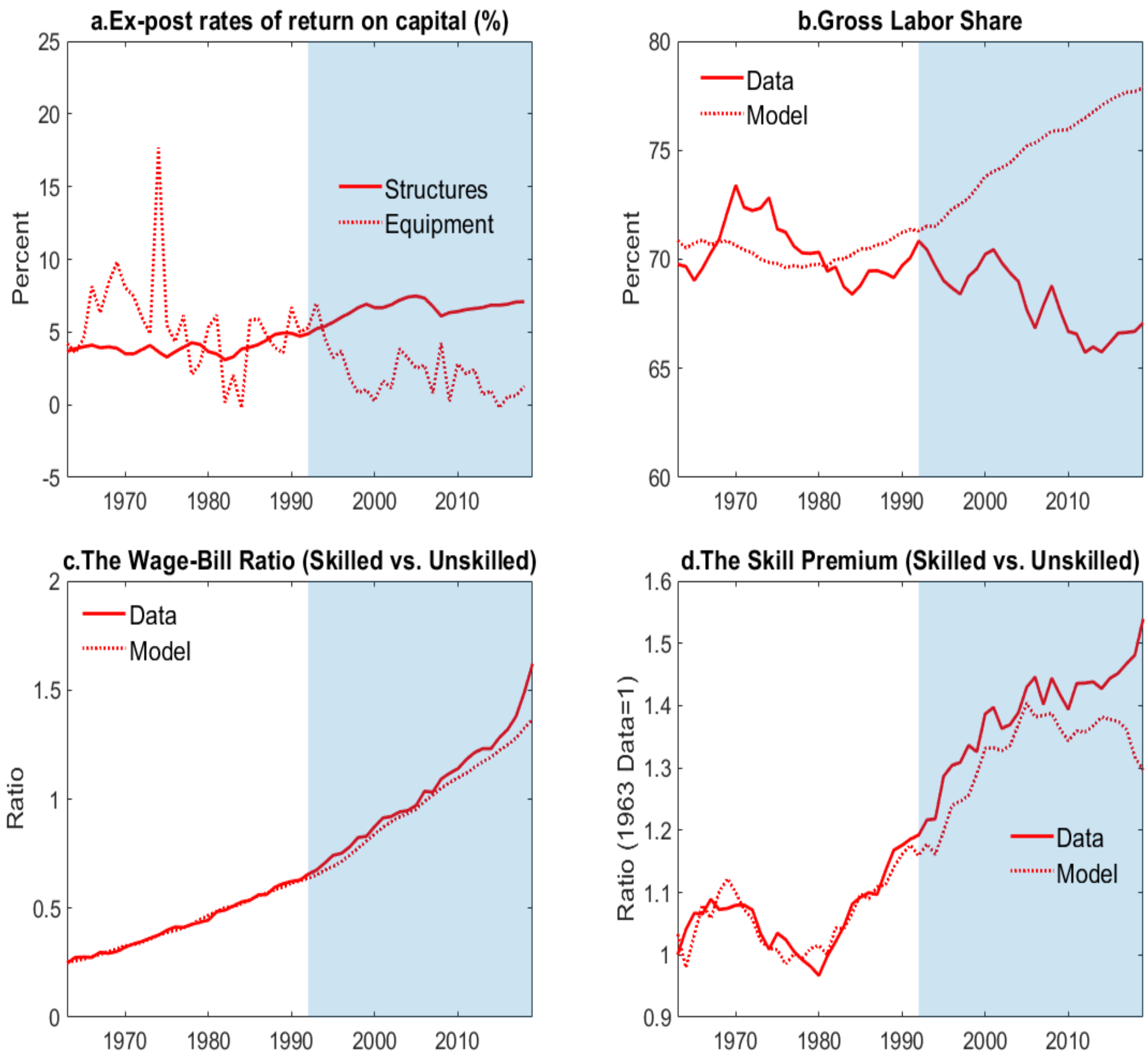
Consider first the green dotted line, which is generated by keeping the skilled and unskilled labor inputs constant at their 1992 levels. The figure shows that keeping these inputs fixed generates an even larger increase in the labor share.

Consider now 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 equipment capital fixed at its 1992 level, respectively. These counterfactuals show that the model's failure to track labor share results from the enormous rise in the stock of equipment capital, which was not matched by a similar rise in the share of the skilled labor input that would be implied by the original KORV elasticities.

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.

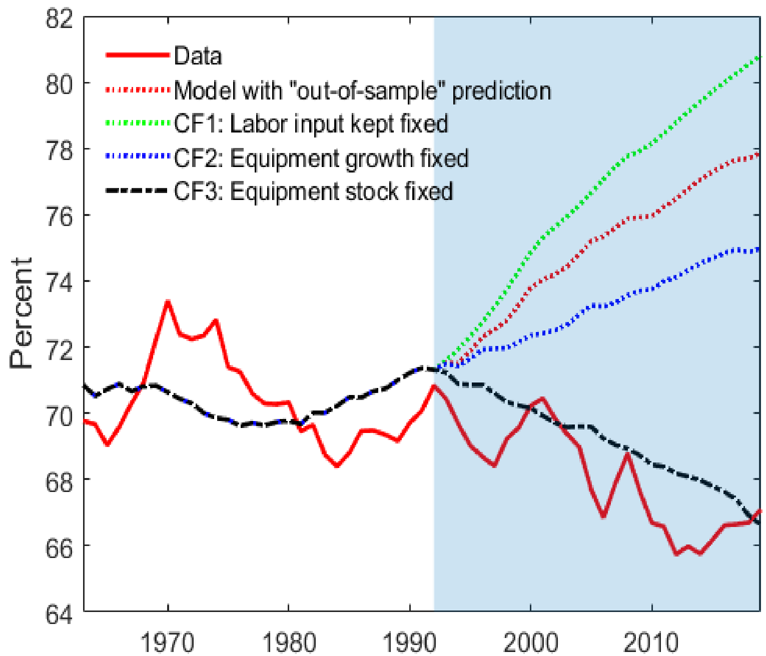
As seen in Table 5.2, the parameters σ and α are almost unchanged from what Krusell et al. (2000) report and what we estimate for the 1963–1992 period. However, ρ, the param-

