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Capital-skill complementarity and inequality: Twenty years after[☆]

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ABSTRACT

We revisit a seminal capital-skill complementarity analysis of Krusell et al. (2000). We extended their 1963–1992 data set to include the 1992–2017 period. We find that over the recent years, the skill premium pattern changed dramatically, from a U-shaped to a monotonically increasing. However, the capital-skill complementarity framework remains remarkably successful in explaining the data. This is true even when the model is estimated using a significantly declining labor share as in Karabarbounis and Neiman (2014). We finally construct a projection for skill premium for 2017–2037, and we conclude that the inequality will continue to grow in the US economy.

1. Introduction

Under the assumption of decreasing marginal products, an increase in 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 (the ratio of their wages) grew by about 0.6% per year. That is, both the number of skilled workers and their wages increased more rapidly than those of unskilled workers which constitutes a puzzle.

Earlier literature had argued that this puzzle 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, Krusell et al. (2000, henceforth, KORV) demonstrated that the skill premium dynamics can be explained with just observable variables if one uses a more realistic production function. They assumed a constant elasticity of substitution (CES) production function with four inputs — skilled labor, unskilled labor, capital equipment and capital structures. They found that skilled labor is complementary with equipment, so if the stock of equipment increases, then so does the stock of skilled labor.

Our title 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 we ask: "Is the KORV's (2000) mechanism of capital-skill complementarity remains empirically relevant?[1]

To answer this question, we first extend KORV data set to include the 1963–2017 period.[2] We find that the skill premium pattern changed dramatically: it was U-shaped in the KORV data, however it became monotonically increasing in recent data. We then reestimate the KORV's (2000) model using the recent data,

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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.

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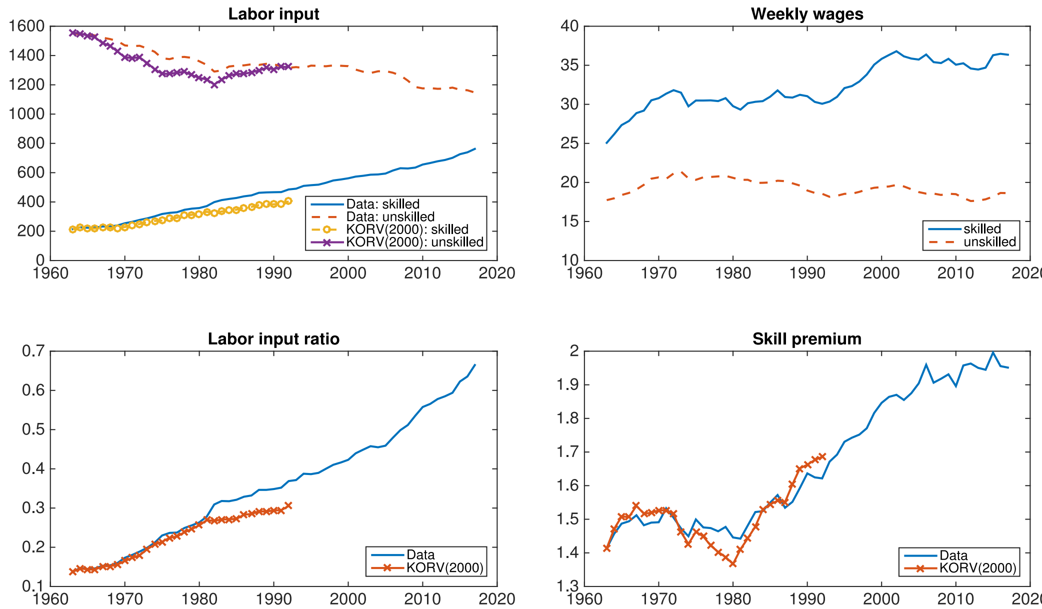

Fig. 1. Selected labor indicators for skilled and unskilled groups.
Source: CPS March Supplements.

and we find that their CES production function still accords remarkably well with the U.S. skill premium data. However, we find that the model fails to account for the evidence of decreasing labor share documented in Karabarbounis and Neiman (2014). To correct for this, we impose exogenously a stronger negative trend in the labor share and reestimate the model. We find that the predictions on the skill premium remain practically unaffected, suggesting that the CES production function is capable of explaining the skill premium data even in the presence of significantly declining labor share.

