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CAPITAL-SKILL COMPLEMENTARITY AND INEQUALITY: TWENTY YEARS AFTER

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Abstract

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JEL Classification: C73, D90, E21

Keywords: skill premium, capital-skill complementarity, CES production function, skilled and unskilled labor

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August 29, 2020

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1 Introduction

Under the assumption of decreasing marginal products, an increase in the quantity of a production factor must decrease the rate of return to this factor. However, this was not the case for skilled and unskilled labor in the U.S. economy. Over the 1963–2017 period, the population of skilled and unskilled workers increased by 7.5 and 1.5 times, respectively, whereas the skill premium (defined as a ratio of wages of skilled to unskilled labor) grew at an average rate of 0.6% per year. That is, both the number of skilled workers and their wages increased more rapidly than those of unskilled workers.

Earlier literature had argued that such puzzling behavior of skill premium is explained by certain unobserved variables that affect differently productivity growth of skilled and unskilled labor, e.g., technical change (Bound and Johnson, 1992) or relative demand shifts (Katz and Murphy, 1992). However, the novel analysis of Krusell, Ohanian, Ríos-Rull and Violante (2000, henceforth, KORV) demonstrated that it is possible to explain the risk premium dynamics with just observable variables if one uses a more realistic model of the production process. Specifically, they introduced a constant elasticity of substitution (CES) production function with four inputs – skilled labor, unskilled labor, capital equipment and capital structures, and they estimated the parameters using the U.S. economy data. They found that skilled labor is more complementary with equipment than unskilled labor, so if the stock of equipment increases, then the stock of skilled labor also does so. The capital-skill complementarity mechanism of KORV (2000) has a major policy implication: all variables that determine economic growth are directly observable in the data and hence, economists must concentrate on policies that affect these observable variables in the way that promotes economic growth and that reduces inequality (while exogenous sources of growth cannot be affected).

The title of the present paper is inspired by "Twenty Years After" – a sequel to "The Three Musketeers" by Alexandre Dumas. The sample of KORV (2000) covers the 1963–1992 period and 20 years have passed since their paper was published. During that time, the world has experienced a dramatic technological change, so the following questions arise: "How do the results of KORV (2000) change if their sample is extended to include more recent data? Will we still observe the same regularities about skill premium? Does their capital-skill complementarity mechanism remain empirically relevant? How do their parameter estimates change? Can the KORV's (2000) framework be used to make projections about the future behavior of skill premium?" These are the questions we address in the present paper.[1]

We first construct an up-to-date data set that contains the key macroeconomic variables of economic growth in the US economy over the 1963–2017 period. Our data set includes labor-market variables such as the population of skilled and unskilled workers, their annual hours worked and their wages; these variables are constructed using household-level data – the Current Population Survey, CPS. Also, our data set includes such aggregate variables as consumption, capital structures, capital equipment, investment and relative prices; these variables are constructed using macro-level data – subcategories of the National Income and Product Accounts, NIPA. In the construction of the data, we closely follow the methodology of KORV (2000) and thus, our data set can be viewed as an actualized version of their data.[2]

We next explore what had changed in the data since the KORV(2000) analysis was implemented. We find that the pattern of the skill premium changed dramatically: it was U-shaped in KORV (2000) data, however it became monotonically increasing in the recent data. We estimate the CES production function using the KORV methodology in the original and extended data samples, and we find that in the recent data, the elasticity of substitution between equipment and unskilled labor is about 1.71, and the one between equipment and skilled labor of about 0.76, whereas the corresponding numbers in KORV (2000) are significantly lower, 1.67 and 0.67, respectively. Nonetheless, we find that their CES production function still accords well with the U.S. economy data and that the capital skill complementarity mechanism remains

[1] There is a large body of related literature that focuses on technological progress, capital-skill complementarity and skill premium dynamics, however, it is beyond the scope of the present paper to discuss the results of this literature; see Goldin and Katz (2008), and Acemoglu and Autor (2012) for comprehensive surveys of the literature; see Dvorkin and Monge-Naranjo (2019) for a recent contribution.

[2] The constructed data set is available at https://sites.google.com/site/innatsener.

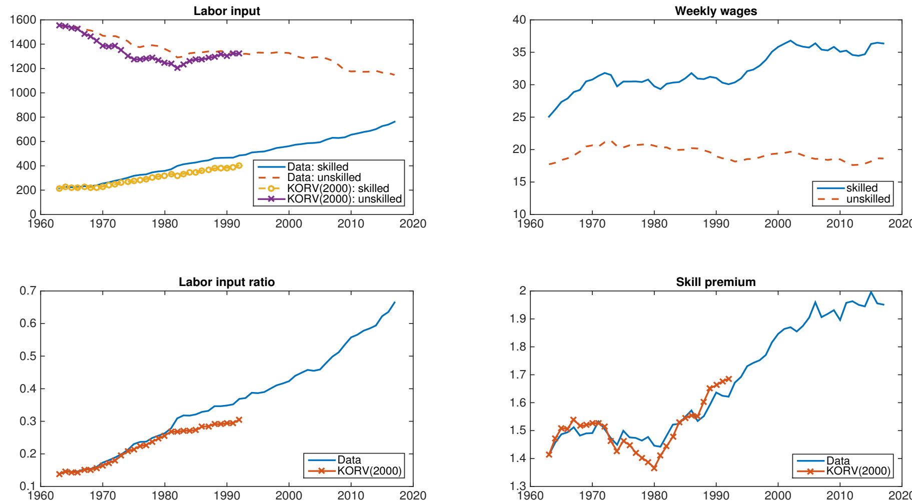

Figure 1: Selected labor indicators for skill and unskilled groups. Source: CPS March Supplements.

remarkably successful in explaining the skill premium dynamics. These findings confirm the main insight of KORV (2000) analysis: we can account for the growth patterns in the U.S. economy data including the skill premium dynamics by using just observable time series on capital and labor.

We finally propose a simple methodology for constructing projections on the basis of the KORV (2000) analysis. In their CES model, the behavior of skill premium is fully determined by three exogenous production inputs: capital equipment, skilled labor and unskilled labor. We first construct forecasts of these three exogenous variables using a simple time-trend model – the resulting forecasts are very accurate. We then use the estimated CES production function to construct the projection if the skill premium for the years 2017-2037. Our analysis suggests that the skill premium and hence, income inequality in the US economy will continue to grow in the future, although at a slower rate.

The rest of the paper is organized as follows: Section 2 describes the data; Section 3 revisits the KORV (2000) analysis; Section 4 extends the analysis to include more recent data; Section 5 construct the projection; and finally, Section 6 concludes.

2 Extending the KORV (2000) sample to include the recent data

The sample of KORV (2000) covers 1963–1992 years. In this section, we extend the KORV sample to include the data over 1993-2017 period and we analyze how the empirical regularities documented in KORV (2000) have changed over the more recent period. We follow the methodology of KORV (2000) in the construction of our data set. In particular, we construct two groups of variables on the US economy: the first group consists of labor-market variables and is constructed using household data, namely, current population survey (CPS) data set; and the second group includes such variables as output, capital, and prices and is constructed using macroeconomic data from the Federal Reserve Bank of St. Louis and Bureau of Economics Analysis; for a detailed description of the two groups of our data, see Appendices A.1 and A.2, respectively.

Labor and wages. In Figure 1, we report the labor variables for 2 representative groups of agents, skilled and unskilled (the skilled individuals are those who have college or higher degree and half of those who have some years of college education, and unskilled workers are the rest of the sample).

In the data, we observe the following three key tendencies:

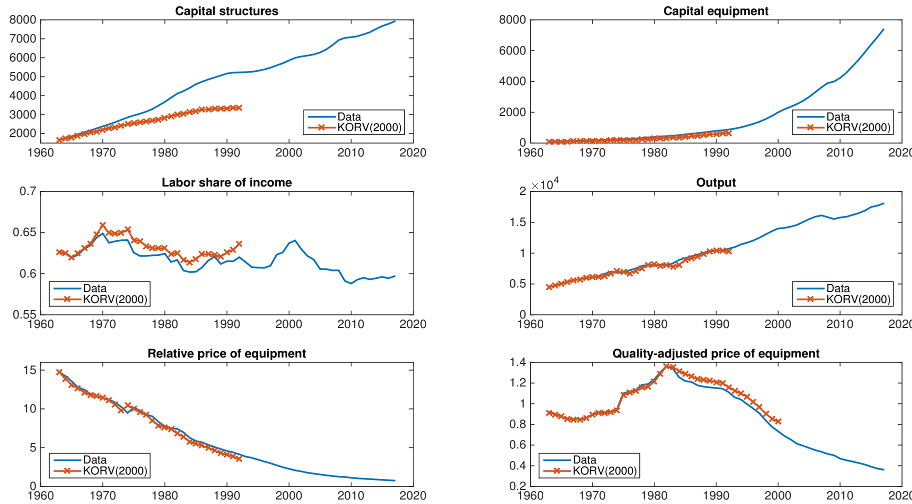

Figure 2: Capital structures and capital equipment are constructed using capital accumulation equation for structures and equipment, respectively. We use the data on real private fixed investment of two types of capital and their prices to recover the annual series for capital. As a measure of output, we use real GDP. The prices for equipment and consumption are quality adjusted. We construct Törnqvist indexes in line with KORV (2000) and Cummins and Violante (2002, henceforth, CV) by using disaggregated data on different types of capital input and consumption expenditures.

i) The number of both skilled and unskilled agents increases over time, however, the percentage increase in skilled labor is much larger than the increase in unskilled labor. In particular, over the period 1963–2017, the population of unskilled workers increased from 62.3 millions to 93.6 millions that corresponds to a 50.2% increase, whereas the population of skilled workers increased over this period from 7.4 to 56 million that corresponds to almost a 652.7% increase.

ii) Hours worked by skilled agents also have a pronounced upward trend, while such a trend is not present for unskilled labor.

iii) The weekly wages of skilled agents grow more rapidly than those of unskilled.

