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Searching for Wage Growth: Policy Responses to the "New Machine Age"

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ABSTRACT: The current wave of technological revolution is changing the way policies work. This paper examines the growth and distributional implications of three policies when "robot" capital (a broad definition of robots, Artificial Intelligence, computers, big data, digitalization, networks, sensors and servos) is introduced in a neoclassical growth model. 1) cuts to the corporate tax rate; 2) increases in education spending; and 3) increases in infrastructure investment. We find that incorporating "robot" capital into the model does make a big difference to policy outcomes: the trickle-down effects of corporate tax cuts on unskilled wages are attenuated, and the advantages of investment in infrastructure, and especially in education, are bigger. Based on our calibrations grounded on new empirical estimates, infrastructure investment and corporate tax cuts dominate investment in education in a "traditional" economy. However, in an economy with "robots" the infrastructure investment dominates corporate tax cuts, while investment in education tends to produce the highest welfare gains of all. The specific results, of course, may depend on the exact modeling of the technological change, but our main results remain valid and can provide more accurate welfare rankings.

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WORKING PAPERS

Searching for Wage Growth: Policy Responses to the "New Machine Age"

Prepared by Andrew Berg, Edward F. Buffie, Mariarosaria Comunale, Chris Papageorgiou, Luis-Felipe Zanna[1]

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I. INTRODUCTION

Stagnant real wages have become a central, problematic feature of several advanced countries — most notably the United States — in recent decades. While the causes are various, advances in technology and particularly automation of routine tasks have been identified as a major factor. In this paper we look specifically at a broad definition of these technologies, we call it "robot", as an umbrella covering not only robots per se, but also including Artificial Intelligence (AI), computers, big data, digitalization, networks, sensors and servos that are emphasized in the literature on the "new machine age". Expert opinion also holds that, sooner or later, a new wave of innovation associated with ever-faster computers, more effective machine learning and generative-AI (gen-AI) algorithms, and pervasive digitalization will usher in a new industrial revolution with even greater macroeconomic repercussions (and initial indications are that these may look somewhat different compared to our broader definition).[1] The recent spreading of advanced gen-AI technologies, especially after the release of ChatGPT by Open AI in November 2022, already started a new debate on impact of these technologies on the labor market.

The macroeconomic literature on the new industrial revolution, including our own earlier work, investigates the implications of improvements in technology for growth, labor markets, and the distribution of income. In this paper we ask a different question, namely: How do the effects of policy differ in the new economy with this "robot" capital? [2]

Employing a variant of the model in Berg, Buffie, and Zanna (2018), we analyze the impact on growth and the distribution of income of three policies: cuts in the corporate tax rate, increases in education spending, and increases in infrastructure investment. The model features low-skill workers who live check-to-check, capitalists and high-skill workers who save and invest, and our broad "robot" capital that differs from traditional capital in being highly substitutable with low-skill labor in production.[3] Moreover, we separate out information and communication

[1] Exposure to generative-AI (gen-AI) is highly heterogeneous across industries, occupations and job titles. Recent empirical studies show that gains from gen-AI accrue primarily to lower-skilled, lower-paid workers (Brynjolfsson, Li, and Raymond (2023)) and that gen-AI adoption tends to flatten firms' hierarchical structures, increasing workers in junior positions and decreasing workers in middle management and senior roles (Babina and others (2023)).

[2] Korinek and Stiglitz (2018) discuss policy issues, particularly with respect to to technology and transfers, at a general level. There is little or no formal examination, however, of how robots, AI, and related technologies change the way the economy responds to policies. Acemoglu and Restrepo (2019a) focus on policy towards technology itself. Acemoglu, Manera, and Restrepo (2020) is an important recent exception, analyzing implications of the U.S. tax code for employment, wages, the labor share, and automation. They find that the U.S. tax system is biased against labor and in favor of capital, increasingly so in recent years. More recently Korinek (2023) analyzed a framework to evaluate the impact of a technological innovation, including Large Language Models (LLMs) examples, on labor demand and inequality, finding that these effects depend on both the pricing strategies of innovators and the institutional structure of the economy.

[3] Caselli and Manning (2019) analyze how improvements in technology affect real wages in the long run. They do not analyze the transition path to the new steady state. Their production function is very general but assumes

technology (ICT) capital from the rest and we look at elasticities of substitution in this context. An important contribution of this paper is to examine empirically a production function with ICT capital, comparing the merits of different specifications. The empirical exercise provides support for the specification that we argued in earlier work is a priori the most plausible. We show that ICT capital—a (poor) proxy for “robots”, to be sure—is different in its relationship to other factors of production compared to the rest of equipment capital. Failing to take this into account gives the wrong results.