We finally construct a projection of the skill premium for the years 2017–2037 on the basis of the KORV (2000) analysis and we conjecture that the income inequality in the US economy will continue to grow, although at a slower rate. The remaining paper is as follows: Section 2 describes the data; Section 3 revisits the KORV (2000) analysis; Section 4 presents the estimations; Section 5 constructs the projections; and finally, Section 6 concludes.

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

Following the methodology of KORV (2000), we extend their 1963–1992 sample to include 1993–2017 period. We construct labor-market variables using household data from the current population survey (CPS); and we construct other variables such as output, capital, and prices using the Federal Reserve Bank of St. Louis and Bureau of Economics Analysis macroeconomic data; see Appendices A1 and A2 for details.

Labor and wages. In Fig. 1, we report the labor variables for the groups of the skilled and unskilled agents over the 1963–2017 period.

We observe three tendencies:

(i) The labor input of skilled workers increases while the labor input of unskilled workers decreases. This is explained by the fact that the population of skilled workers grows much faster than that of unskilled workers, specifically, the former population increases from 7.4 to 56 million (652.7% increase) while the latter population increases from 62.3 to 93.6 millions (50.2% increase).

(ii) The wages of skilled agents grow more rapidly than those of unskilled agents.

(iii) The skill premium pattern was U-shaped in the original (KORV) 1963–1992 sample but it is monotonically increasing in our extended 1963–2017 sample.

Observations (i) and (ii) 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 referred to as a *skill-premium puzzle*.

Capital and prices. In Fig. 2, we report other relevant aggregate macroeconomic indicators for the US economy.

We observe the following regularities:

(i) The stock of equipment grows much faster than that of structures, specifically, the former stock grows from 91.2 to 7373.6 billions of dollars (7983.9% increase) while the latter stock grows from 1676.4 to 7917.3 billions of dollars (390% increase).

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

These tendencies are qualitatively similar in both original KORV (2000) and our extended samples.[3]

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

The data suggests that dramatic growth in the stock of skilled labor might be related to a dramatic increase in the stock of equipment. Such relation was first hypothesized by 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

[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 that can be explained by data revisions. 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), CV2002 henceforth, 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.

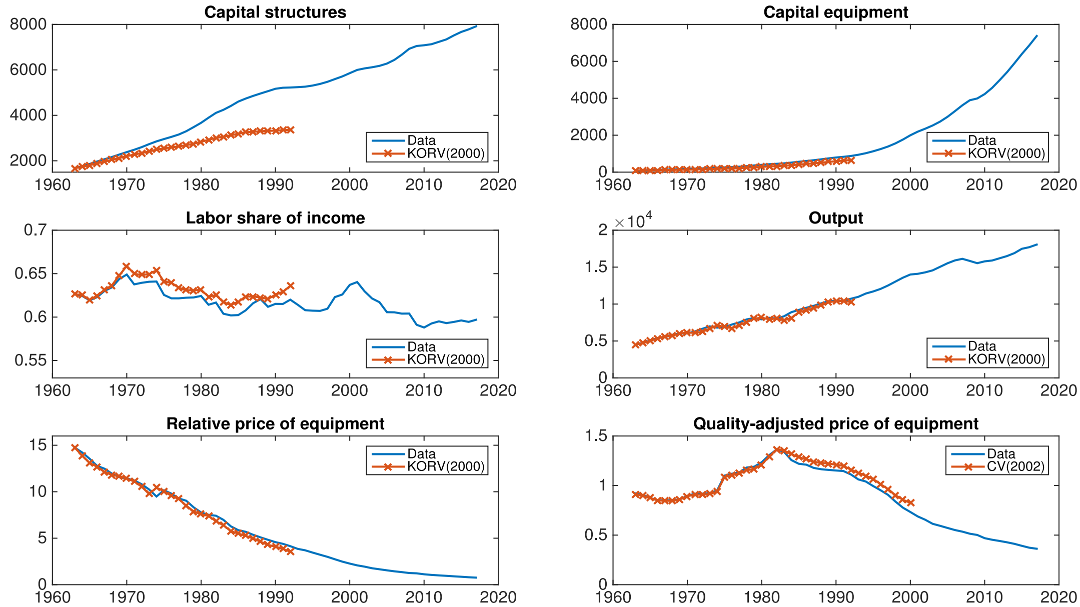

Fig. 2. Selected macroeconomic variables for the US economy.
Source: The Federal Reserve Bank of St. Louis and Bureau of Economics Analysis.

price)". The KORV's (2000) analysis provides strong evidence in support of the capital-skill complementarity mechanism. They formulated a CES production function