Both *i)* and *ii)* drive the labor input ratio of skilled versus unskilled labor to increase over time. In turn, *iii)* means that the skill premium (a ratio of wages of skilled to unskilled workers) have an upward time trend. These tendencies are observed for both the sample period 1963–1992 studied in KORV (2000) and for our extended sample 1963–2017. Interestingly, the skill premium pattern was U-shaped in the KORV (2000) data but it becomes monotonically increasing over the more recent period. Thus, the labor data reveal a regularity that appears to be at odds with basic economic theory: both the quantity and the return to skilled labor increase more than those of unskilled labor, which is also referred to as a *skill-premium puzzle.*

Capital and prices. To gain intuition into the puzzling behavior of labor markets, in Figure 2, we report other selected aggregate macroeconomic indicators for the US economy.

In the data, we observe the following regularities:

i) Capital structures increased from 1676.4 to 7917.3 billions of dollars over the sample period which corresponds to a 390% increase.

ii) Equipment increased from 91.2 to 7373.6 billions of dollars which corresponds to a 7983.9% increase. In particular, the growth rate of equipment increases starting from 1995 that reflects the introduction and extension of modern technologies such as internet, computers, etc.

iii) The relative price of equipment and the quality adjusted price of equipment decreased over time by roughly a factor of 20 and 3, respectively.

iv) Labor share of income did not have a pronounced time trend.

Again, the tendencies we observe are qualitatively similar in both KORV (2000) sample and our extended sample. The most striking tendency in the recent years is an increase in the growth rate of the stock of equipment; this fact will play a critical role in our estimation results.[3]

Capital-skill complementarity mechanism. The data seem to suggest that a dramatic growth in the stock of skilled labor maybe be related to a comparable dramatic increase in the stock of equipment. This regularity was noticed in the literature long time ago. The hypothesis of capital-skill complementarity dates back to Griliches (1969): "If skilled labor is more complementary with equipment than unskilled labor, then an increase in the stock of equipment will lead to an increase in the stock of skilled labor (and the reason for the growth of equipment is a reduction in its relative price)". There is a large body of subsequent literature that analyzes a relation between technological progress, capital-skill complementarity and skill premium dynamics, but it is beyond the scope of the present note to discuss the results of this literature; see Goldin and Katz (2008) and Acemoglu and Autor (2012) for comprehensive surveys. We will limit ourselves to revisiting the KORV (2000) analysis which provided a prominent illustration of the capital-skill complementarity mechanism.

3 The past: revisiting the analysis of KORV (2000)

To carry out their analysis, KORV (2000) formulate the constant elasticity of substitution (CES) production function:

$$Y_t = A_t G\left(K_{st}, K_{et}, L_{st}, L_{ut}\right) = A_t K_{st}^{\alpha}\left[\mu L_{ut}^{\sigma} + (1-\mu)\left(\lambda K_{et}^{\rho} + (1-\lambda)\, L_{st}^{\rho}\right)^{\frac{\sigma}{\rho}}\right]^{\frac{1-\alpha}{\sigma}}, \tag{1}$$

where Y_t is output; A_t is an exogenously given level of technology; K_{st} and K_{et} are the inputs of capital structures and capital equipment, respectively; functions $L_{st} = h_t^s \psi_t^s$ and $L_{ut} = h_t^u \psi_t^u$ give the efficiency labor inputs of skilled and unskilled agents, respectively; h_t^s and h_t^u are hours of work of skilled and unskilled agents, respectively; ψ_t^s and ψ_t^u are a labor technical change specific to skilled and unskilled agents, respectively; $\alpha \in (0,1)$, $\mu \in (0,1)$, $\lambda \in (0,1)$, ρ and σ are the parameters governing the elasticities of substitution between structures, equipment, skilled labor and unskilled labor.[4]

They use three structural equations derived from the profit maximization under (1) to estimate the model parameters, namely,

$$\frac{w_{st}h_{st} + w_{ut}h_{ut}}{Y_t} = lsh_t(\psi_t, X_t; \phi), \tag{2}$$

$$\frac{w_{st}h_{st}}{w_{ut}h_{ut}} = wbr_t(\psi_t, X_t; \phi), \tag{3}$$

$$(1-\delta_s) + G_1(\psi_{t+1}, X_{t+1}; \phi) = E_t\left(\frac{q_t}{q_{t+1}}\right)(1-\delta_e) + q_t G_2(\psi_{t+1}, X_{t+1}; \phi), \tag{4}$$

where $\psi_t = \{\psi_t^s, \psi_t^u\}$ is a vector of unobserved latent variables, $X_t = \{K_{st}, K_{et}, L_{st}, L_{ut}\}$ is a vector of endogenous variables; G_1 and G_2 are partial derivatives of G in (1) with respect to the first and second

[3] Our data on output and capital equipment are similar to KORV (2000). Those on structure grow at a somewhat higher rate due to the difference in the quality adjusted price index. The mean labor share of income in our sample is equal to 0.65 that slightly differs from the one reported in KORV (2000), so we show normalized shares in the graph for the sake of comparison. Finally, our quality adjusted price of equipment is compared to Cummins and Violante (2002) who use the same methodology but report the relative price of equipment over a longer period of 1947–2000, while KORV (2000) provide the data only up to 1992.

[4] Following the literature we combine the data on hours worked per week and number of skilled and unskilled workers into a single composite labor input.

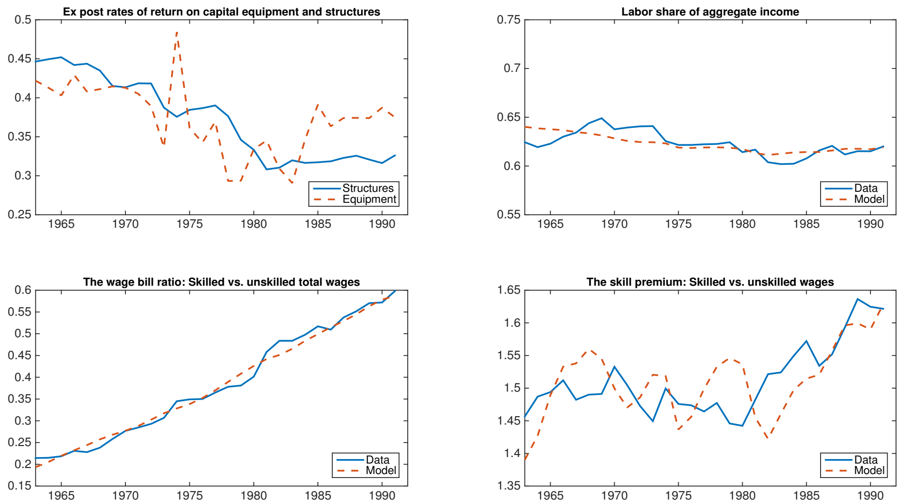

Figure 3: Estimation results for the 1962-1993 sample. In the first three figures, we report the fitted series for three estimated equations and in the last figure, we report the fitted series for skill premium.

arguments, respectively; δ_s and δ_e are the depreciation rates of structures and equipment; E_t is conditional expectation, the vector of parameters ϕ includes α, μ, λ, ρ and σ, among others.

We implement the estimation procedure of KORV (2000) and replicate their results by using our data sample for the same period 1963–1992 as they do. We use the estimated series to construct skill premium (see equation (3) in KORV, 2000),

$$\pi_t = \frac{(1-\mu)(1-\lambda)}{\mu}\left[\lambda\left(\frac{K_t^e}{L_t^s}\right)^{\rho} + 1 - \lambda\right]^{(\sigma-\rho)/\rho}\left(\frac{h_t^u}{h_t^s}\right)^{1-\sigma}\left(\frac{\psi_t^s}{\psi_t^u}\right)^{\sigma}. \tag{5}$$

The results are shown in Figure 3.

We make three observations. First, although there are some differences between the KORV (2000) data set and ours, these differences do not show a visible impact on the results, in particular, our Figure 3 is very similar to an analogous figure, Figure 9, in KORV (2000). Second, the estimates of KORV (2000) support strongly the hypothesis of capital-skill complementarity, namely, such hypothesis requires $\sigma > \rho$ and our estimates of these parameters, 0.432 and -0.489, respectively, support this hypothesis as well. Finally, the capital-skill complementarity mechanism explains remarkably well the behavior of skill premium in the U.S. data over the 1962–1993 period.

4 The present: insights from the 1993-2017 sample

We now explore what had changed since the KORV (2000) analysis was implemented by analyzing more recent data. We first ask if the capital-skill complementarity mechanism still empirically relevant. Formula (5) implies that we can decompose the growth rate of skill premium into three effects: relative quantity, relative efficiency and capital-skill complementarity,

$$g_{\pi t} = \underbrace{(1-\sigma)\left(g_{h_{ut}} - g_{h_{st}}\right)}_{\text{relative quantity effect}} + \underbrace{\sigma\left(g_{\psi_{ut}} - g_{\psi_{st}}\right)}_{\text{relative efficiency effect}} \underbrace{+ (\sigma-\rho)\,\lambda\left(\frac{K_t^e}{L_t^s}\right)^{\rho}\left(g_{k_{et}} - g_{h_{st}} - g_{\psi_{st}}\right)}_{\text{capital-skill complementarity effect}},$$

where $g_{\pi t}$ denotes the growth rate of the corresponding variables. Figure 4 plots two of these three effects for our extended sample.