The dominant theme running through our results is that robots (and AI) indeed can make a big difference to how policies work; old theoretical assumptions and benchmark models need to be revisited and earlier empirical work taken with some cautions.

Based on our calibrations, in the case of corporate tax cuts (CTC), standard Cobb-Douglas and CES models readily deliver standard results: a lower tax rate encourages capital deepening, the marginal product of labor rises as a result, and real wages increase equally (in percent) for low- and high-skill workers. If, instead, we assume that “robot” capital is highly substitutable with low-skill workers, then long-run GDP growth is higher by 1–2 percentage points, but the skill premium rises sharply: the increase in the high-skill wage equals or exceeds GDP growth while the low-skill wage increases very little or even declines.

Infrastructure investment (II) follows similar patterns: unskilled wages rise less and skilled wages more as “robot” capital becomes more substitutable with unskilled labor. Compared to CTC, labor across the skill spectrum benefits more. For rates of return in line with empirical estimates, the private capital stock increases *more* than with the comparable CTC; even under pessimistic assumptions about the return to infrastructure, strong crowding-in of private capital lifts GDP growth 3-4 percentage points above that with the CTC. The larger increase in unskilled wages with II relative to CTC becomes more salient as “robot” capital becomes more substitutable with unskilled labor: with CTC, the low-skill wage may fall; with II, it increases substantially in all runs.

Even starker implications of new technologies, and bigger contrasts with CTC, emerge for investment in education (IE). Wage inequality is lower, and growth higher, dramatically so with more highly substitutable ‘robot” capital. IE gives an especially strong boost to accumulation of “robot” capital, due to both the large decrease in unskilled labor that competes with it and the increase in the supply of complementary skilled labor. Strikingly, in the great majority of runs where “robot” capital is highly substitutable with low-skill labor, traditional capital increases 2-5 times as much as with CTC.

These positive results inform many of our welfare results. At the initial equilibrium, the return on infrastructure and the pre-tax return on private capital both equal 10 percent, while the return

only one type of capital, thus missing out on many important interactions of traditional and “robot” capital with different degrees of substitutability with different types of labor.

on investment in education is 7 percent. The private time preference rate equals 6 percent. Consequently, there is too little investment in all types of capital. The social welfare function allows policy makers to discount the future less heavily than the private sector and/or value income of the poor more than income of the non-poor. When policy makers do neither, they maximize welfare of the representative private agent.[4]

Because the three policies have very different effects on aggregate capital accumulation and real wages, the welfare rankings are sensitive to the social discount factor and weight on distributional objectives, as well as the parameters of the production function. One result, however, is completely robust: II *always* dominates CTC. This result is a corollary of the aforementioned positive results. Because II strongly crowds in private capital, it always increases the aggregate capital stock (inclusive of infrastructure) and the low-skill wage more than CTC. Hence it is always more effective than CTC in reducing underinvestment and increasing real income of the poor. The results for IE are less robust. In a partial equilibrium setting, the low (direct) return on IE (7 vs. 10 percent for private capital and infrastructure) dooms it to last place in the welfare ranking. This is also the case in general equilibrium when the social welfare function is the *same* as the welfare function of the representative agent. The word "same" is important. Since IE increases the aggregate capital stock and the low-skill wage much more in the long run than the other two policies, its position in the welfare ranking changes dramatically when policy makers discount future gains less heavily than the private sector and care more about welfare of the poor than welfare of the representative agent. In our preferred calibration, for example, IE beats CTC when the social discount factor is two basis points higher than the private discount factor; when the social discount factor is 140 basis points higher (0.957 vs. 0.943), it also beats II. And if real income of the poor enters the social welfare function with a small positive weight, IE beats both CTC and II even when policymakers apply the same discount factor as the private sector.

The elasticities of substitution between the various factors of production play a critical role in our analysis, particularly between "robot" capital and low-skilled labor. The novelty of our specification, notably the introduction of "robot" capital as a distinct factor of production measured by ICT capital, means that empirical estimates from the literature are not directly comparable. We extract data on the capital and labor stocks, and wages and rates of return, that correspond to our production function. We then infer the elasticities implied by this data for our specification, as well as for two alternative plausible CES production functions with different nesting structures. We find that our preferred specification is the most empirically plausible, and for both the baseline and the alternative specifications, the elasticity of substation between "robot" capital is above 2 and higher than the other elasticities, lending broad support to the most important assumption we make in this paper.

[4]Our model has poor and non-poor agents. The reference to the "representative agent" means that only aggregate consumption enters the welfare function.

The rest of the paper is organized as follows. In Sections II and III, we lay out the model and calibrate it to the data for the U.S. Section IV discusses the extent to which certain choices in the specification of the model and its calibration condition our results. It also reports the empirical exercise and the subsequent estimated values for the elasticities of substitution. In Section V, we analyze the three policy experiments: corporate tax cuts, investing in infrastructure, and investing in education. For each experiment, we provide analysis of the long run—including analytical results—and the transition path to the new steady state. We also rank the welfare gains generated by the policies in Section VI. Section VII concludes.