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

where Y_t, A_t, K_{st}, K_{et}, L_{st} and L_{ut} are output, technology, capital structures, capital equipment, skilled labor and unskilled labor, respectively; $L_{st} = h_{st}\psi_{st}$ and $L_{ut} = h_{ut}\psi_{ut}$, where h_{st} and h_{ut} are hours worked; and ψ_{st} and ψ_{ut} are a specific technical change of the skilled and unskilled agents, respectively; $\alpha \in (0,1)$, $\mu \in (0,1)$, $\lambda \in (0,1)$; and the parameters ρ and σ govern the elasticities of substitution between structures, equipment, skilled labor and unskilled labor. Formula (1) yields the skill premium:

$$\pi_t = \frac{(1-\mu)(1-\lambda)}{\mu} \times \left[\lambda\left(\frac{K_{et}}{L_{st}}\right)^{\rho} + 1 - \lambda\right]^{(\sigma-\rho)/\rho}\left(\frac{h_{ut}}{h_{st}}\right)^{1-\sigma}\left(\frac{\psi_{st}}{\psi_{ut}}\right)^{\sigma}. \tag{2}$$

KORV (2000) estimated (1) by using their 1963–1992 sample and constructed the skill premium (2); see Fig. 3. The bottom right panel of Fig. 3 illustrates that the capital-skill complementarity mechanism explains remarkably well the behavior of skill premium over the 1963–1992 period. The estimates of KORV (2000) reported in Table 1 support strongly the hypothesis of capital-skill complementarity $\sigma > \rho$.

4. The present: insights from the 1993–2017 sample

We next ask how the estimates obtained by KORV (2000) have changed in the more recent period. To this purpose, we re-do the analysis of KORV (2000) for our extended 1963–2017 sample, and we compare the results with their estimates in Table 1. In our extended sample, the elasticities of substitution between equipment and unskilled labor and that between equipment and skilled labor are 1.71 and 0.76 respectively. These elasticities are somewhat higher than those estimated by KORV (2000) equal to 1.67 and 0.67, respectively, which suggests that the role of the capital-skill complementarity mechanism continues to increase.

Table 1
Estimates of parameters of production function.

Parameter	σ	ρ	α	λ	μ	η_{ω}^2
KORV (2000)	.401 (0.234)	−.495 (0.048)	.117 (0.007)	–	–	.043 (0.003)
1963–1992	.432 (0.027)	−.489 (0.033)	.183 (0.003)	.536 (0.004)	.402 (0.065)	.012 (0.003)
1963–2017	.415 (0.011)	−.325 (0.022)	.190 (0.002)	.534 (0.007)	.406 (0.130)	.068 (0.008)
1963–2017 D	.421 (0.012)	−.273 (0.023)	.197 (0.003)	.538 (0.007)	.401 (0.017)	.089 (0.012)

One question which was left unexplored in the original KORV (2000) analysis is how much of the variation in the model is explained by observable versus unobservable components. To address this question, we reestimated the model by setting the variability of unobservables η_{ω} to a very small value 0.0005; the resulting simulated series and parameter estimates are shown in Appendix C in Figure C1 and Table C1, respectively. We find that there is a trade off between fitting the skill premium and making the rates of return on capital structures and capital equipment roughly equal. With smaller η_{ω} the rates of return on capital are very different in the second half of the sample which is reflected in significantly lower estimate of μ which decreases from .406 to .245. However, the key predictions of the model remain valid even when we use only observable variables for estimation.

We then ask: "Can the CES production function (1) explain the recent data?" In Fig. 4, we plot the same variables as in Fig. 3 for the 1992–2017 period. As we see, the skill premium pattern changed dramatically in the recent data. In KORV's (2000) 1963–1992 sample, the skill premium is roughly U-shaped while in the recent data, it increases monotonically. 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.