Figure 5.2: The model's out of sample predictions for the 1993–2019 period with original KORV data until 1992



Note: These charts are produced using the observed factor inputs and the parameters estimated with original KORV data until 1992. The shock terms are set to zero when producing the charts. 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.

Figure 5.3: Gross labor share counterfactuals



Note: The chart is produced using parameters estimated using the original KORV data until 1992. The shock terms are set to zero when producing the charts as in KORV. 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. Finally, in counterfactual 3, we keep equipment capital fixed at its 1992 level.

eter governing the elasticity of substitution between equipment capital and the skilled labor input shows somewhat less complementarity than in Krusell et al. (2000); negative 0.309 compared with negative 0.517, which we obtain 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 fact that equipment-specific technology is now replacing jobs involving skilled labor (for example, artificial intelligence, machine learning).

The optimization algorithm chooses a somewhat lower complementarity between skilled labor and equipment capital to attenuate the model's rising prediction of labor's share of income, as a very high complementarity substantially increases skilled labor's productivity and thus labor's share.

Table 5.2: Parameters estimated for the 1963–2019 period

	σ	ρ	α	η_ω
Mean	0.431	-0.309	0.109	0.085
Standard Error	0.012	0.026	0.002	0.005

Nonetheless, significant capital-skill complementarity is still estimated. Table 5.3 compares our elasticity estimates with those of Krusell et al. (2000).

Table 5.3: Estimated elasticities of substitution

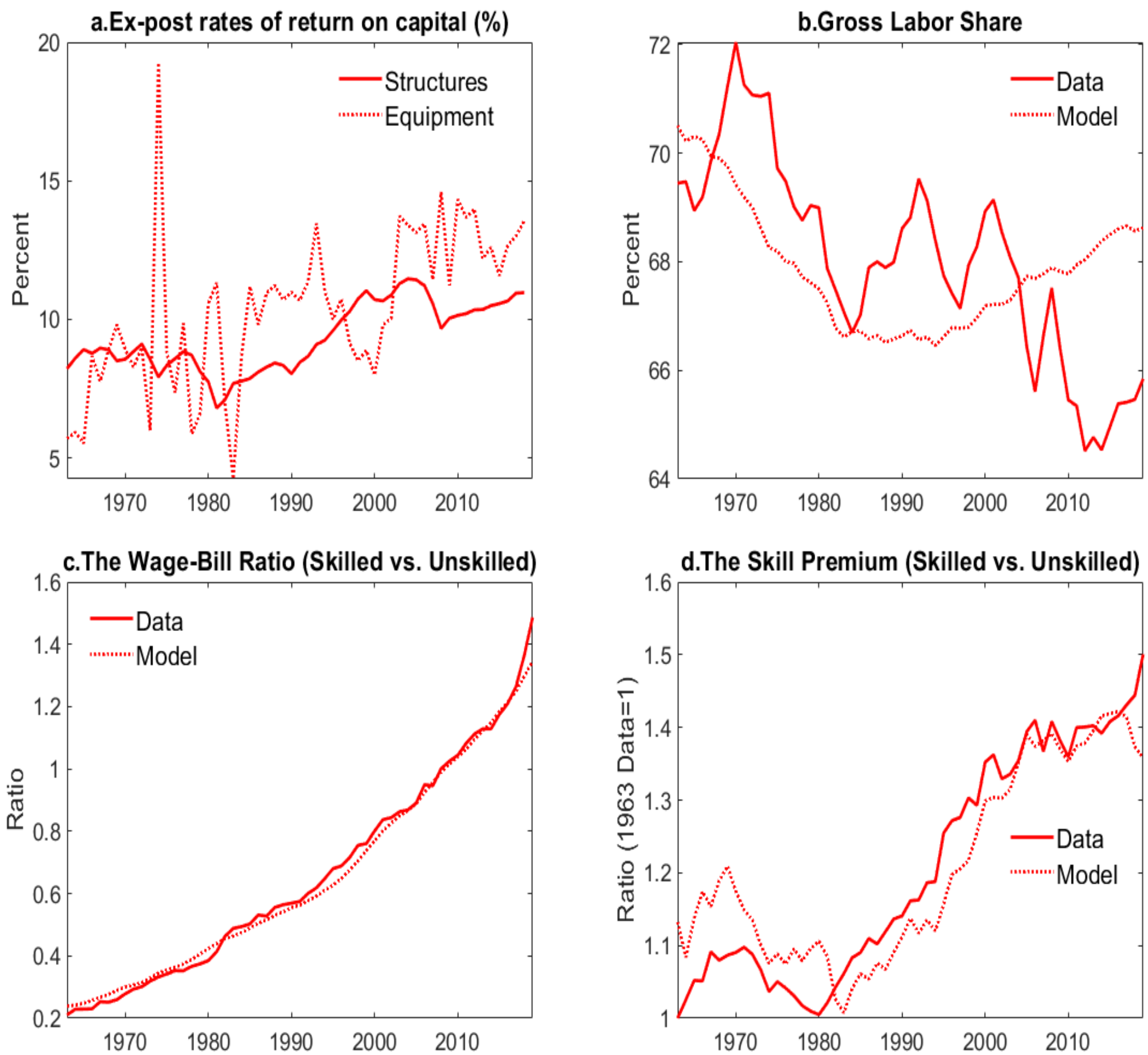
	KORV (1963-1992)	Updated (1963-1992)	Updated (1963-2019)
$\frac{1}{1-\sigma}$	1.67	1.77	1.76
$\frac{1}{1-\rho}$	0.67	0.66	0.76