II. The Model

We introduce a corporate profits tax, international capital flows, and investment in infrastructure and education into the model developed by Berg, Buffie, and Zanna (2018). To isolate the effects of each policy change, transfer payments to capitalists and high-skill workers pay for changes in the corporate tax rate and in infrastructure and education investment.[5]

A. Technology

Competitive firms produce a single good using traditional capital K_t, "robot" capital Z_t, infrastructure capital G_{t-1}, high-skill labor S_t, and low-skill labor L_t. The production function is $Q_t = G_{t-1}^{\eta} F[H(S_t, K_t), V(L_t, Z_t)]$, where $F(\bullet)$, $H(\bullet)$, and $V(\bullet)$ are linearly homogeneous CES aggregates of their respective inputs. To facilitate the derivation of analytical results, we bypass the production function and work with the firm's unit cost function:

$$\overline{\mathbb{C}}_t = \frac{[ah_t^{1-\sigma_1} + (1-a)f_t^{1-\sigma_1}]^{1/(1-\sigma_1)}}{G_{t-1}^{\eta}}, \tag{1}$$

where

$$f_t = [ew_{l,t}^{1-\sigma_2} + (1-e){r_{z,t}}^{1-\sigma_2}]^{1/(1-\sigma_2)}$$

and

$$h_t = [gw_{s,t}^{1-\sigma_3} + (1-g){r_{k,t}}^{1-\sigma_3}]^{1/(1-\sigma_3)}$$

are sub-cost functions dual to the composite inputs $H(\bullet)$ and $V(\bullet)$; σ_1 denotes the elasticity of substitution between H and V; σ_2 corresponds to the elasticity of substitution between low-

[5] Because the capitalists/high-skill workers face the usual intertemporal budget constraint and labor supply is fixed, these changes in transfers in themselves have no behavioral effects. If the government were to finance the policies with reductions in transfers to low-skilled hand-to-mouth workers, there would be first-order effects on their consumption but, with fixed labor supply, no general equilibrium effects; overall (pre-tax) inequality would not change.

skill labor L_t and "robot" capital Z_t; σ_3 is the elasticity of substitution between high-skill labor S_t and traditional capital K_t; $w_{l,t}$ and $w_{s,t}$ are the wages of low- and high-skill labor; and $r_{k,t}$ and $r_{z,t}$ are the rental rates for traditional capital and "robot" capital.

The cost function in (1) is no less cumbersome than the corresponding production function. It is not necessary, however, to manipulate (1) when deriving analytical results. We employ instead the compact specification $\overline{\mathbb{C}}_t = \mathbb{C}[h(w_{s,t}, r_{k,t}), f(w_{l,t}, r_{z,t})]/G_{t-1}^{\eta}$ and invoke well-known formulas that link the derivatives of the cost function to the substitution elasticities and factor cost shares.

Flexible factor prices ensure that demand equals supply for each private input, while the supply of infrastructure is determined by public investment. Using Shepherd's lemma, the market-clearing conditions may be written as:

$$K_t = \mathbb{C}_h h_{r_k} \frac{Q_t}{G_{t-1}^{\eta}}, \qquad Z_t = \mathbb{C}_f f_{r_z} \frac{Q_t}{G_{t-1}^{\eta}}, \tag{2}$$

and

$$L_t = \mathbb{C}_f f_{w_l} \frac{Q_t}{G_{t-1}^{\eta}}, \qquad S_t = \mathbb{C}_h h_{w_s} \frac{Q_t}{G_{t-1}^{\eta}}, \tag{3}$$

where $\mathbb{C}_h$, $\mathbb{C}_f$, h_{r_k}, f_{r_z}, f_{w_l}, and h_{w_s} are partial derivatives. L_t and S_t are perfectly inelastic. Under this simplifying assumption, a single variable, the wage, measures the impact of policy on income of low- or high-skill workers.

Utilization of the two capital inputs is subject to the following adding-up constraint:

$$K_{a,t-1} = K_t + Z_t, \tag{4}$$

where $K_{a,t-1}$, the aggregate capital stock, is predetermined. Although K_t and Z_t are free to jump, they do not do so. In the scenarios we analyze, traditional capital is never dismantled and instantaneously converted into robots. Both capital stocks behave as state variables because on the transition path they depend solely on $K_{a,t-1}$.[6]

[6]When investment in education or infrastructure increases, K_t and Z_t depend on $K_{a,t-1}$, S_{t-1}, and G_{t-1}. But S_{t-1} and G_{t-1} are also predetermined state variables.