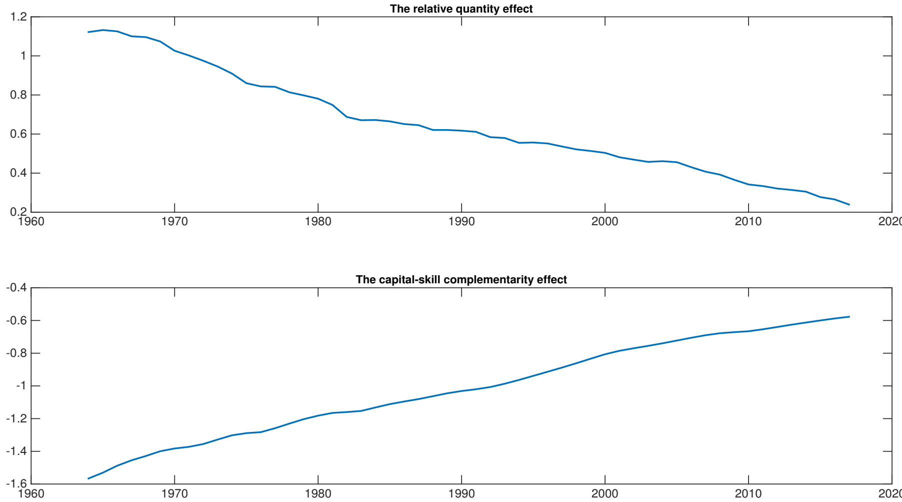

Figure 4: Decomposition of the benchmark model's skill premium (logs) using (5).

We therefore observe that the importance of the capital-skill complementarity effect only increased with time.

Second, we ask how the estimates obtained by KORV (2000) have changed. To this purpose, we re-do the analysis of KORV for our extended data set covering 1963–2017, and we compare the results with those for the period 1963–1992. In Table 1, we provide the resulting two sets of estimated parameters, as well as KORV's (2000) estimates for comparison.

Parameter value	σ	ρ	α	λ	μ
KORV (2000)	.401 (0.234)	−.495 (0.048)	.117 (0.007)	−	−
1963–1992	.432 (0.027)	−.489 (0.033)	.183 (0.003)	.536 (0.004)	.402 (0.065)
1963–2017	.415 (0.011)	−.324 (0.022)	.190 (0.002)	.534 (0.007)	.405 (0.135)

Table 1. Estimated regression coefficients.

Our estimate of the elasticity of substitution between equipment (skilled labor) and unskilled labor is about 1.7, and that of the elasticity of substitution between equipment and skilled labor is about 0.76. Both estimates are in line with the results obtained in the literature. KORV (2000) estimated these elasticities to be 1.67 and 0.67, respectively, Ohanian and Orak (2016) who analyze the same model for the period 1963-2013 find similar estimates. Our econometric analysis reinforces our previous conjecture about the increasing role of the capital-skill complementarity mechanism.

Finally, we ask: "Can the CES production function of KORV (2000) explain recent data?" In Figure 5, we plot the fitted values of the same variables as in Figure 3 for the extended sample of 1992–2017 under the estimated parameters .

We see that in more recent data, the skill premium pattern changed dramatically. In KORV's (2000) 1963–1992 data, the skill premium is roughly U-shaped while in the recent data, it resembles a monotonically increasing function. More importantly, a good fit in the figure tells us that the capital-skill complementarity mechanism is still remarkably successful in explaining the skill premium dynamics.

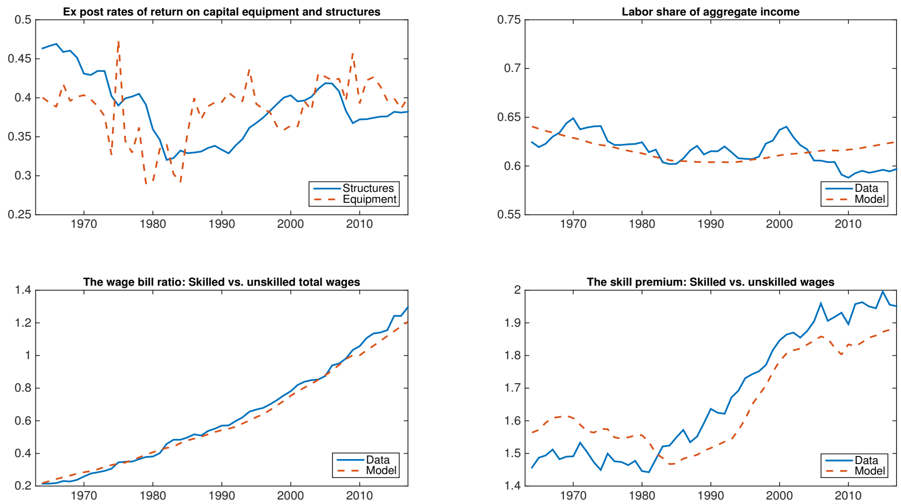

Figure 5: Estimation results for the 1963-2017 sample. In the first three figures, we report the fitted series for three estimated equations and in the last figure, we report the fitted series for skill premium.

5 The future: the projection of skill premium for 2017-2037 period

Finally, we make predictions about the evolution of the skill premium in the future. Specifically, we ask: "How can we use KORV's (2000) framework for projection of skill premium, and how accurate such projection will be?"

Formula (5) in KORV (2000) yields the skill premium given three exogenous variables, namely, capital equipment, skilled labor and unskilled labor. By using this formula, we can predict the evolution of the skill premium in the future if we had these three series. As a first step, we forecast the evolution of these three series using a simple linear trend in Figure 6.

"Projection 1993-2017" and "Projection 2017-2037" are constructed using the trends obtained from the 1963–1992 and 1963–2017 samples, respectively. For the former counterfactual projection, we include both the trend and business cycle component, while for the latter projection, we include just a trend since the future cyclical component is not available. Visually, our projections appear to be very accurate and reliable, in particular, for the former two series that are nearly linear. The last series is subject to fluctuations but our projection still captures the trend correctly.

We subsequently use the projected exogenous variables to construct the skill premium path using KORV's (2000) formula (5), and we compare the projection with the actual skill premium series in the US data in Figure 7.

Let us discuss these three experiments.

Projection 1963-2017. This is our first counterfactual experiment. We place ourselves back to year 1993 when the analysis of KORV (2000) was carried out and ask: "How accurately could KORV (2000) have predicted the evolution of the skill premium over the period 1993-2017 on the basis of their estimations if they knew the exogenous variables over 1993-2017?" To answer this question, we substitute into formula (5) the actual series on capital equipment, skilled and unskilled labor. The resulting skill premium series "KORV projection 1963-2017" is shown with the blue line in Figure 7. We observe that the projected and actual skill premium series show very similar patterns in the figure. Thus, the fact that we use the coefficients estimated over the past 1963-1992 period for constructing projections over the present period 1993-2017 does not produce qualitatively-important forecast errors. We conclude that the regression coefficients obtained from the past data remain roughly valid for future periods.

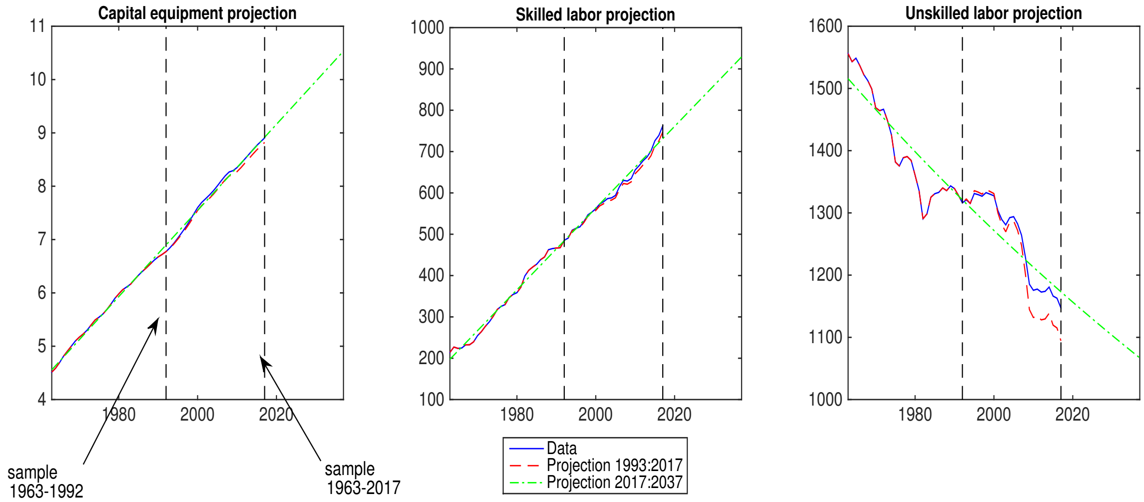

Figure 6: The projections of capital equipment, skilled and unskilled labor for the periods 1993-2017 and 1993-2037.

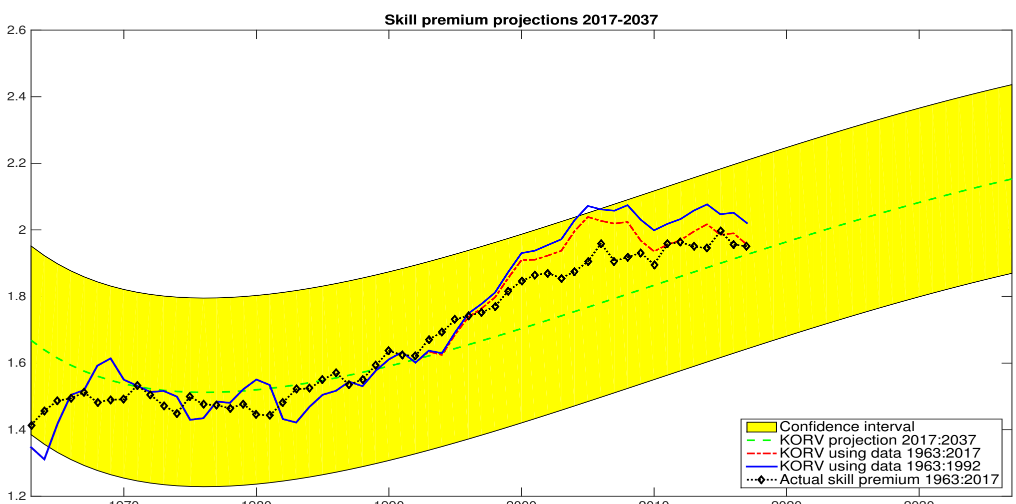

Figure 7:

Projection 1963-1992. In our second counterfactual experiment, we go a step further. We again place ourselves back to year 1993 and ask: "How accurately could KORV (2000) have predicted the evolution of the skill premium over the period 1993-2017 if they were not given the exogenous variables over 1993-2017 but had to project them by using a simple linear time trend as we did in Figure 6?" The resulting skill premium series "KORV projection 1963-1993" is shown with the red line Figure 7. We observe that the projection on forecasted inputs look very similar to the previous projection that used actual inputs over the period 1963-2017. There is a difference in the two projections closer to the end which appears because our projection for unskilled labor is less accurate at the end of the sample but this difference is not qualitatively important.