Additionally, on Fig. 4 we observe that the model has difficulties in explaining the labor share dynamics: if the skill premium keeps rising, and the relative supply of skilled/unskilled labor

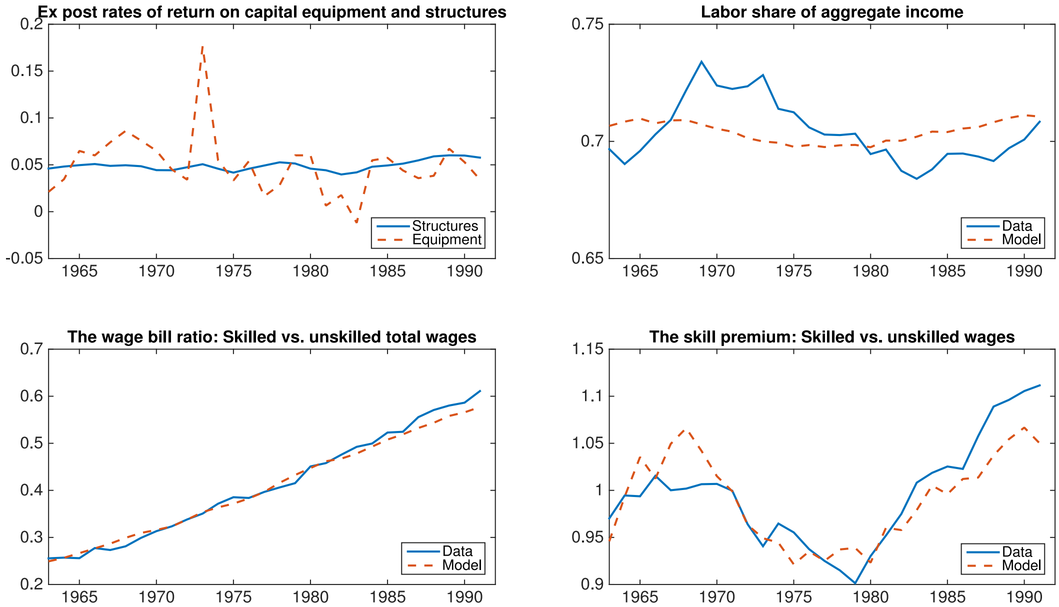

Fig. 3. Estimation results: the fitted series for the KORV (2000) 1963–1992 sample.

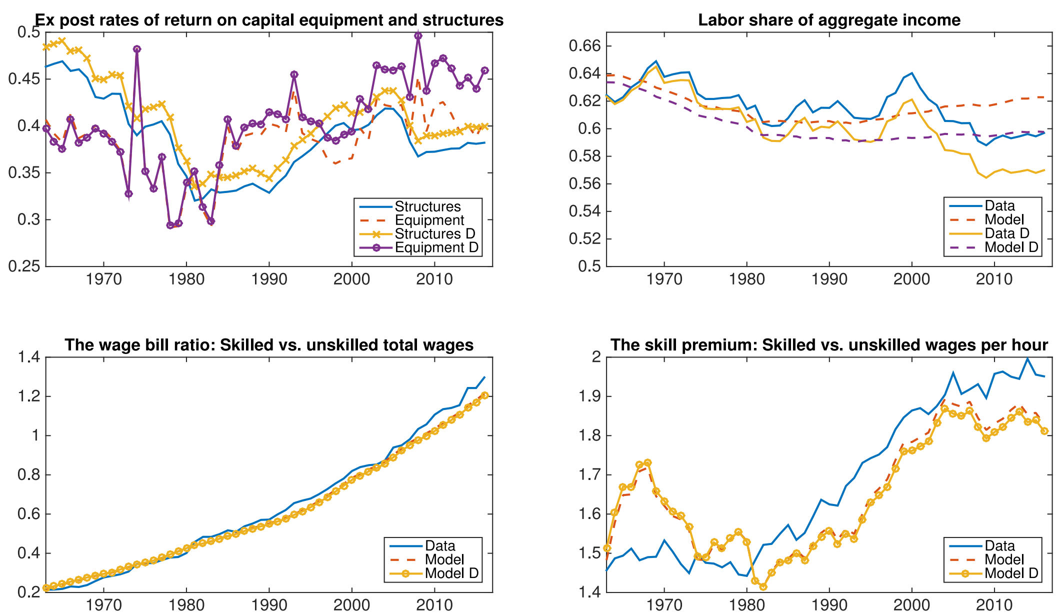

Fig. 4. Estimation results: the fitted series for the 1963–2017 sample.

keeps increasing, then a natural consequence would be that of an increasing labor share, as is seen in Fig. 4. This is not consistent with the data which suggests that the labor share is falling.

In our dataset the decline in the labor share is modest, but Karabarbounis and Neiman (2014) argue that the decline in the labor share is more pronounced within the corporate labor sector. To see how sensitive our results are to this evidence, we reestimate the model by imposing a stronger negative trend on the labor share in line with Karabarbounis and Neiman (2014); see "Model D" in Fig. 4 for the simulated series; and see the last row of Table 1 for the parameter estimates. To generate the artificial data for this exercise, we fit the trend to the actual labor share and we set the slope coefficient equal to the one estimated for the labor share from Karabarbounis and Neiman (2014). From Fig. 4 and Table 1, we see that in both cases the fit of the model is very similar and we conjecture that the CES production function can explain the skill premium data even in the presence of a pronounced negative trend in the labor share.