Figure 5.4 presents the model's fit for 1963 to 2019. Compared to using parameters estimated for the original KORV period (Figure 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 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 (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 has increased from 6 percent in 1980s to around 10 percent in late 1990s, before falling back to around 8 percent by 2010 and remaining there. In contrast, our model predicts return on capital to rise to a little 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 early 1980s, and the rise thereafter, together with a slowdown in the rise since the early 2000s until recently. This indicates that the

Figure 5.4: The model's fit for the 1963–2019 period



Note: These charts are produced using the observed factor inputs and the parameters estimated employing data for the 1963–2019 period. The shock terms are set to zero when producing the charts. KORV's definition of gross labor share 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.

KORV model, 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 with enormous technological change.

The results with constant depreciation rates, along with capital stocks constructed using these constant rates, are almost unchanged from the baseline estimation (see Table C.1), suggesting that our assumption on depreciation rates has no substantive effect on our findings. Because the resulting model fit is nearly the same as those presented in Figures 5.1 and 5.4, we do not report them.

Estimation with nonfarm business sector labor share

The findings are very similar when using non-farm business sector output rather than real GDP. We use this measure of output as an alternative because it is frequently used in the literature on income shares. Although the parameter estimates change slightly in this case, as seen in Table 5.4, capital-skill complementarity remains sizable and significant, as in the baseline case, which uses KORV's definition of the labor share.[11]

Table 5.4: Comparison of parameter estimates with KORV and NFBS gross labor shares

	1963–1992		**1963–2019**	
	KORV	**NFBS**	**KORV**	**NFBS**
σ	0.436	0.390	0.431	0.382
	(0.020)	(0.019)	(0.012)	(0.012)
ρ	−0.517	−0.531	−0.309	−0.335
	(0.043)	(0.051)	(0.026)	(0.026)
α	0.105	0.150	0.109	0.153
	(0.002)	(0.002)	(0.002)	(0.002)
η_ω	0.083	0.088	0.085	0.086
	(0.008)	(0.008)	(0.005)	(0.005)

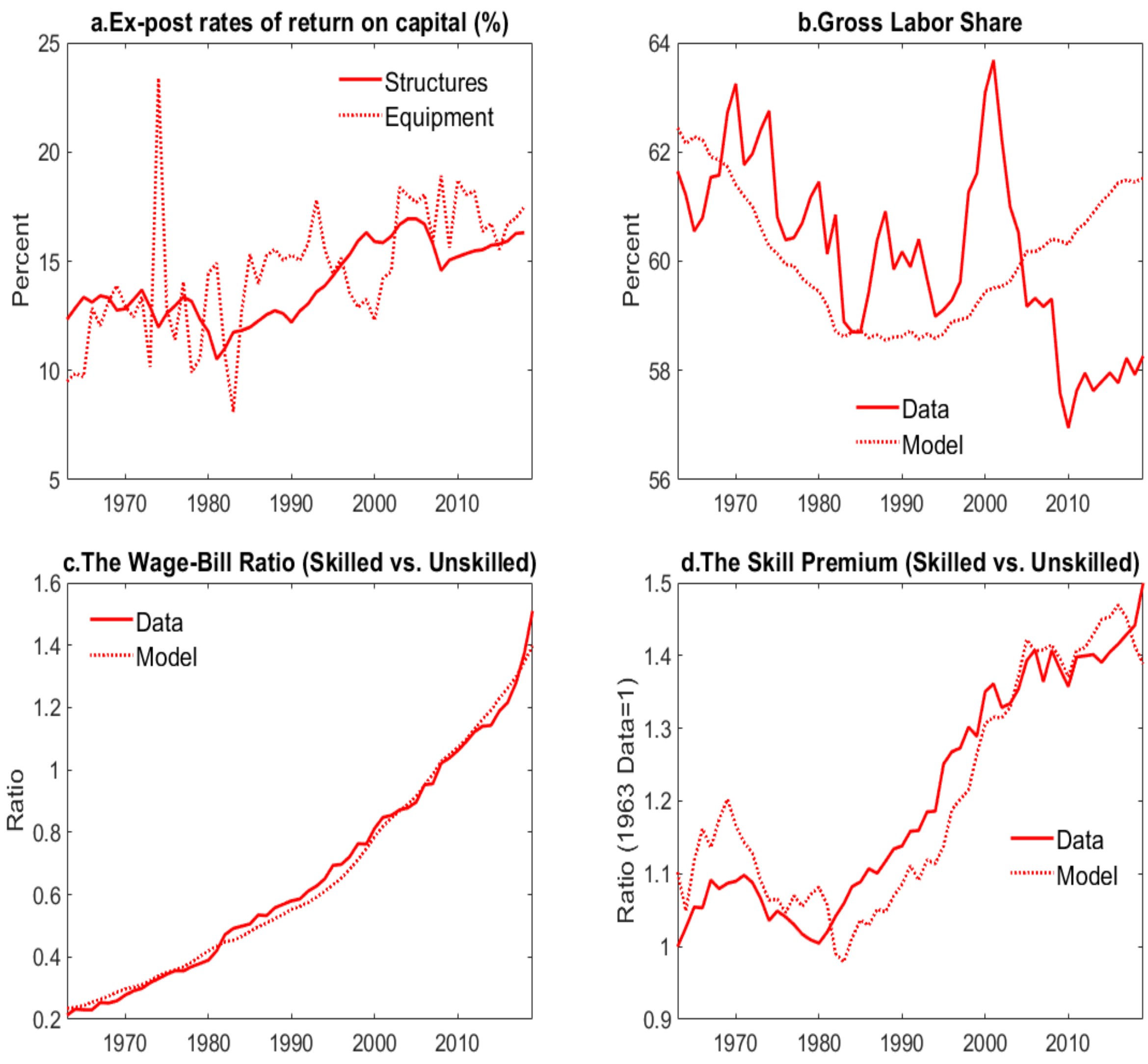
Note: The values in parentheses are standard errors.