Projection 1963-2017. This is our main projection experiment. We now place ourselves in the year 2017 which is the year in which our data sample ends, and we use the estimated coefficients over the period 1963-2017 and projected exogenous variables over the period 2017-2037 to construct the projection for the skill premium over the period 2017-2037. For this experiment, the cyclical components of exogenous variables are not available, so we use just a time trend for these variables which we substitute into (5). We also provide a two-standard-deviation confidence interval for the skill premium projection. Our results in Figure 7 suggest that the skill premium will continue to raise in the future although at a somewhat slower rate and so will do the degrees of the income inequality in the US economy.

How accurate is our projection – we cannot be sure. But our first experiment suggests that the CES regression coefficients estimated with the past data lead to meaningful projections and our second experiment suggests that using the projected exogenous variables instead of actual ones does not significantly affect the quality of projections. Of course, these regularities are only valid for the past data and there is no guarantee that they will carry over to the future. But this seems to be as much as we can hope to achieve when trying to guess the future.

6 Conclusion

The analysis of KORV (2000) was remarkably successful in the past: it accurately reproduced the evolution on skill premium over the period 1963–1992. In this paper, we show that the capital-skill complementarity mechanism remains empirically relevant at present: it can successfully account for recent data as well, even though the skill premium pattern changed dramatically in the recent years. Moreover, we find that the KORV (2000) framework produces meaningful projections for the future, provided that the exogenous variables are projected with a sufficient degree of accuracy. We obtain that the skill premium and hence, the degree of the inequality will continue to rise in the US economy although at a slightly lower rate. A shortcoming of KORV's (2000) analysis is that their partial equilibrium framework does not have a methodology for predicting the production inputs. Therefore, it appears of interest to extend their framework to general equilibrium in order to endogenize the capital and labor choices.

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Appendix A. Data construction

In this section, we explain how we construct the data. In Appendix A.1, we describe the construction of labor market variables using household data, and in Appendix A.2, we outline the construction of the remaining variables using aggregate data.

- We need data on such aggregate/average variables as capital equipment, k^e; capital structures, k^s; consumption, c; output, y; (average) labor supply, population and wages of skilled workers l^s, N^s and w^s, respectively; labor supply, population and wages of unskilled workers l^u, N^u and w^u, respectively; the relative price of equipment $1/q$.
- To construct the series of labor supply, population and wages of skilled and unskilled workers, l^j, N^j and w^j, $j \in \{s, u\}$, we use March Supplements of Current Population Survey, CPS, also known as CPS Annual Social and Economic Supplements, ASEC. This data set contains individual and labor market characteristics of the US population.[5] We downloaded these data from the Integrated Public Use Microdata Series (IPUMS)[6].
- The rest of the variables is constructed using the aggregate data of the Bureau of Economic Analysis (BEA) and the FRED Database.[7]
- We refer to the data constructed using the CPS databases as household data and the data constructed using BEA and FRED databases as aggregate data.
- We construct the household data for the period $1963 - 2017$. (The first survey that we use is from year 1964; since a survey supplies information on a year prior to the survey).

Appendix A1: Household data

CPS March Supplements contain questions on income received by the respondents in the previous calendar year and are used by economists for constructing the data on wages and labor supply; see Katz and Murphy (1992), Krusell et al. (2000) and Acemoglu and Autor (2010) among others. We use self-reported information on respondents' individual demographic characteristics and labor market participation statistics. The individual demographic characteristics that we use include age, race, sex, and education. The labor market participation in the year prior to the survey is described by the following variables: the usual number of hours worked per week last year; the number of weeks worked last year; labor force participation status (full-time, part-time or not in labor force); employment status (self-employed or wage and salary worker); population status (an adult civilian, armed forces or a child); annul wage income; reason for not working last year; the person-level weight. We also use information on the number of hours worked last week.

[5] See Flood et al. (2015), https://www.ipums.org, for raw data and their description.

[6] CPS March Supplement data is also available from the NBER website: http://www.nber.org/cps/

[7] See https://bea.org and https://fred.stlouisfed.org/, respectively.

Sample selection

As a first step, we select adult civilians who worked for at least one week last year and were at age 16 or older. We discard observations with missing or negative person-level weights.

Number of weeks and number of hours usually worked per week. A respondent's annual labor supply is defined as a product of two variables:
(i) the number of weeks worked in the last year;
(ii) the number of hours usually worked per week in the last year.
In two subperiods 1964–1975 and 1976–2017, these two variables were recorded in different ways.

Regarding (i), we have the following issue. Prior to 1976, the variable which contains information on weeks worked last year is recorded in intervals, i.e., the responses of the respondents are given in six intervals: 1-13 weeks; 14-26 weeks; 27-39 weeks; 40-47 weeks; 48-49 weeks; and 50-52 weeks. To deal with such incomplete information, we assume that for each interval over $1964-1975$, the number of weeks worked is equal to the average number of weeks worked by respondents of the same sex and race over the period $1976-1978$.

Regarding (ii), for the period $1964-1975$ the information on the number of hours usually worked per week last year is unavailable. The information that is available is on the number of hours worked in a week prior to the survey. We cannot use this variable as a proxy for the missing number of hours usually worked per week but we can use it to construct an estimated number of hours usually worked per week last year. Specifically, we estimate a set of linear equations using a pooled data set of 1976, 1977 and 1978 (namely, we pooled all the considered years and all agents), in which both labor supply variables (i.e., (ii) and number of hours worked a week prior to survey) are available, and we use the estimates to recover the number of hours usually worked per week for the period $1964-1975$. That is, for each sex (male, female) and race (white, black and other) group, we fit an equation where an individual i's usual weekly labor supply (hours), h^i, depends on a set of dummy variables and their interactions:[8]

$$h^i = \beta_0 + \sum_{j=1}^{8} \beta_j h_w^{i,j} + \sum_{j=9}^{16} \beta_j h_w^{i,j-8} FT^i + \beta_{17} FT^i + \epsilon^i, \tag{6}$$

where $h_w^{i,j}$ is a j dummy variable that indicates whether an individual worked $0, 15-29, 30-34, 35-39, 40, 41-48, 49-59$ or more than 60 hours a week prior to the survey, respectively; FT^i is an indicator variable of a full-time worker in the previous calendar year; ϵ^i is an error term.[9] The six linear equations (one per each sex-race group) are fitted to different samples which sizes vary from 1844 observations (female of another race) to 109,674 observations (male of white race). R^2 for these regressions varies from 62% to 77%. The variables $h_w^{i,1}, ..., h_w^{i,8}$ and FT^i are recorded for each person in the years prior to 1976. We use the estimated coefficients of equation (6) to recover respondents' hours usually worked per week last year for $1964-1975$ samples.

Education. We construct additional variables that characterize years spent on education and years of experience for each person in our sample. In particular, we create an educational variable *educ*, that takes on values from 0 to 18 years depending on the highest level of education completed and use it to form five more broad educational categories in the following way:

1. High school drop-out (HSD): individuals with no education or those who completed grades 1-11;
2. High school graduate (HSG): individuals who completed 12th grade, have a high school diploma or equivalent;

[8] For exposition purposes we drop the time subscript t.
[9] Full-time worker is an individual who usually worked thirty five hours or more per week

3. Some College (SMC): individuals who studied some years in college (1-3 years) or have an associate degree;
4. College Graduate (CLG): individuals with 4 years of college or a bachelor degree;
5. Greater than college (GTC): individuals holding a Master's, professional school or PhD degree.[10]

We define a variable *school* that represents this classification.

Experience. Following Katz and Murphy (1992) and Acemoglu and Autor (2011), the years of potential experience, *exp*, are then calculated based on the years of education and age of the respondent according to

$$exp = \max(\min(age - educ - 7, age - 17), 0). \tag{7}$$

Individuals whose potential experience is higher than 48 are dropped from our sample. Depending on the workers' potential experience levels, we create five experience groups ($0-9$, $10-19$, $20-29$, $30-39$ and $40-48$ years).

Sample. As the last step, we exclude from our sample people who were not wage workers, self-employed or were older than 65 in the year of the survey. As a result, in each year we discard approximately 50% of observations in the original sample. The size of the remaining sample varies with the year of the survey. For instance, for the years 1964 and 2015, the resulting sizes of the selected sample are 28,658 and 92,260 observations, respectively.[11]

Labor supply

We define a skilled worker as the one who has a college degree or higher. The rest of the individuals are considered to be unskilled in our sample. The aggregate annual labor supply of each group is calculated as a sum of annual individual labor supplies,

$$L^u = \sum_i \upsilon^i wk^i h^i, \quad \text{if } i \text{ is such that } school \in \{\text{HSD,HSG,SMC}\}, \tag{8}$$

$$L^s = \sum_i \upsilon^i wk^i h^i, \quad \text{if } i \text{ is such that } school \in \{\text{CLG,GTC}\}, \tag{9}$$

where υ^i is a personal level supplement weight, wk^i is a number of weeks worked last year and h^i is a number of hours usually worked per week last year.

The average annual labor supply (in terms of hours) of a skilled and unskilled worker is computed as a ratio of the corresponding aggregate annual labor supply and population,

$$l^s = \frac{L^s}{N^s} \quad \text{and} \quad l^u = \frac{L^u}{N^u} \tag{10}$$

Figure A1 plots the relative labor supply of all skilled workers to all unskilled workers, defined as a ratio L^s/L^u.