Price always equals unit cost as perfect competition prevents firms from earning supranormal profits.[7] Hence the following zero-profit condition holds:

$$1 = \frac{\mathbb{C}(w_{s,t}, r_{k,t}, w_{l,t}, r_{z,t})}{G_{t-1}^{\eta}}. \tag{5}$$

B. Preferences

The poorest 40 percent of U.S. households live check-to-check. We equate this group with low-paid, low-skill workers L_t, who consume all of their income $w_{l,t}L_t$ each period.

Capitalists and skilled workers are rich enough to save and can borrow in the world capital market at the interest rate i_t. They live together peacefully in a representative agent who chooses consumption C_t, aggregate investment $I_{a,t}$, and "robot" capital Z_t to maximize

$$U = \sum_{t=0}^{\infty} \beta^t \frac{C_t^{1-1/\tau}}{1-1/\tau},$$

subject to

$$\begin{aligned} C_t + I_{a,t} + \Gamma(I_{a,t}, K_{a,t-1}) + (1+i_{t-1})B_{t-1} \quad &= \quad w_{s,t}L_{s,t} + T_t + B_t + [r_{z,t}(1-x_t) + \delta x_t]Z_t \\ &\quad + [r_{k,t}(1-x_t) + \delta x_t](K_{a,t-1} - Z_t), \end{aligned} \tag{6}$$

$$K_{a,t} = I_{a,t} + (1-\delta)K_{a,t-1}, \tag{7}$$

where $\beta = 1/(1+\rho)$ is the discount factor; ρ is the pure time preference rate; τ is the intertemporal elasticity of substitution; δ is the depreciation rate; B_t is foreign debt; T_t is lump-sum transfers/taxes; and x_t is the tax on corporate profits (net of depreciation). In the budget constraint (6),

$$\Gamma(I_{a,t}, K_{a,t-1}) = \frac{\nu}{2}\left(\frac{I_{a,t}}{K_{a,t-1}} - \delta\right)^2 K_{a,t-1}$$

captures adjustment costs incurred in changing the aggregate capital stock.

Per the Maximum Principle, the first-order conditions for an optimum consist of

$$C_t^{-1/\tau} = \lambda_{1,t}, \tag{8}$$

$$r_{k,t} = r_{z,t} = r_t, \tag{9}$$

[7] This is a simplification assumption, with the caveat that technological revolutions may cause markups to rise for some goods and imperfect competition in the labor market due to increasing market power may also lead to falling real wages.

$$\lambda_{1,t}\left[1+v\left(\frac{I_{a,t}}{K_{a,t-1}}-\delta\right)\right]=\lambda_{2,t}, \tag{10}$$

and the co-state equations

$$\lambda_{1,t}=\beta(1+i_t)\lambda_{1,t+1}, \tag{11}$$

$$\lambda_{2,t}=\beta\lambda_{2,t+1}+\beta\lambda_{1,t+1}\left[(r_{t+1}-\delta)(1-x_{t+1})+\frac{v}{2}\left(\frac{I_{a,t+1}}{K_{a,t}}-\delta\right)^2\right], \tag{12}$$

where $\lambda_{1,t}$ and $\lambda_{2,t}$ are multipliers attached to the constraints (6) and (7). Equations (11)-(12) can be consolidated into two familiar Euler equations. On an optimal path, consumption satisfies

$$\left(\frac{C_{t+1}}{C_t}\right)^{1/\tau}=\beta(1+i_t) \tag{13}$$

and investment adjusts so that the after-tax capital rental, net of depreciation and adjustment costs, continuously equals the interest rate:

$$\frac{(r_{t+1}-\delta)(1-x_{t+1})+1+v\left(\frac{I_{a,t+1}}{K_{a,t}}-\delta\right)+\frac{v}{2}\left(\frac{I_{a,t+1}}{K_{a,t}}-\delta\right)^2}{1+v\left(\frac{I_{a,t}}{K_{a,t-1}}-\delta\right)}=1+i_t. \tag{14}$$

The representative saver views the world market interest rate as parametric when solving their optimization problem. In the aggregate, however, U.S. borrowing is large enough to influence i. For the analysis that follows, a full-blown two-country model of the world economy would be overkill. We assume simply[8]

$$i_t=\rho e^{\mu\left(\frac{B_t}{B}-1\right)}, \quad \mu>0, \tag{15}$$

where $\rho=\left(\frac{1-\beta}{\beta}\right)$ is the private time preference rate associated with the discount factor β

and B corresponds to the initial value of B_t—the value at the initial steady state. When the U.S. borrows more ($B_t>B$), it pushes i_t above ρ by an amount that depends on the slope of the supply curve for external loans. The limiting cases $\mu\to\infty$ and $\mu\to 0$ correspond to the closed economy and an open economy that faces a fixed world market interest rate, respectively.