As seen in Figure 5.5, the model fit improves slightly for the skill premium (see figure C.2 in Appendix C for the 1963–1992 version of the model fit). This improvement is also observed

[11] The only parameter that is considerably different from the baseline case is α—income share of structural capital. This difference is driven by the level difference between KORV and NFBS labor shares.

in the smaller normalized root mean squared model errors (NRMSEs) for the skill premium compared with that of the baseline model for the 1963–2019 period (columns II and I, respectively, in Table 5.5). The model fit improves for the ex-ante no-arbitrage condition too, though ex-post rates are even larger than in the baseline case. In terms of the labor share, using the NFBS gross labor share brings no improvement to our results, as can be seen in Table 5.6, which reports a larger NRMSE for the 1963–2019 period for this case than in the baseline case with KORV's definition of the gross labor share.

Figure 5.5: The model's fit for the 1963–2019 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. The shock terms are set to zero when producing the charts. 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.

Table 5.5: Normalized RMSE for the skill premium

	I. KORV Gross	**II. NFBS Gross**	**III. KORV Net**	**IV. NFBS Net**
1963-1992*	0.033	0.035	0.035	0.037
1963-1992**	0.064	0.059	0.053	0.058
1963-2019**	0.051	0.048	0.044	0.048

Table 5.6: Normalized RMSE for the labor share

	I. KORV Gross	**II. NFBS Gross**	**III. KORV Net**	**IV. NFBS Net**
1963-1992*	0.015	0.015	0.018	0.020
1963-1992**	0.023	0.022	0.026	0.027
1963-2019**	0.028	0.033	0.028	0.035

*: Estimated for only the 1963–1992 period.
**: Estimated for the entire 1963–2019 period.
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.

5.3 Estimation with Net Labor Share

This section presents model 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 the higher deprecation.

When using net labor share in estimation, we change the profit function as follows:

$$\widetilde{\Pi}_t = A_t G_t - (\widetilde{r_{st,t}} + \delta_{s,t}) k_{st,t} - (\widetilde{r_{eq,t}} + p_{eq,t}\delta_{eq,t}) k_{eq,t} - w_{u,t} h_{u,t} - w_{s,t} h_{s,t},$$

where $\widetilde{r_t}$ is the rental rate of capital net of depreciation. In this case, the labor share equation is

$$\widetilde{lshare}_t = \frac{A_t G_{s,t} h_{s,t} + A_t G_{u,t} h_{u,t}}{A_t G_t - p_{eq,t}\delta_{eq,t} k_{eq,t} - \delta_{st,t} k_{st,t}}. \tag{5.5}$$

The wage-bill-ratio equation does not change as shown:

$$\widetilde{wbr}_t = \frac{G_{s,t} h_{s,t}}{G_{u,t} h_{u,t}}. \tag{5.6}$$

The no-arbitrage condition is now written as follows:

$$\frac{1}{p_{eq,t}}(\widetilde{r_{eq,t+1}} + p_{eq,t}\delta_{eq,t+1}) + (1-\delta_{eq,t+1}) E\left(\frac{p_{eq,t+1}}{p_{eq,t}}\right) = (\widetilde{r_{st,t+1}} + \delta_{st,t+1}) + (1-\delta_{st,t+1}) + \epsilon_t, \tag{5.7}$$

which is very similar to that in the model with gross labor share:

$$\frac{1}{p_{eq,t}} A_{t+1} G_{keq,t+1} + (1-\delta_{eq,t+1}) E\left(\frac{p_{eq,t+1}}{p_{eq,t}}\right) = A_{t+1} G_{kst,t+1} + (1-\delta_{st,t+1}) + \epsilon_t.$$

Table 5.7 presents the parameter estimates with net labor share, together with our baseline parameter estimates for comparison. The capital-skill complementarity remains quantitatively important and significant. The parameter ρ is estimated to be slightly more complementary with equipment, -0.380 compared to -0.309, delivering a lower elasticity of substitution between skilled labor and equipment capital, 0.72 in contrast to 0.76 for gross labor share.