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

We designed a methodology for predicting the evolution of skill premium in the future. Specifically, we ask: "How can the KORV's (2000) framework be used for projection of skill premium, and how accurate such projection will be?" We construct the projections using the model with a strong negative trend in the labor share as in Karabarbounis and Neiman (2014) but the results are indistinguishable from our baseline model with a less pronounced trend.

Formula (2) in KORV (2000) allows us to predict the evolution of the skill premium given three exogenous variables, namely, capital equipment, skilled labor and unskilled labor. As a first

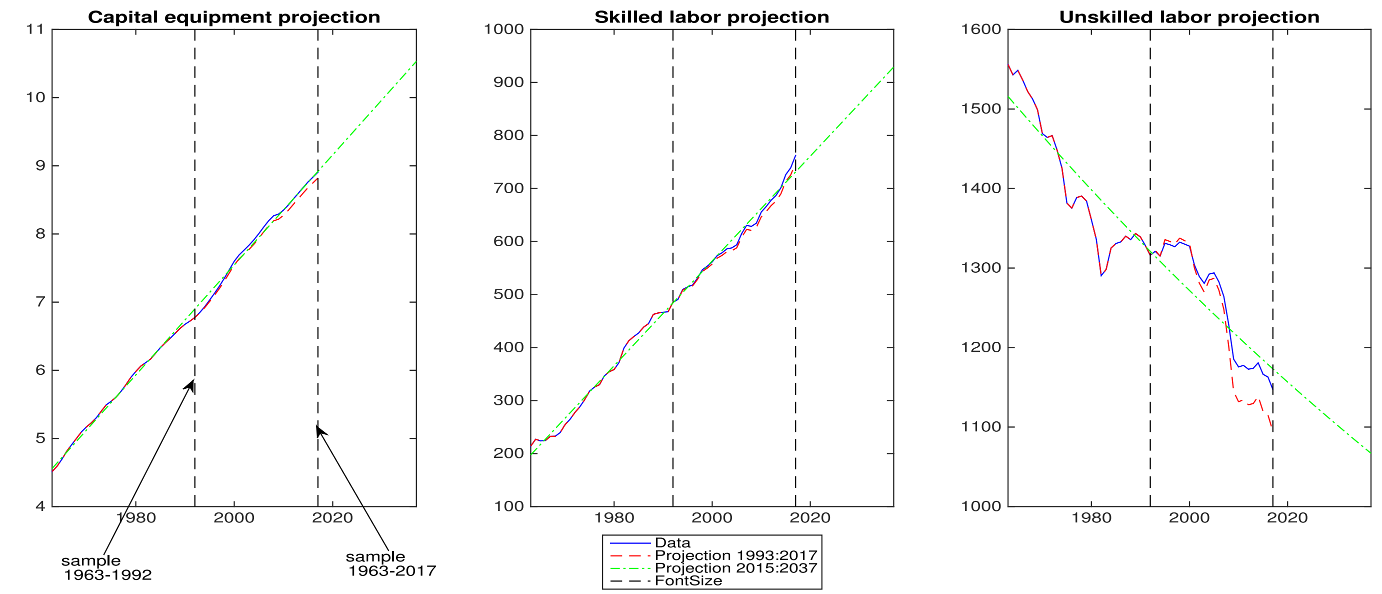

Fig. 5. The projections of log of capital equipment, skilled and unskilled labor for the periods 1993–2017 and 1993–2037.

step, we forecast the evolution of these three series using a simple linear trend in Fig. 5.

"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 components, while for the latter projection, we include just a trend since the future cyclical component is not available. Visually, our projections appear to be accurate and reliable, in particular, for the former two series that are nearly linear. The last series is subject to some fluctuations but our projection still captures the trend correctly.

We subsequently use the projected exogenous variables to construct the skill premium path using formula (2), and we compare the projection with the actual skill premium series in the US data in Fig. 6. Let us discuss these three experiments in Fig. 6.