We incorporate an open capital account in the model not to be realistic but rather to properly join the debate between proponents of the CTC and its detractors. The proponents contend that the CTC will stimulate a quick, large increase in investment thanks to capital inflows that keep

[8] The specification in (15) is common in open economy models. See Turnovsky (1997) and Uribe and Schmitt-Grohe (2017).

increases in the interest rate "relatively small."[9] Critics of the tax cut dispute this, asserting that, because of the sheer size of its economy, the U.S. cannot attract large capital inflows without "driving up interest rates world-wide" (Krugman (2017)). Varying μ in (15) to accommodate different views about the elasticity of capital flows allows us to faithfully represent the debate in the literature.

C. The Government Budget Constraint

Cuts in transfer payments to capitalists and high-wage skilled workers pay for reductions in the corporate income tax and for additional investments in education ($I_{s,t}$) and infrastructure ($I_{g,t}$).[10] This is captured by the following government budget constraint:

$$T_t = x_t(r_t - \delta)K_{a,t-1} - I_{g,t} - I_{s,t}. \tag{16}$$

D. Public Investment in Infrastructure and Education

The law of motion for infrastructure capital is

$$G_t = I_{g,t} + (1 - \delta_g)G_{t-1}, \tag{17}$$

where δ_g is the depreciation rate. $I_{g,t}$—a policy variable—jumps once at $t = 1$.

Public investment in higher education $I_{s,t}$ increases the supply of education capital $S_{u,t}$ according to the stock accumulation equation:

$$S_{u,t} = I_{s,t} + (1 - \delta_s)S_{u,t-1}, \tag{18}$$

where δ_s is the depreciation rate. A fixed input-output coefficient ϕ connects the increase in the supply of education capital to the supply of high-skill labor:

$$S_t = S + \phi(S_{u,t-1} - S_u), \tag{19}$$

where S and S_u correspond to the initial values of S_t and $S_{u,t}$—the values at the initial steady state.

[9] See the guest column by Feldstein (2017) and the open letter from nine macroeconomists to Treasury Secretary Mnuchin, both in the Wall Street Journal in November 2017.
[10] We thus sidestep the controversial direct distributional effects of the recent U.S. tax reform.

E. Debt Accumulation and the Current Account Deficit

Substituting for T_t in (6) (and recognizing that $r_{z,t} = r_{k,t} = r_t$) produces the accounting identity that links debt accumulation (left-hand side) to the current account deficit (right-hand side):

$$B_t - B_{t-1} = i_{t-1}B_{t-1} + C_t + I_{a,t} + I_{g,t} + I_{s,t} + \Gamma(I_{a,t}, K_{a,t-1}) - r_t K_{a,t-1} - w_{s,t}S_t, \tag{20}$$

or, equivalently,

$$B_t - B_{t-1} = i_{t-1}B_{t-1} + w_{l,t}L_t + C_t + I_{a,t} + I_{g,t} + I_{s,t} + \Gamma(I_{a,t}, K_{a,t-1}) - Q_t. \tag{21}$$

The current account deficit equals the difference between national spending and national income. Note that the sum $w_{l,t}L_t + C_t$ equals aggregate consumption in (21), since low-skill workers L_t consume all of their income each period.

III. Calibration of the Model

To calibrate the model for large changes, we assign values to structural parameters, the old and new tax rates, and factor cost shares at the initial steady state. The calibration is summarized in Table 1.

The discount factor, the depreciation rate for private capital, the intertemporal elasticity of substitution, and the q-elasticity of investment (Ω) all take ordinary values.[11]

With respect to the other choices:

- Data on AI, industrial robots, ICT capital, etc., is scarce, especially going beyond the U.S. We set the income share of this broad "robot" capital at 4 percent as in Eden and Gaggl (2018). This to be consistent with the share of ICT capital in the aggregate capital stock.[12] Clearly, this is only an approximation to the sorts of new technologies described in the introduction. Industrial robots or AI *per se* are not included in ICT capital (see for instance Eden and Gaggl (2018) and Online Appendix II). On the other hand, not all ICT capital substitutes for low-skill labor.

[11]The value assigned to Ω pins down the adjustment cost parameter v. The first-order condition for investment is $1 + v\left(\frac{I_a}{K_a} - \delta\right) = q$, where $q \equiv \frac{\lambda_2}{\lambda_1}$ and λ_1 and λ_2 are multipliers attached to the constraints in (6) and (7). q is Tobin's q, the ratio of the demand price of capital to its supply price. Evaluated at a steady state, $v = \frac{1}{\Omega\delta}$, where $\Omega \equiv \frac{\hat{I}_a}{\hat{q}}$.