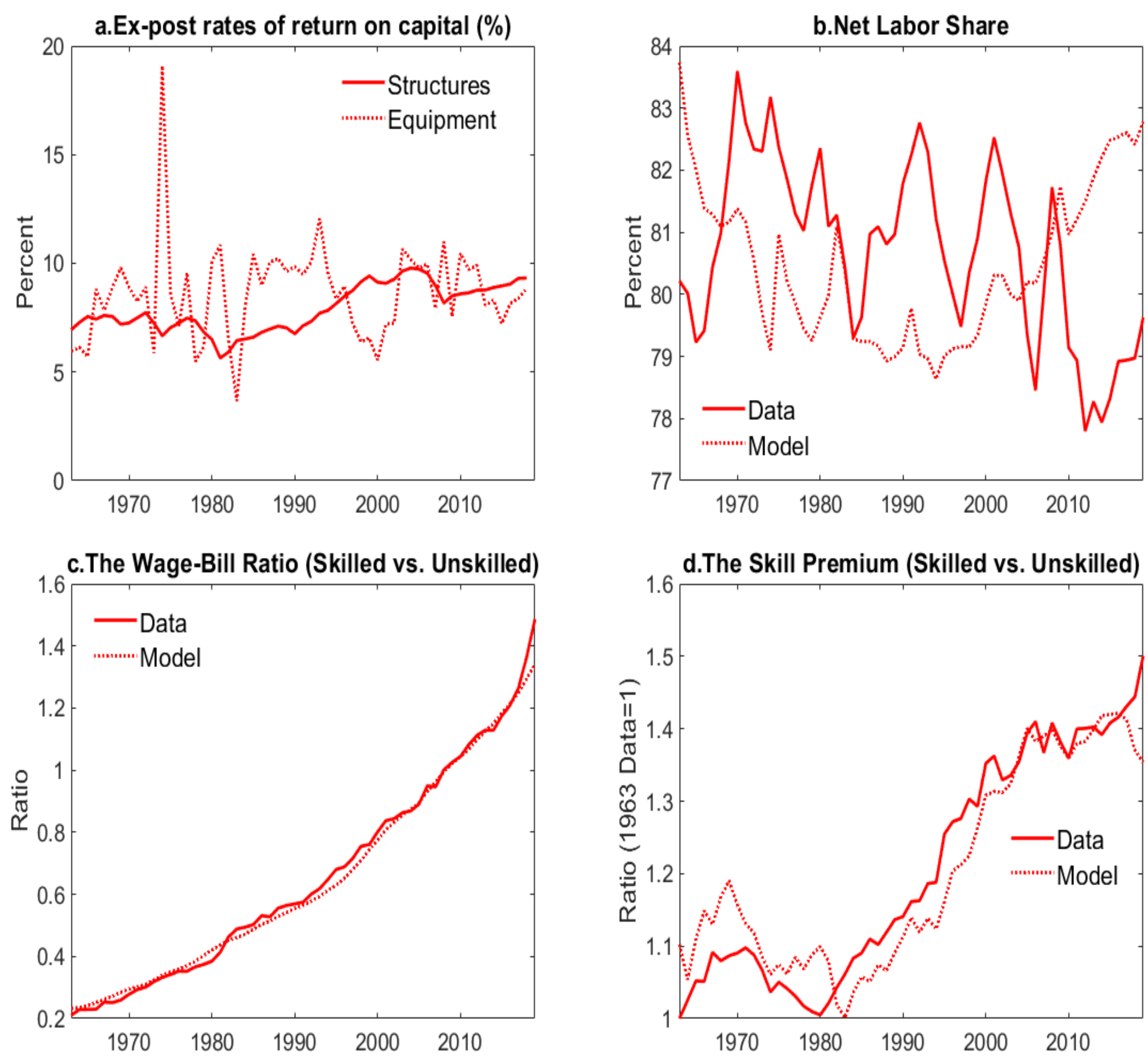
Table 5.7: Comparison of parameter estimates with gross and net labor shares (with KORV definition of the labor share)

	1963-1992		**1963-2019**	
	Gross	**Net**	**Gross**	**Net**
σ	0.436 (0.020)	0.411 (0.024)	0.431 (0.012)	0.423 (0.017)
ρ	−0.517 (0.043)	−0.606 (0.047)	−0.309 (0.026)	−0.380 (0.033)
α	0.105 (0.002)	0.098 (0.003)	0.109 (0.002)	0.096 (0.002)
η_ω	0.083 (0.008)	0.111 (0.016)	0.085 (0.005)	0.090 (0.006)

Note: The values in parentheses are standard errors.

Figure 5.6 presents the model fit with net labor share for the 1963–2019 period. 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). Moreover, 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 share, with an average net labor share of 80.5 percent, compared with 80.7 percent in data.

Figure 5.6: The model's fit for the 1963–2019 period
(with KORV's definition of net labor share)



Note: These charts are produced using the observable factor inputs and the parameters estimated employing data for the 1963–2019 period. The shock terms are set to zero when producing the charts. 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.

To analyze the model fit for labor share, we compare normalized RMSEs for both gross and net income, for both the KORV income definition, and for nonfarm business income.[12] Table 5.6 presents these statistics. As the table suggests, once the RMSEs are corrected (normalized) to account for different levels of labor share definitions, all versions do similarly for both periods. Yet, for the original period (1963–1992), the models with gross labor share gives the smallest deviation from the data, while for the full period (1963–2019), models with KORV's definition, both on gross and net terms, slightly outperform the model with NFBS labor shares.