Figure A2 plots the average labor supply of a skilled worker and an unskilled worker, i.e., l^s and l^u, respectively.

Additionally, we divide our sample into several demographic groups, based on sex, education and potential working experience, and construct aggregate labor supply for each demographic group. There are two sex groups (male/female), five education groups (high school dropout, high school graduate, some

[10] For each of these five categories the variable *educ* takes on the values $[0, 11], 12, [13, 15], [16, 17]$ and 18, respectively

[11] Our computer codes for the household data are written in Stata 14. We benefited from consulting a Stata code of Acemoglu and Autor (2011) and followed closely the conventions set by prior studies to facilitate the comparisons.

Figure 8: Figure A1. Relative labor supply of skilled workers to unskilled workers, 1963-2017.

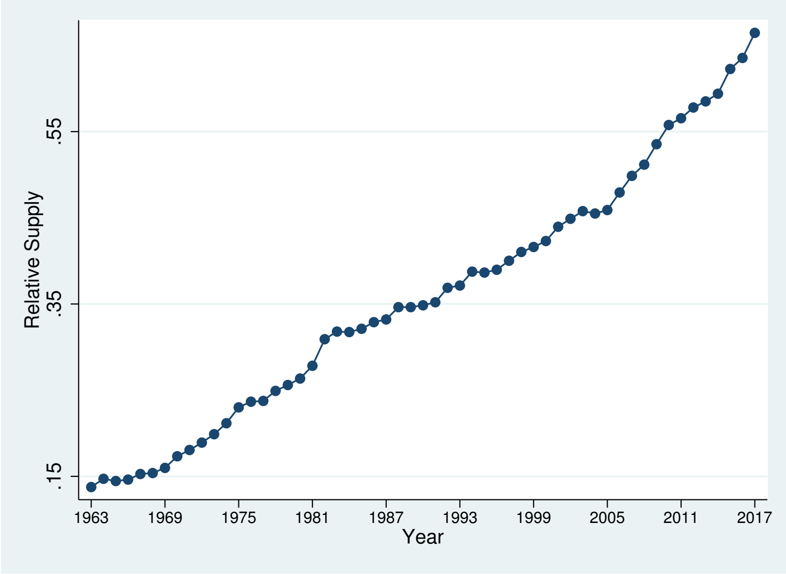
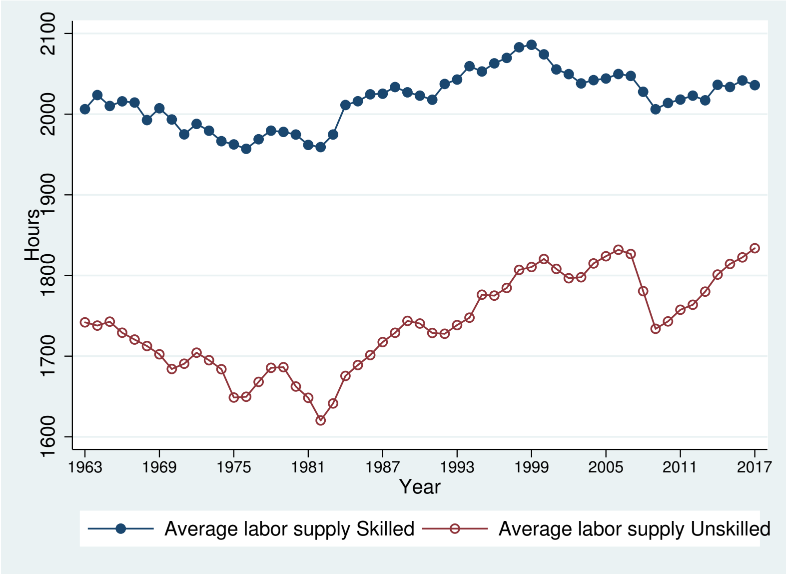


Figure 9: Figure A2. Average annual labor supply, 1963-2017.



college, college graduate, and greater than college) and five experience groups ($0-9$, $10-19$, $20-29$, $30-39$ and $40-48$ years). Therefore, there are 50 demographic groups. The aggregate labor supply of a group j is

$$L^j = \sum_i v^{i,j} wk^{i,j} h^{i,j}, \quad j = 1, ..., 50.$$

We will use these measures of labor supply across demographic groups for calculating wages of skilled and unskilled workers in Section 2.3.

Wages

We now explain how we obtain the data on wages.

Sample and corrections in the values. Our wage sample includes full-time, full-year wage workers who participated in the labor force for at least 35 hours a week for more than 40 weeks.[12] We exclude workers with real weekly earnings below 67$ in 1982 dollars and with real hourly earning below 1.675$ in 1982 dollars.[13] We drop the observations with "allocated" earnings in those years where the allocation flag is available. ("allocated" means recovered/computed in some way). We correct the top coded earnings by multiplying them by a factor of 1.5. [14]

Estimated wages. Following the literature, e.g., Katz and Murphy (1992), Katz and Autor (1999), and Autor et al. (2008), we do not use actual wages. Instead, we obtain an estimate of real hourly wages from a linear regression model. For this purpose, we use previously-constructed potential experience levels ($0-9, 10-19, 20-29, 30-39, 40-48$ years, respectively) to create five experience groups (5, 15, 25, 35, 45 years). We compute (predicted) mean real hourly wages in each year for 50 sex-education-experience groups. Hourly wages are regressed separately by sex in each year on four education dummies (high school dropout, some college, college graduate and greater than college), a quadratic in experience level, interactions of the education dummies and a quadratic in experience level, two race categories (black and non-white other) and a dummy variable for part-time workers

$$\begin{aligned} w^i_{hr} &= \beta_0 + \beta_1 HSD^i + \beta_2 SMC^i + \beta_3 CLG^i + \beta_4 GTC^i + \sum_{j=1}^{4} \beta_{4+j} (exp^i)^j \\ &+ \sum_{j=1}^{4} \beta_{9+j} (exp^i)^j HSD^i + \sum_{j=1}^{4} \beta_{13+j} (exp^i)^j SMC^i + \sum_{j=1}^{4} \beta_{17+j} (exp^i)^j (CLG^i | GTC^i) \\ &+ \beta_{22}\ \text{black}^i + \beta_{23}\ \text{other}^i + \beta_{24} PT^i. \end{aligned} \tag{11}$$

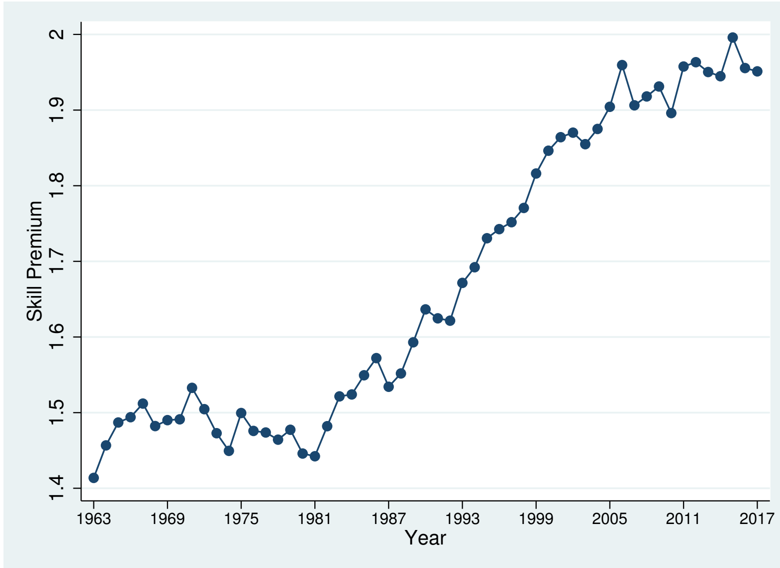
As a general rule, for a given year the male regression gives a higher R^2; this is because in earlier years it is estimated on a bigger subsample than the female regression. For example, the R^2 is 17% and 12% with the sample sizes of 14,277 and 40,978 for a male regression in years 1964 and 2015, respectively. For the female regression, the R^2 is 15% and 9% with the sample sizes of 8,134 and 40,283 in the same years, respectively.

[12] Therefore, self-employed individuals are included in the labor input sample and are excluded from the wage sample. As Katz and Murphy (1992) note, the use of a different sample for measuring wages ensures comparability of the wages through time. The group of full-time, full-year workers has a strong labor force attachment and therefore provides better estimates of the wages received by workers of given skills.

[13] We compute real wages in constant 2012 dollars by deflating nominal wages in each year by the implicit price deflator for personal consumption expenditures on nondurable goods and services calculated in Appendix A2.

[14] See the Topcodes Tables for earnings topcodes for each year at https://cps.ipums.org/cps/topcodes_tables.shtml

Figure 10: Figure A3. Skill premium, 1963-2017.



Wages of skilled and unskilled. Mean wages of skilled/unskilled workers are calculated as a weighted sum of wages of the corresponding education groups. As weights, we use average shares of total hours worked for each group over 1963 to 2017; see (14) and (15). To compute such shares, we first compute shares of aggregate labor supply, $\tilde{L}_j$, for each demographic group in each year,

$$\tilde{L}_{j,t} = \frac{L_{j,t}}{\sum_{j=1}^{50} L_{j,t}}, \quad j = 1, ..., 50. \tag{12}$$

We then define the average share of total hours worked for each demographic group over 1963 to 2017 as a mean share of each group across time,

$$s_j = \sum_{t=1963}^{2017} \frac{\tilde{L}_{j,t}}{55}, \quad j = 1, ..., 50, \tag{13}$$

where 55 stands for the number of years in the sample. By using these constant shares when computing wages, we hold constant the relative employment shares of demographic group across all years of the sample.