[12]The share of ICT capital in the aggregate capital stock is 5.7 percent extending data from Eden and Gaggl (2018) to 2020, while is of 11 percent based on the definition and data reported in Nordhaus (2015).

- The tax rate x_{old} combines the effective marginal tax rate on corporate profits with the tax rate on capital income. The effective marginal corporate profits tax is much less than the statutory rate of 35 percent. Our guess is 27 percent. The tax rate on capital gains and dividends in the U.S. is 15 percent for most income brackets and 20 percent for the highest bracket. We use the average of the two rates. The overall pre-2018 tax rate is thus $x_{\text{old}} = 1 - \frac{(1-0.27)}{(1-0.175)} = 0.40$.

- The reduction in the effective marginal corporate profits tax from 27 percent to 20 percent lowers the overall tax on capital income from 40 percent to 34 percent. In line with estimates for the U.S. tax-cut bill of 2017, the revenue loss in the initial period equals 1.5 percent of GDP.[13]

- The parameter that governs the elasticity of capital flows, μ, takes either the very low value 0.10 or the intermediate value 0.60. When $\mu = 0.1$, capital flows are highly elastic and an increase in the U.S. foreign debt from 40 to 50 percent of initial GDP raises the world market interest rate from 6 to 6.15 percent; for $\mu = 0.6$, the rate increases to 6.97 percent.

- $\frac{B}{Q}$ equals the ratio of net foreign debt to GDP in the U.S.

- The depreciation rate of public capital is set at 4 percent ($\delta_g = 0.04$). This is in line with the values used by the International Monetary Fund (2015) to calculate public capital stocks for high-income countries.

- According to the Congressional Budget Office (2017), public infrastructure investment equals 2.4 percent of GDP for all levels of government (local, state, and federal). But 2.4 percent isn't nearly enough to maintain the infrastructure stock in the U.S., which has been deteriorating for decades. Europe spends on average 5 percent of GDP on infrastructure. Hence our educated guess is that 4 percent of GDP $(\xi_g = 0.04)$ is needed to offset depreciation.

- In their comprehensive survey of the literature, Bom and Ligthart (2014) report that the average rate of return on infrastructure in OECD countries ranges from 17 to 19 percent for core public capital and from 12 to 15 percent for all public capital. For the U.S., the range for all public capital is 10-20 percent. We carry out runs for a low, conservative return of 10 percent—the same as the pre-tax return on private capital—and a normal high return of 15 percent. The value of η in the production function is backed out from the values assigned to δ_g, ξ_g, and R_g (see Section V.B).

- Public investment in higher education (ξ_s) equals 1.3 percent of GDP, its value in the U.S. in 2017.

[13]The Tax Policy Center estimates the revenue loss from the corporate tax cut at approximately 1.1 percent of GDP ($200 billion a year). Other business tax cuts included in the bill push the figure close to 1.5 percent of GDP.

- The depreciation rate for education capital (δ_s) is 3 percent. This is a common choice in growth models—see, e.g., Mankiw, Romer, and Weil (1992), Basu and Getachew (2015). It is also quite close to the estimated value of δ_s (0.027) in Polachek, Das, and Thamma-Apiroam (2015) and the value of δ_s (0.0316) consistent with the stylized facts describing cross-country growth and inequality in Bandyopadhyay and Basu (2005).

- Following Gennaioli and others (2011), we set the return on education (R_s) at 7 percent. The value for ϕ, the input-output coefficient that maps growth in education capital into increases in the supply of skilled labor, is backed out from the values of R_s, δ_s, ξ_s, the skill premium, and θ_s at the initial steady state.

Remarks on the Structure of the Model and Its Calibration

For reasons discussed below, a lot of questions can be asked about the structure of the model. Before moving on, we elaborate on certain choices and the extent to which they condition our results.

- *Inelastic supply of skilled labor*. The empirical justification for treating the supply of skilled labor as exogenous is the evidence presented in Autor (2014) and Murphy and Topel (2016) that the share of college-educated workers has changed very little in response to the large increase in the skill premium since 1980. Sometimes small responses have big effects in general equilibrium. But variations in the supply of skilled labor induced by changes in the skill premium are a *second-round effect*. Bringing the effect into play would not alter any of our qualitative results. It could significantly affect our quantitative results, but only if the supply response to the skill premium is unusually large.

- *Infrastructure is factor-neutral*. We model increases in the supply of infrastructure as equivalent to Hicks-neutral technological progress. This is the specification of choice in the literature for the many types of infrastructure that lower transport costs (Ramey (2020)).[14] Certainly, however, some infrastructure is not factor-neutral: improvements in the power grid probably complement capital more than labor; investments in rural broadband probably enhance the productivity of skilled labor and ICT capital more than the productivity of low-skill labor and traditional capital. Analyzing these types of infrastructure requires a more complicated production function in which G enters as an additional in the composite inputs $H(K,S)$ and $V(L,Z)$.