In summary, all the different cases studied in this paper confirm that capital-skill complementarity remains important, though it has weakened somewhat over time. The model with KORV's definition of *net* labor share slightly outperforms the others, given that it has a bit better fit of the skill premium, it is empirically consistent with the observed rates of return on capital, and it captures the long-term stability of (net) labor share.

6 Conclusion

This paper analyzes capital-skill complementarity as a quantitatively important determinant of U.S. wage inequality, using data through 2019, compared with Krusell et al. (2000), which used data only through 1992. A major change in the post-1992 data is increased depreciation, which in turn has reduced labor's share of gross income. We therefore used both labor's share of gross income, as in the original KORV analysis, and labor's share of net income. We also used two definitions of income, the original KORV measure, and nonfarm business income, which is frequently used in the income share literature.

We find that capital-skill complementarity continues to be a critical determinant of U.S. wage inequality, irrespective of which definition of income is used to measure labor's share. Labor's share of income does influence the degree of estimated complementarity between equipment and skilled labor, but it does not have a sizable effect on the model's ability to account for the skill premium. The findings indicate that capital-skill complementarity

[12] The estimation results and the model fit with non-farm business net labor share are presented in Table C.2 and Figure C.3 in Appendix C.

remains a quantitatively important determinant of U.S. wage inequality.

We find that capital-skill complementarity continues to be a critical determinant of U.S. wage inequality, irrespective of which definition of income is used to measure labor's share. Labor's share of income does influence the degree of estimated complementarity between equipment and skilled labor, but it does not have a sizeable effect on the model's ability to account for the skill premium. The findings indicate that capital-skill complementarity remains a quantitatively important determinant of U.S. wage inequality.

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A Data description

A.1 Construction of labor inputs and wage rates

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 the previous year, and who did not report their education level. Following Domeij and Ljungqvist (2019), 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 also 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

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

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:

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

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

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

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 from 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.

B Estimation technique

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: $\tilde{X}_t = \left\{k_{st,t}, k_{eq,t}, \hat{h}_{s,t}, \hat{h}_{u,t}\right\}$, 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:

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

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:

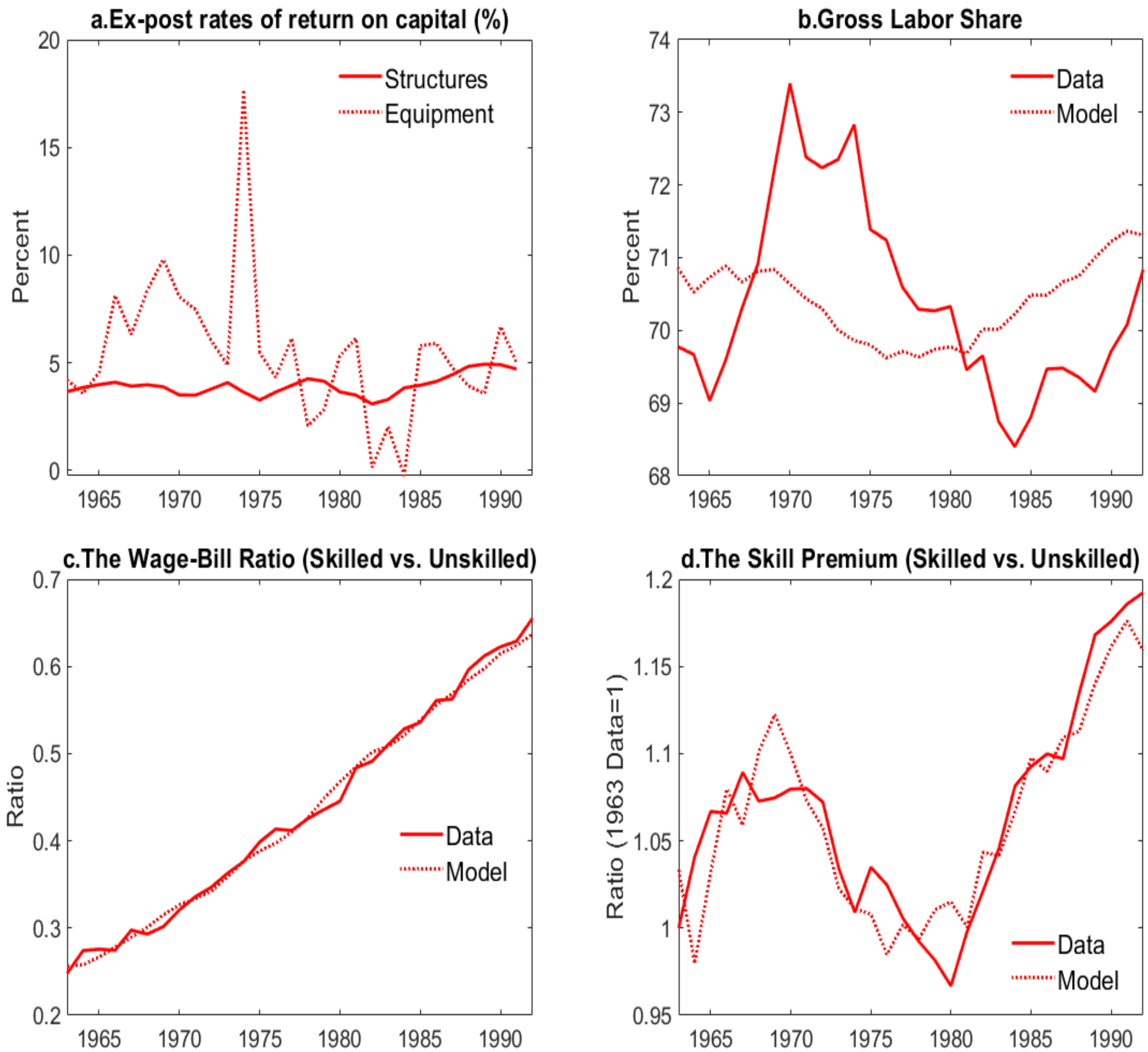
$$H^*=\begin{bmatrix}\nabla_{\theta\theta}\ell^1\left(\theta^*,\phi^*\right) & \nabla_{\theta\phi}\ell^1\left(\theta^*,\phi^*\right)\\ \nabla_{\phi\theta}\ell^2\left(\theta^*,\phi^*\right) & \nabla_{\phi\phi}\ell^2\left(\theta^*,\phi^*\right)\end{bmatrix}=\begin{bmatrix}\nabla_{\theta\theta}\ell^1\left(\theta^*,\phi^*\right)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