The mean real hourly wages of skilled and unskilled groups are calculated in each year as follows:

$$w^u_{hr} = \sum_j w_{k,hr} \frac{s_j}{\sum_j s_j}, \quad \text{if } j \text{ is such that } \textit{school} \in \{HSD,\, HSG,\, SMC\}, \tag{14}$$

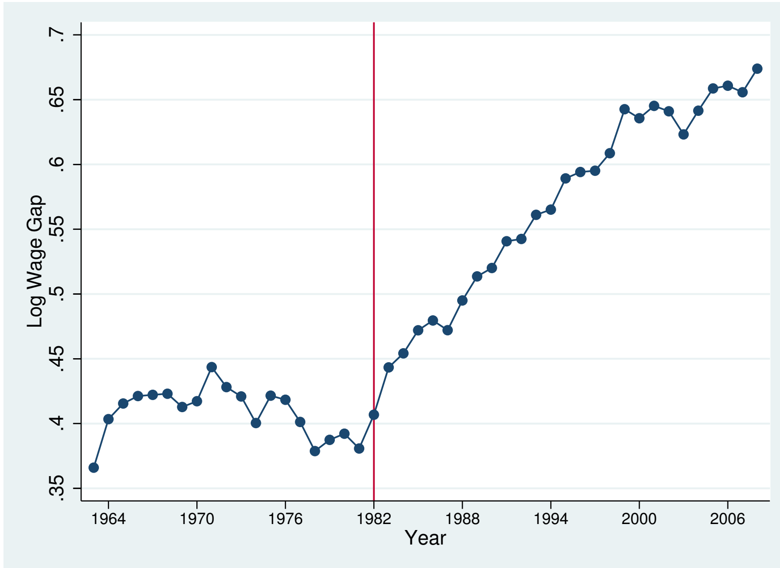
$$w^s_{hr} = \sum_j w_{j,hr} \frac{s_j}{\sum_j s_j}, \quad \text{if } j \text{ is such that } \textit{school} \in \{CLG,\, GTC\}. \tag{15}$$

Therefore, our measures of wages are composition adjusted.

Skill premium. Given wages of skilled and unskilled population, we now compute the skill premium, defined as $\frac{w^s_{hr}}{w^u_{hr}}$.

Figure A3 plots the composition-adjusted skilled/unskilled hourly wage premium in the US labor market. Note that our methodology for obtaining the skill premium differs from that of Acemoglu and Autor (2011) in two respects. First, Acemoglu and Autor (2011) construct the log wage premium by predicting log weekly wages and by forming mean log wages for broader groups. Second, when Acemoglu and Autor

Figure 11: Figure A4. Skill premium constructed as in Acemoglu and Autor (2011).



(2011) form mean wages for broader groups they consider only individuals belonging to two educational groups, high school graduates (unskilled) and college and greater than college graduates (skilled).

Figure A4, plots the composition-adjusted log college/high school weekly wage premium as in Acemoglu and Autor (2011) obtained from our data set. The two skill premia resemble each other, however, the log college/high school weekly wage premium has a smoother pattern.

Appendix A2. Aggregate data

Following the methodology of Greenwood et al. (1997), we construct series of capital equipment, k^e; capital structures, k^s; consumption, c; and output, y, measured in units of consumption of nondurable goods and services. Additionally, we construct the relative price of equipment, $1/q$. We construct all these variables for the period $1963 - 2017$. In our analysis the price index of investment in equipment is additionally adjusted for changes in quality of some equipment goods.

In order to obtain the data on the stocks of capital structures and equipment we have to take into consideration two issues. First, the data on quality adjusted stock of capital equipment is not observed directly. BEA provides current and constant dollar estimates of the net stocks of fixed assets, however literature suggests that BEA's estimates of the different categories of equipment goods do not fully take into account the rapid changes in their quality. To recover the evolution of quality-adjusted stock of capital equipment we use the quality adjusted data on investment in capital equipment measured in units of consumption, i^e. Second, in order to obtain the quality adjusted series of investment in capital equipment, we need to construct *quality adjusted price index* of investment in capital equipment.

Our data on investment in equipment goods comes from BEA, Detailed Data for Fixed Assets and Consumer Durable Goods, Nonresidential Detailed Estimates (current and fixed cost tables contain detailed estimates for private nonresidential fixed assets by detailed industry and by detailed asset type). The data on GDP, labor share of income and prices of equipment goods come from FRED Data base. We proceed by describing the methodology used for construction of price indexes that eliminate both the effects of changing price and quality.

Törnqvist aggregation

At different stages of our analysis we obtain a price of a good i by aggregating the price indexes of the $j = 1, ..., J$ goods that form that good using the Törnqvist price index. Let s_t^j be the nominal share of spending on a good $j = 1, ..., J$, and p_t^j be the corresponding quality adjusted price index. Törnqvist price index is a weighted geometric average of the price indexes $\frac{p_t^j}{p_{t-1}^j}$ where the weights are the arithmetic averages of the spending shares of the two consecutive periods $\frac{s_t^j + s_{t-1}^j}{2}$.[15] The change in the quality adjusted price of the good i, Δp_t^i, is defined as

$$\Delta p_t^i = \sum_{j=1}^{J} \left(\frac{s_t^j + s_{t-1}^j}{2} \right) \log \frac{p_t^j}{p_{t-1}^j}, \tag{16}$$

and the value of the price index can be recovered recursively as follows

$$p_t^i = p_{t-1}^i \exp(\Delta p_t^i). \tag{17}$$

Prices of consumption and investment in capital structures

The price of *consumption of nondurable goods and services* is not available directly and we compute it as a Törnqvist index of the price of *consumption of nondurable goods* and the price of *consumption of services* using shares of consumer expenditures on two types of goods as weights.[16] As for *investment in capital structures*, BEA develops quality adjusted price indexes for several types of nonresidential structures, for example warehouses and factories (see Bruce T. Grimm (2003) for more details) and therefore we rely on BEA's data on price of investment in structures as quality adjusted.

Figure A5 plots evolution of the price of consumption of nondurable goods and services and the price of investment in capital structures over 1947–2017. As we can see, the dynamics of both variables is very similar up to early 2000's. Afterwards, the prices of structures spikes, while the price of consumption continues growing at a constant rate. Because of such similar behavior, we assume a unique price for both consumption and structures and deflate the nominal investment in nonresidential structures and consumption to real terms using the calculated price index of consumption of nondurable goods and services.

Price of investment in capital equipment

The quality adjusted price of investment in capital equipment is harder to measure than that of consumption (and investment in capital structures). There has been a huge improvement in the quality of equipment goods in the last decade, specially for information processing equipment (e.g., computers and communication equipment) that was documented by the literature; see Gordon (1990), Berndt et al. (1995), Krusell et al. (2000), Cummins and Violante (2002). BEA develops quality adjusted price index for different categories of equipment, however, many economists consider that this adjustment sometimes underestimates the corresponding declines in prices; see Berndt et al. (1995), Gordon (1990). We follow the literature and construct an adjusted-for-quality price index for investment in equipment goods by extrapolating Gordon's (1990) data.

Gordon's (1990) data cover the period 1947 − 1983. For the sample period after 1983, the quality adjusted indexes for equipment goods are not available in the literature and we construct them as accurately as we can based on the information available.[17] In our analysis, we follow Cummins and Violante (2002).

[15] See OECD Glossary of Statistical Terms for a definition of the Törnqvist price index .

[16] See BEA data on personal consumption expenditures on consumption of nondurable goods and services, FRED St. Louis codes: DNDGRG3A086NBEA, DSERRG3A086NBEA,PCESVA and PCNDA.

[17] KORV(2000) construct quality adjusted price index for investment into equipment by aggegrating price indexes of four broad equipment categories of office and information processing (OIP), general industrial (INDEQ), transportation (TRANSP) and other (OTHER) equipment using Törnqvist index. Cummins and Violante (2002) update and improve KORV's (2000) methodology for the construction of the quality-adjusted price of investment in equipment. As a result, KORV(2000) and Cummins and Violante (2002) have a quality adjusted index for investment in equipment from 1963 to 1992 and 2000, respectively.

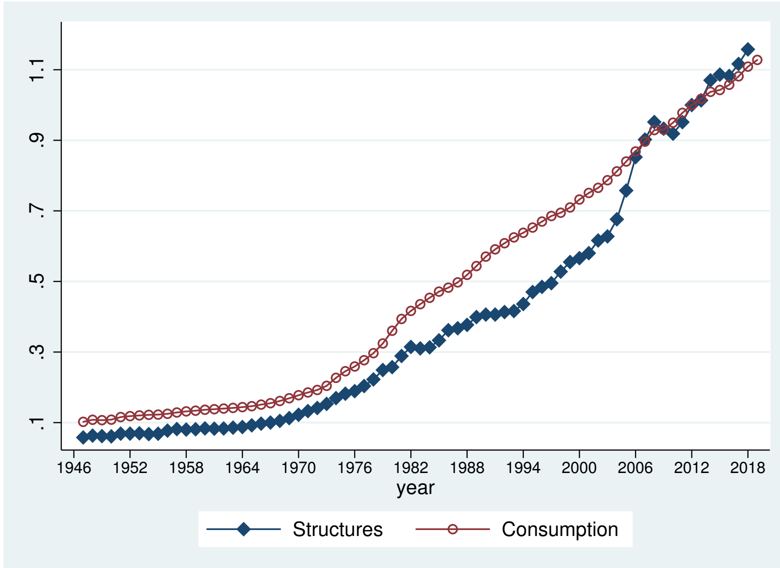


Figure 12: Figure A5. Prices of investment in structures and nondurable goods and services

Gordon (1990) constructs prices and shares in total nonresidential investment of 22 equipment goods that are grouped in four major categories according to NIPA classification of producers durable equipment: office information processing equipment (OIP), general industrial equipment (INDEQ), transportation (TRANSP) and other equipment (OTHER)[18].