[14]Ramey notes that typically infrastructure enters as a Hicks-neutral shift factor in a Cobb-Douglas production with constant returns to scale in private inputs. Prominent examples include Aschauer (1989), Baxter and King (1993), Fernald (1999), Leeper, Walker, and Yang (2010), and Bouakez, Guillard, and Roulleau-Pasdeloup (2017).

IV. Calibration (and Estimation) of the Elasticities of Substitution

The elasticities of substitution between the various factors of production play a critical role in our analysis and deserve special empirical attention. The novelty of our specification, notably the introduction of "robots" capital as a distinct factor of production measured by ICT capital, means that empirical estimates from the literature are not directly comparable. In this section we discuss our preferred calibration and relate it to the literature, before delving briefly into the new empirical exercise that supports this calibration. For this analysis, we extract data on the capital and labor stocks, and wages and rates of return, that correspond to our production function. We then infer the elasticities implied by this data for our specification, as well as for two different CES production functions with different nesting structures. We draw three main conclusions: (1) our preferred specification is the most empirically plausible; (2) the best estimates of the elasticities support the assumptions we have laid out immediately above; (3) For both the baseline and the alternative specifications, the elasticity of substitution between "robot" capital is above 2 and higher than the other elasticities, lending broad support to the most important assumption we make in this paper.

A. Calibration

Table 1 defines our preferred calibration, including for the main elasticities of substitution, "σ_i" for $i = 1,2,3$. For reasons discussed later, we also present results for the values of σ_1 and σ_3 in Krusell and others (2000b).

- Estimates of σ_1 with macroeconomic data typically deliver values close to unity. Newer estimates based on microeconomic data disagree, placing σ_1 between 0.4 and 0.6. This is more in line with our own estimated values with more recent macroeconomic data (approx. 0.35, see Table 3).[15] We put more faith in the lower estimates but generate solutions for $\sigma_1 = 1$ as well.[16]

- The empirical estimates in Griliches (1969), Fallon and Layard (1975), Hamermesh (1993), Krusell and others (2000b), and Raval (2011) suggest that σ_3 is 20 - 60 percent smaller than σ_1. In our estimation, we confirm σ_3 being very close to the value of σ_1. Accordingly, the runs assume either $\sigma_3 = \sigma_1$ or $\sigma_3 = 0.5\sigma_1$.

[15] See Klump, McAdam, and Willman (2007), Chirinko (2008), Chirinko and Mallick (2017), Raval (2011), and Oberfield and Raval (2014).

[16] In our production function, σ_{kl} is a function of the three substitution elasticities and factor shares, while σ_1 is the elasticity of substitution between the composite inputs $H(K,S)$ and $V(K,L)$. Strictly speaking, therefore, the empirical estimates we cite do not correspond to either σ_{kl} or σ_1. This is also the reason why we do estimate them ourselves based on our production function and alternatives. Our focus also stays on cases where $\sigma_1 = \sigma_3$.

- In the literature, there are no econometric estimates of σ_2, the most important parameter in the model. Technology experts concur that substitution between "robots" (but also AI) and human labor (in tasks where substitution is possible) is much easier than substitution between most primary inputs, but it is difficult to translate "much easier" into a number for σ_2. Employing a different nesting structure and calibrating to data for 1950 - 2013, Eden and Gaggl (2018) conclude that σ_2 has increased rapidly since the late 90s, rising from 2.5 to 3.27. Calibrating to their data with our nesting structure yields $\sigma_2 = 2.13$. Our econometric estimations (see next sub-section) with data up to 2020 points already at a slightly larger σ_2 between 2.2 and 2.5 (see Table 3) and this has been increasing since the 1990s, as we show and discuss below. Lastly, estimates in Acemoglu and Restrepo (2019b) also provide some guidance looking at robots. Their finding that one robot directly eliminates 10.6 jobs suggests that σ_2 might be quite large and getting bigger with time passing.[17] Reflecting also the probability that "robots" will keep getting smarter, the runs let σ_2 vary between 1.5 and 5.[18]

These elasticity of substitutions are defined by using a CES model of "robot" technology rather than in a task-based framework. The task-based framework investigates the microeconomic mechanisms through which robots substitute for labor. Simplifying a bit, when robots become cheaper or smarter relative to labor, some tasks previously performed by labor get allocated to robots. The task-based framework can analyze granular labor market issues outside the purview of our CES framework. For the issues addressed here, however, we are confident the two frameworks give similar results. Ease of task substitution between labor and "robots" corresponds to a particular elasticity of substitution (σ_2) in the CES framework.