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

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 $\hat{\phi}_{ST}$.

C Additional figures and tables

Figure C.1: Replication with original KORV data



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. The shock terms are set to zero when producing the charts. While panel a runs through 1991, the rest of the panels plot the data and the model fit for the entire 1963–1992 period.

Table C.1: Comparison of parameter estimates with constant depreciation rates (with KORV definition of gross labor share)

	1963-1992		**1963-2019**	
	Time-varying	**Constant**	**Time-varying**	**Constant**
σ	0.436	0.435	0.431	0.418
	(0.020)	(0.019)	(0.012)	(0.011)
ρ	-0.517	-0.534	-0.309	-0.293
	(0.043)	(0.050)	(0.026)	(0.024)
α	0.105	0.106	0.109	0.109
	(0.002)	(0.002)	(0.002)	(0.002)
η_ω	0.083	0.082	0.085	0.090
	(0.008)	(0.006)	(0.005)	(0.005)

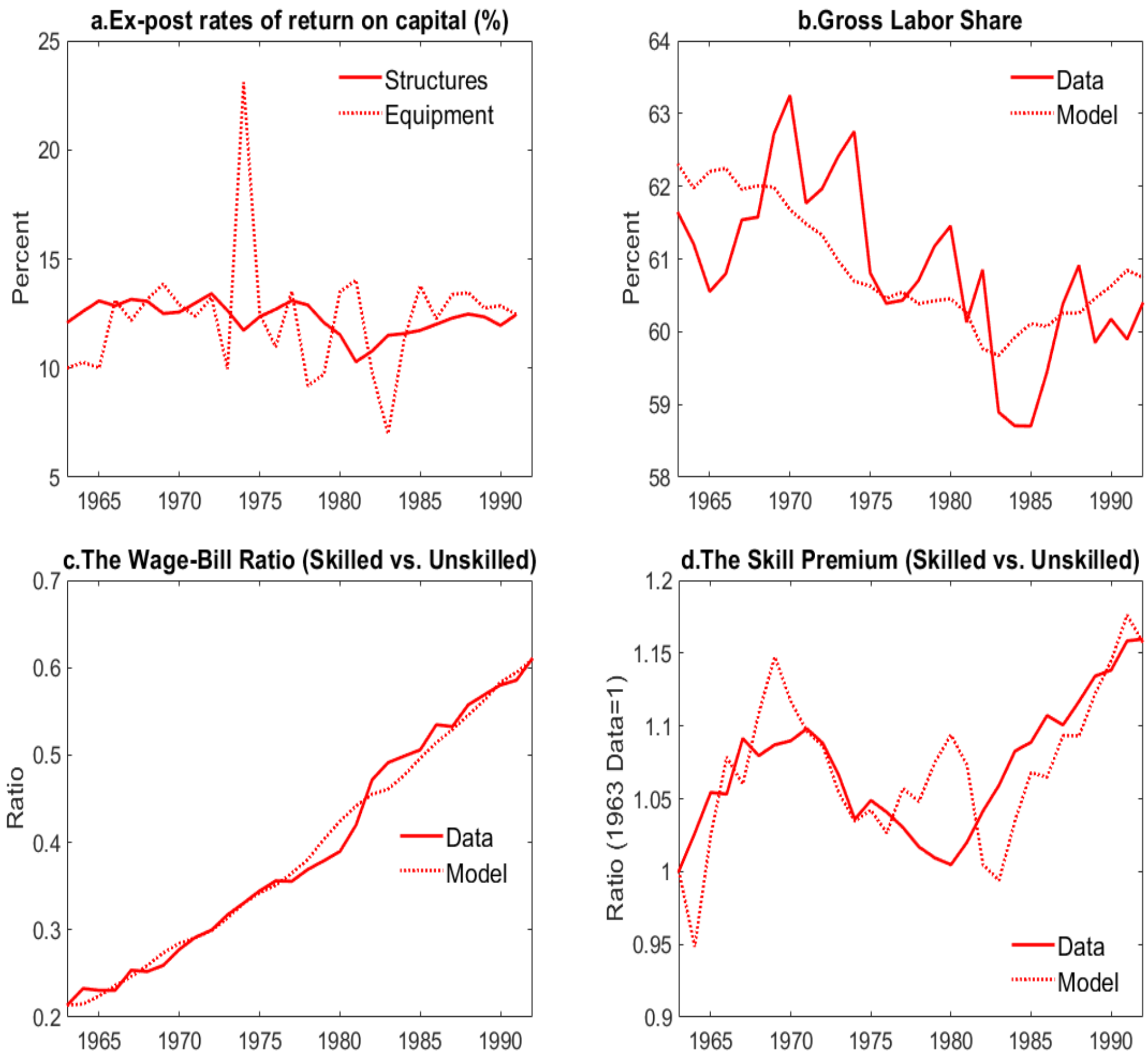
Note: The values in parentheses are standard errors.