Projection 1963–2017. In our first counterfactual experiment, we place ourselves back to the year 1992 when KORV's (2000) analysis 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 (2) the actual series on capital equipment, skilled and unskilled labor for the 1993–2017 period. The resulting skill premium series "KORV projection 1963–2017" is shown with the blue line in Fig. 6. We observe that the projected and actual skill premium series are very similar. The fact that we use the coefficients estimated over the past 1963–1992 period for constructing the 1993–2017 projection does not produce qualitatively important forecast errors. Thus, our first conjecture is: *"The regression coefficients obtained from the past data lead to accurate projections in the future periods".*

Projection 1963–1992. In our second counterfactual experiment, we again place ourselves back to year 1992 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 Fig. 5?" The resulting skill premium series "KORV projection 1963–1993" is shown with the red line Fig. 6. We observe that the projection constructed on forecasted inputs look very similar to the previous projection constructed on 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. In our main projection experiment, we place ourselves in the year 2017, a terminal year of our sample, 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 2017–2037 period. For this experiment, the cyclical components of exogenous variables are not available, so we substitute linear trends into (2). We also provide a two-standard-deviation confidence interval for the skill premium projection. Our results in Fig. 6 suggest that the skill premium will continue to rise in the future although at a somewhat slower rate and so will do the degrees of the income inequality in the US economy. While any extrapolation is risky, our two counterfactual experiments show that our methodology led to accurate projections in the past, and the results suggest that it will carry over to the future.

6. Conclusion

Our findings confirm that the main insight of KORV's (2000) analysis continues to hold for more recent data and likely, it will continue to hold in the future: we can account for the growth patterns in the U.S. aggregates by using just observable time series on capital and labor. This is true even when the model is estimated using a significantly declining labor share as in Karabarbounis and Neiman (2014). A shortcoming of KORV's (2000) analysis is that their partial equilibrium framework does not provide a methodology for predicting the production inputs. Maliar et al. (2019) introduce a tractable framework for analyzing nonstationary applications that can be used to extend KORV's (2000) production function to a general equilibrium setup – a promising agenda for future work.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.econlet.2022.110844.

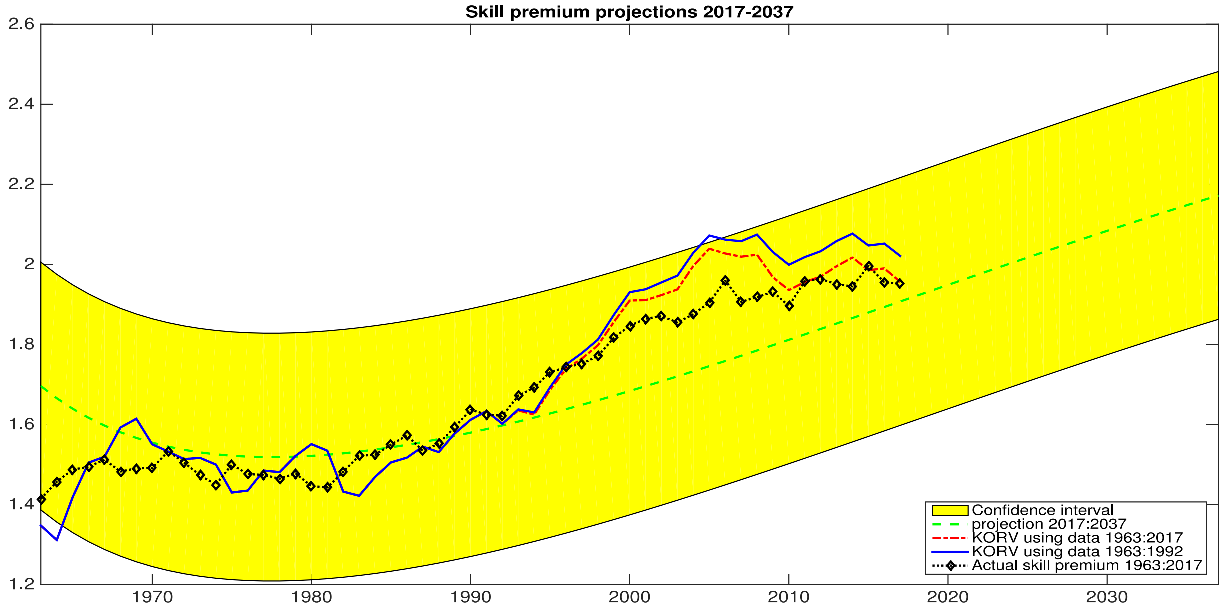

Fig. 6. Skill premium projections 2017–2037.

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