The above four categories include the following components:

- OIP: Computers and peripherals; other office information processing; communication equipment; Instruments, photocopy and related equipment.
- INDEQ: fabricated metal products; engines and turbines; metalworking machinery; general industrial equipment; electrical transmission, distribution, etc.; special industry machinery.
- TRANSP: automobiles; aircraft; railroad equipment; trucks, buses, and track trailers; ships and boats.
- OTHER: furniture and fixtures; tractors; agricultural machinery (except tractors); construction machinery (except tractors); service industry machinery; electrical equipment; other equipment; mining and oilfield machinery.[19]

The current BEA taxonomy of equipment goods differs from the taxonomy used by Gordon (1990) and therefore, we have to put an effort in making it comparable to his data for 1917–1983. First, "tractors", that are explicitly included into Gordon's data in category OTHER, are currently accounted for as parts of agricultural machinery and construction machinery in BEA classification; we construct investment and price index for "tractors" using desaggregated data for farm tractors and construction tractors. As a result, we use three separate price indexes provided by BEA: one for tractors, another for agricultural machinery (except of tractors) and the other for construction machinery (except of tractors). Second, in BEA, we have information on medical equipment and instruments; nonmedical instruments; and photocopy and related equipment, while in Gordon's (1990) data all three goods are grouped into the category "instruments, photocopy and related equipment". To obtain the price index for investment in this category we aggregate

[18] See Tables B1 – B18 in Appendix B and Tables C1 – C6 in Appendix C of Gordon (1990).

[19] This taxonomy of goods is according to Gordon (1990). The current NIPA classification is similar to the one used by Gordon (1990).

the prices of BEA's variables, medical equipment and instruments; nonmedical instruments; and photocopy and related equipment using a Törnqvist index. The aggregate investment in "instruments, photocopy and related equipment" is the sum of investments in medical equipment and instruments, nonmedical instruments, and photocopy and related equipment.

To extrapolate Gordon's (1990) quality-adjusted price series, we estimate for each type of asset j an econometric model of Gordon's quality-adjusted price index as a function of a time trend and a cyclical indicator, augmented with the current and lagged values of the NIPA series:

$$\log p_{j,t}^{QA} = \beta_0 + \beta_1 t + \beta_3 \log p_{j,t} + \beta_3 \log p_{j,t-m} + \beta_4 \Delta y_{t-n} + \epsilon_{j,t}, \tag{18}$$

where $p_{j,t}^{QA}$ is the quality-adjusted price index for asset category j constructed by Gordon (1990), β's *are* coefficients, t is a linear time trend, $p_{j,t}$ and $p_{j,t-m}$ are current and lagged values of the official BEA price index, respectively, Δy_{t-n} is the growth rate of the lagged real GDP and $\epsilon_{j,t}$ is the disturbance term[20]. We present the results of the estimation in Table 1. Using the estimated coefficients, we predict the price indexes for each good j over $1984 - 2017$.

There are two equipment goods, namely, computers & peripherals, and office & accounting equipment, for which we do not estimate the econometric model (18). The literature argues that BEA's quality adjustment for these two goods leads to reasonably good price measures. We therefore use these BEA's measures in our analysis.[21]

Real variables

We divide the nominal consumption, output and investment in structures by the price index of consumption of nondurable goods and services and we construct the real quality adjusted series of investment in equipment using the price index for investment computed as described in the previous section. We use a basic perpetual inventory method to recover the stocks of capital structures and capital equipment from the data on real investment in these two types of capital. In particular, given an initial value of capital stocks for equipment and structures we recursively construct the sequences of capital stocks using the respective capital accumulation equations,

$$k_{t+1}^e = (1 - \delta^e) k_t^e + i_t^e, \tag{19}$$

$$k_{t+1}^s = (1 - \delta^s) k_t^s + i_t^s, \tag{20}$$

where δ^e and δ^s are the depreciation rates, and i_t^e and i_t^s are real investment in capital equipment and structures, respectively.[22]

Following Greenwood et al. (1997), we assume that $\delta^e = 0,125$ and $\delta^s = 0,05$. Figure A6 plots the series of capital structures and equipment.

Figure A7 shows the evolution of the price of equipment relative to the price of consumption goods. We construct it as a price index of investment in equipment divided through the price index of consumption of nondurable goods and services.

Figure A8 compares the price index for investment in equipment that we constructed to that constructed in Cummins and Violante (2002). As we can observe, the two price indexes are very similar.

[20] Cummins and Violante (2002) tested for unit root and cointegration in the quality adjusted and BEA series and concluded that the series are $I(1)$ and cointegrated. For each equipment good j, we follow a mixture of Akaike and Schwarts criteria to select the optimal lag length in each equation.

[21] Cummins and Violante (2002) also treat software as an equipment good. In 2013, BEA began presenting expenditures on software as fixed investment in new investment category "Intellectual property products" and therefore we do not include this good in our analysis of the price of investment in equipment goods.

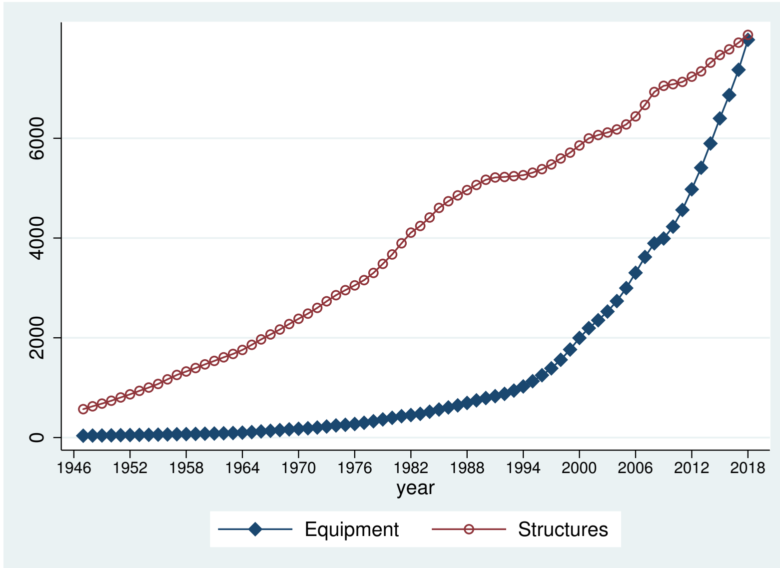
[22] Following Hall and Jones (1999), we estimate the initial value of the stocks of capital equipment and capital structures as $i_{1947}^e/(g^e + \delta^e)$ and $i_{1947}^s/(g^s + \delta^s)$, respectively, where g^e and g^s are the average geometric growth rates from 1947 to 1956 of the corresponding real investment.

Table 1: OLS estimates of the quality-adjusted price indexes of equipment goods[a]

Variable	t	$\log(p_{j,t-m})$	Δy_{t-n}	$\bar{R}^2$	$[m,n]$
Information processing equipment:					
Communication equipment	-0.066	1.622	–	0.92	$[0,-]$
	(0.004)	(0.151)			
Instruments and photocopy	-0.026	-1.886	–	0.81	$[2,-]$
	(0.008)	(0.863)			
Industrial equipment:					
Fabricated metal products	-0.031	1.195	-0.698	0.93	$[0,1]$
	(0.003)	(0.079)	(0.485)		
Engines and turbines	-0.060	1.477	–	0.78	$[0,-]$
	(0.008)	(0.148)			
Metalworking machinery	–	0.672	-0.575	0.97	$[0,1]$
		(0.020)	(0.390)		
Special industry machinery	-0.046	0.983	–	0.91	$[0,-]$
	(0.003)	(0.053)			
General industrial equipment	-0.012	0.813	-0.461	0.98	$[0,1]$
	(0.003)	(0.057)	(0.242)		
Electrical industrial apparatus	-0.032	1.379	–	0.87	$[0,-]$
	(0.003)	(0.103)			
Trasportation equipment:					
Trucks and buses	-0.036	1.613	–	0.92	$[1,-]$
	(0.002)	(0.237)			
Autos	-0.009	1.063	0.728	0.72	$[0,1]$
	(0.003)	(0.145)	(0.533)		
Aircraft	-0.150	2.368	–	0.89	$[0,-]$
	(0.013)	(0.282)			
Ships and boats	-0.032	1.364	–	0.99	$[2,-]$
	(0.002)	(0.186)			
Railroad equipment	-0.008	0.858	–	0.99	$[0,-]$
	(0.001)	(0.029)			
Other equipment:					
Furniture and fixtures	-0.008	0.968	-0.695	0.99	$[0,1]$
	(0.002)	(0.045)	(0.213)		
Tractors	-0.008	0.898	0.425	0.98	$[0,1]$
	(0.003)	(0.065)	(0.361)		
Agricultural machinery (except tractors)	–	2.088	-0.214	0.99	$[1,1]$
		(0.239)	(0.306)		
Construction machinery (except tractors)	-0.019	0.763	-0.455	0.99	$[1,1]$
	(0.002)	(0.131)	(0.197)		
Mining and oilfield machinery	-0.008	0.715	-0.330	0.98	$[0,1]$
	(0.002)	(0.038)	(0.265)		
Service industry machinery	-0.045	1.215	–	0.97	$[0,-]$
	(0.001)	(0.050)			
Electrical equipment	0.004	0.841	-0.888	0.96	$[0,0]$
	(0.001)	(0.057)	(0.317)		
Other equipment	-0.009	1.064	–	0.91	$[2,-]$
	(0.003)	(0.394)			

[a] Notes: Each row contains estimates of a separate equation in which the dependent variable is $\log p^{QA}_{j,t}$; $\bar{R}^2$ is the adjusted R^2; m and n are the lag orders for BEA price index and output growth rate, respectively. For example, a regression for a good j with $[2,-]$ lags contains $\log p_{j,t}, \log p_{j,t-1}, \log p_{j,t-2}$ as regressors and does not include Δy_t. In cases where equation contains more than one lag, we report the coefficients for $\log p_{j,t}$ or Δy_t to economize on space.

Figure 13: Figure A6. Quality adjusted series of capital structures and equipment.