Table C.2: Comparison of parameter estimates with gross and net labor shares (with nonfarm business sector labor shares)

	1963-1992		**1963-2019**	
	Gross	**Net**	**Gross**	**Net**
σ	0.390	0.349	0.382	0.349
	(0.019)	(0.023)	(0.012)	(0.014)
ρ	-0.531	-0.612	-0.335	-0.405
	(0.051)	(0.048)	(0.026)	(0.028)
α	0.150	0.156	0.153	0.152
	(0.002)	(0.002)	(0.002)	(0.002)
η_ω	0.088	0.111	0.086	0.123
	(0.008)	(0.023)	(0.005)	(0.011)

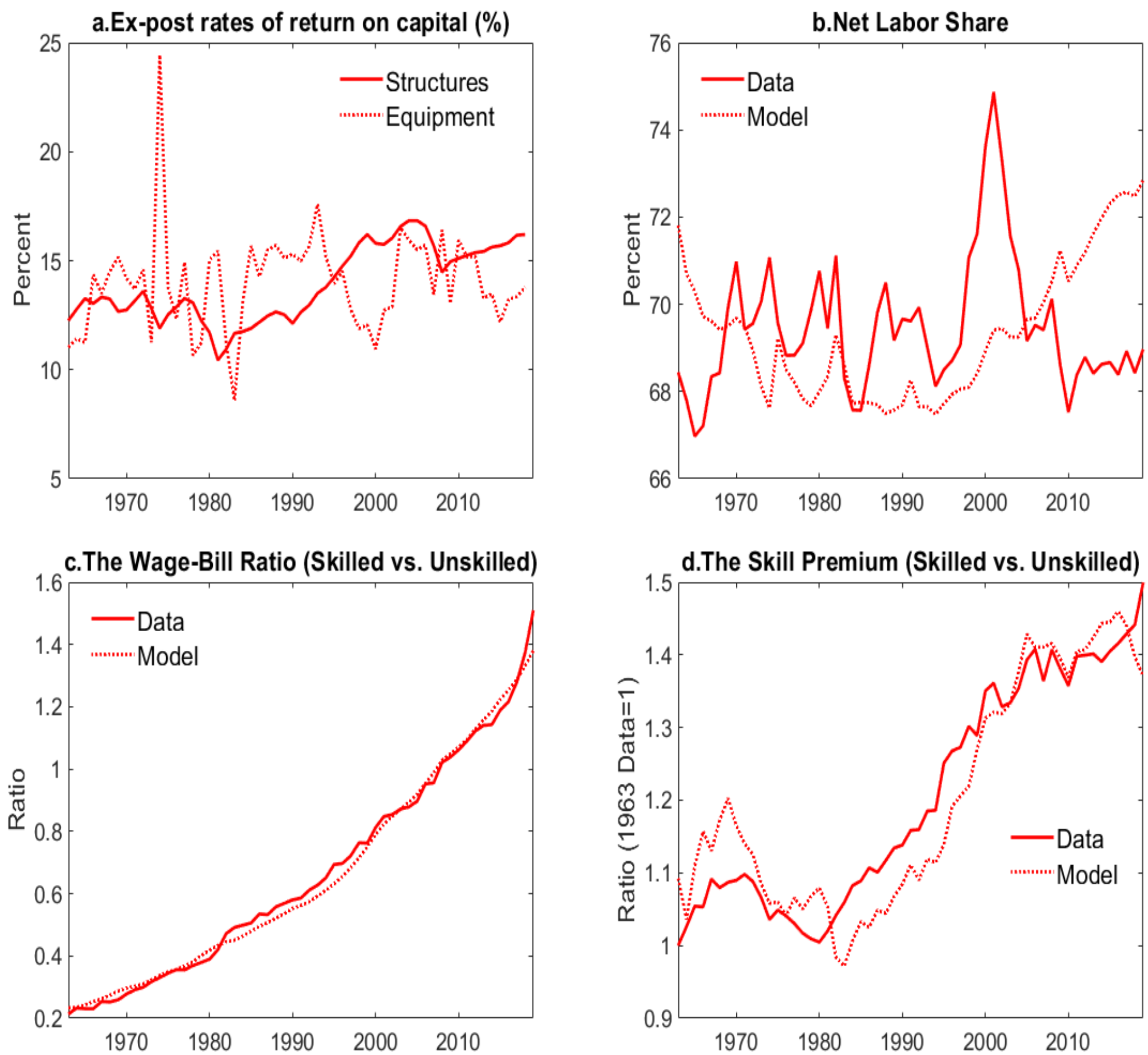
Note: The values in parentheses are standard errors.

Figure C.2: The model's fit for the 1963-1992 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 1963–1992 period. The shock terms are set to zero when producing the charts. Nonfarm business sector gross labor 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.

Figure C.3: The model's fit for the 1963–2019 period
(with nonfarm business sector net labor share)



Note: These charts are produced using the observable factor inputs and the parameters estimated employing data for the 1963–2019 period. The shock terms are set to zero when producing the charts. 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.