Appendix B: Estimation

Following notation of KORV (2000), we consider a nonlinear model of the form

$$\begin{aligned} \text{Model:} \quad Z_t &= f(X_t, \psi_t; \phi) + \epsilon_t, && (21) \\ \text{State:} \quad \psi_t &= \psi_0(\gamma)^t \exp(w_t), && (22) \end{aligned}$$

where Z_t is a 3×1 vector; $f(\cdot)$ contains three nonlinear observational equations corresponding to (2)–(4); X_t is a set of inputs, namely, capital structures and equipment, labor inputs of skilled and unskilled workers; $\psi_t = \{\psi_t^s, \psi_t^u\}$ is a 2×1 vector of unobserved variables; $\epsilon_t = [0, 0, \epsilon_t^3]'$ and $w_t = [w_t^s, w_t^u]'$ are the vectors of i.i.d. normally distributed random disturbances, with mean zero and covariance matrix; ϕ is the vector of parameters to be estimated.

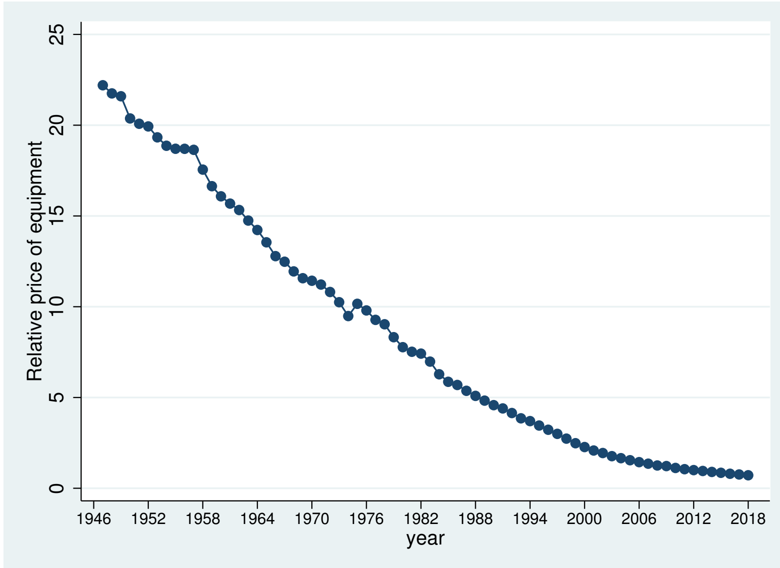
We allow for a possible dependence between shocks and hours worked, and we use a simulated pseudo MLE (SPMLE) procedure developed of White (1994). The procedure includes two steps: In step 1, we treat capital structures and capital equipment as predetermined and project skilled and unskilled labor input onto exogenous variables; hence, we treat the skilled and unskilled labor inputs as endogenous. We project these variables onto a constant, the current and lagged stock of capital equipment, current stock of capital structures, lagged relative price of capital equipment, a time trend and the lagged value of the Commerce Department's composite index of business cycle indicators. In step 2, we estimate the model (21)-(22) using the fitted values of the labor inputs.

To estimate the model (21)-(22) we draw a $T \times S$ matrices of shocks for $w_t^1, w_t^2, \epsilon_t^3$ to construct latent variables ψ_t and Z_t. Next, we obtain first and second (simulated) moments of Z_t

$$\begin{aligned} m_S(\tilde{X}_t; \phi) &= \frac{1}{S} \sum_{i=1}^{S} f(\tilde{X}_t, \psi_t^i, \epsilon_t^i; \phi), \\ V_S(\tilde{X}_t; \phi) &= \frac{1}{S-1} \sum_{i=1}^{S} \left(Z_t^i - m_S(\tilde{X}_t; \phi)\right)\left(Z_t^i - m_S(\tilde{X}_t; \phi)\right)', \end{aligned}$$

where $\tilde{X}_t = \{K_t^e, K_t^s, \hat{h}_t^s, \hat{h}_t^u\}$ with $\hat{h}_t^s$ and $\hat{h}_t^u$ obtained on Step 1. These moments, $m_S(\tilde{X}_t; \phi)$ and $V_S(\tilde{X}_t; \phi)$, are constructed for each t. The simulated pseudo maximum likelihood estimator, $\hat{\phi}$, is defined to be a

Figure 14: Figure A7. Relative price of equipment.



minimizer of

$$l^{HT}(\phi) = \frac{1}{2T}\sum_{t=1}^{T}\left(Z_t - m_S(\tilde{X}_t;\phi)\right)' V_S(\tilde{X}_t;\phi)^{-1}\left(Z_t - m_S(\tilde{X}_t;\phi)\right) + \log|V_S(\tilde{X}_t;\phi)| \tag{23}$$

We calculate standard errors using Theorem 6.11 in White (1994).

Detailed description of the estimation procedure. Equations (2)-(4) are based the firm's first order conditions: (2) defines total labor share of income as a function of the parameters of the production function; (3) specifies the wage bill ratio as a function of the parameters; and (4) is obtained from the Euler equations and related unobserved rental rates of capital equipment and structures. In the data, we observe left-hand sides (2) and (3), as well as the relative price of equipment $1/q_t$ in (4). Our analysis assumes that changes in unobserved latent variables can account for fluctuations in the skill premium.

The labor share and wage bill ratio equations used in the estimation take the following form:

$$\frac{G_{3t}L_{st}}{G_{4t}L_{ut}} = \frac{1-\mu}{\mu}(1-\lambda)\left(\lambda + (1-\lambda)\left(\frac{L_{st}}{K_{et}}\right)^{\rho}\right)^{\sigma/\rho-1}\left(\frac{L_{st}}{K_{et}}\right)^{\rho}\left(\frac{L_{ut}}{K_{et}}\right)^{-\sigma} \tag{24}$$

$$\frac{G_{3t}L_{st} + G_{4t}L_{ut}}{Y_t} = (1-\alpha) \tag{25}$$

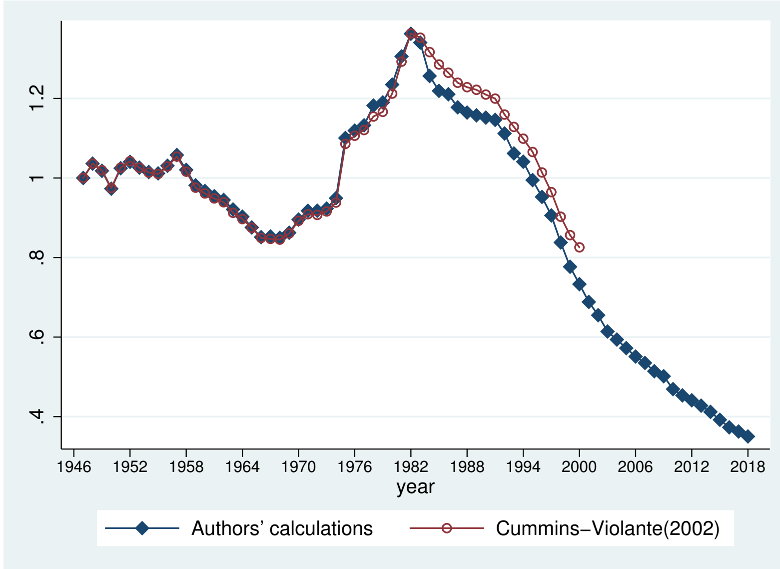
$$\cdot\frac{[(1-\mu)(1-\lambda)\left(\lambda + (1-\lambda)\left(\frac{L_{st}}{K_{et}}\right)^{\rho}\right)^{\sigma/\rho-1}\left(\frac{L_{st}}{K_{et}}\right)^{\rho} + \mu\left(\frac{L_{ut}}{K_{et}}\right)^{\sigma}]}{(1-\mu)\left(\lambda + (1-\lambda)\left(\frac{L_{st}}{K_{et}}\right)^{\rho}\right)^{\sigma/\rho}\left(\frac{L_{st}}{K_{et}}\right)^{\rho} + \mu\left(\frac{L_{ut}}{K_{et}}\right)^{\sigma}} \tag{26}$$

We specify the stochastic process (22) for the unobserved latent variables ψ_t^s and ψ_t^u as a stationary process:

$$\log(\psi_t) = \log\psi_0 + w_t, \quad w_t \sim N(0, \Omega_\omega)$$

In equation (4), we make a simplifying assumption that the expectation term $E_t\left(\frac{q_t}{q_{t+1}}\right)(1-\delta_e)$ can be

Figure 15: Figure A8. Quality adjusted price of equipment, authors' calculation vs. Cummins-Violante(2002).



approximated by $\frac{q_t}{q_{t+1}}(1-\delta_e)+\epsilon_t$, where ϵ_t is the i.i.d. forecast error, which is assumed to be normally distributed: $\epsilon \sim N(0, \sigma_\epsilon^2)$.

Therefore, the parameters to be estimated are $\phi = \{\sigma, \rho, \alpha, \mu, \lambda; \psi_0^s,\ \psi_0^u, \gamma_{\psi^s}, \gamma_{\psi^u}, \gamma_A, \Omega_\omega, \sigma_\epsilon, \delta_e, \delta_s\}$. It is challenging to estimate the model (2)–(4) for two reasons. First of all, the CES production function introduces highly nonlinear patterns in the equations to be estimated. Second, there is a relatively large number of parameters to be estimated for the amount of data points available.

Following KORV (2000), we make additional assumption. We fix $\delta_s = 0.05$ and $\delta_e = 0.125$; we estimate a time series ARMA model for the relative price of equipment $1/q_t$ to get an estimate for the standard deviation of ϵ: $\hat{\sigma}_\epsilon = 0.028$. We have four scaling parameters $\mu, \lambda, \psi_0^s, \psi_0^u$ and for identification, we need to fix one of them. We choose to fix $\psi_0^s = 1$, and we also assume that the two shock w_t^s and w_t^u are uncorrected and are distributed normally with zero mean, so we only need to estimate the variance. The number of simulations is set equal to $T = 500$.