In the model, traditional capital and skilled labor form a composite input H with substitution elasticity σ_3. The elasticity of substitution (EOS) of H vis à vis the composite input for low-skill labor services is σ_1. We carry out runs for $\sigma_1 = 0.5$-1 and $\sigma_3 = 0.5\sigma_1$, σ_1. The associated EOS between low- and high-skill labor (σ_{sl} or EOS(L,S)) is slightly larger than unity when $\sigma_1 = \sigma_3 = 1$. In all other runs, it is below unity.[19] This is at odds with the many empirical

[17] The estimate that one robot directly eliminates 10.6 jobs is not a pure empirical estimate. It depends on the regression coefficient in the employment equation and the values assigned to the inverse of the Frisch elasticity of labor supply and the inverse elasticity of supply of robots.

[18] Robots and AI experts clearly expect that automation capital will be much more substitutable with labor in the near future. If they are right, calibrating to historical data underestimates the value of σ_2 that will prevail in upcoming decades. (The advent of driver-less vehicles, for example, is sure to have a big impact on σ_2 in the transport industry.)

[19] In nested CES production functions, σ_{sl} is the harmonic mean of the relevant substitution elasticities, with weights given by factor shares as in Sato (1967). In our case,

$$\sigma_{sl} = (a+b+c)(a/\sigma_3 + b/\sigma_2 + c/\sigma_1)^{-1},$$

where $a = \theta_k/[\theta_s(\theta_s+\theta_k)]$, $b = \theta_z/(\theta_z+\theta_l)$, and $c = 1/[(\theta_s+\theta_k)((\theta_z+\theta_l)$. Since $\sigma_2 = 1.5$ - 5 in our runs, $\sigma_{sl} = 1.008 - 1.020$ for $\sigma_1 = \sigma_3 = 1$. We are indebted to a referee for bringing Sato (1967) to our attention *and* extending Sato's results to our three-level CES production function.

estimates that report an EOS well above unity. Cantore, Ferroni, and Leon-Ledesma (2017) observe, for example, that the "consensus estimate" in the literature is "around 1.5."[20]

Meta-analysis in a recent paper provides strong support for our preference to calibrate to a lower EOS based on our estimates that σ_{sl} is around 0.4 for the U.S. (see next sub-section). Havranek and others (2020) note that estimates of σ_{sl} vary widely and that elasticities smaller than unity are not uncommon.[21] More importantly, they find that after correcting for publication and attenuation bias, the evidence suggests the mean σ_{sl} lies in the range 0.6-0.9 for the U.S. Arguably, an EOS of 0.6 is more plausible than 1.5. We agree with Mollick (2010) that "A high elasticity of substitution between workers is not exactly what one expects since human capital of educated and poorly educated workers have comparative advantages in performing different tasks."

Havranek et al.'s paper will not settle the debate about what the empirical evidence tells us—meta-analysis *is* controversial. We decided therefore to test the sensitivity of our results to alternative specifications/calibrations of the model with a high EOS between low- and high-skill labor. Our production function is similar to that in Krusell and others (2000b), a prominent paper in the literature. The main difference is that our production function introduces "robots" that produce services highly substitutable with low-skill labor.[22] Krusell et al. calibrate to estimates of 1.69 for σ_1 and 0.67 for σ_3. The associated value for σ_{sl} is 1.40.[23] For each policy, we carry out runs with Krusell et al.'s values for σ_1 and σ_3. (σ_{sl} ranges from 1.35 - 1.37 for $\sigma_2 = 1.5$ - 5.) The results lie between the results for the runs where $\sigma_1 = 1$ and $\sigma_3 = 0.5$, 1, two of our preferred calibrations.

One drawback of Krusell et al.'s calibration is that a high EOS between low- and high-skill labor implies, in contradiction to most empirical estimates, an equally high EOS between traditional capital and low-skill labor. To obviate this limitation, we firstly solved the model for the 3-tiered CES production function $Q = F\{K, H[S, J(L,Z)]\}$, with $\sigma_1 \leq 1$ and σ_4, the EOS between skilled labor S and the composite input for low-skill labor services J, equal to 1.5.[24] Analytical and numerical results for this specification are available in a longer version of the paper (Berg and others (2023)). For $\sigma_2 > \sigma_4$, the quantitative results are slightly weaker than

[20] See also Table 5 in Ciccone and Peri (2005) and the estimates in McAdam and Willman (2018) of 4-factor, 2- and 3-level CES production functions that generalize the production functions in Krusell and others (2000b).

[21] In their sample, 29.6 percent of the estimates lie in the (0,1) interval and 34.7 percent in the (1,2) interval, with many estimates clustering around 0.5 and 1.5.

[22] The production function in Krusell and others (2000b) is of the form $Q = K_b^{\alpha} H[J(K_e, S), L]^{1-\alpha}$, where K_b and K_e denote capital structures and capital equipment. The marginal rate of substitution between K_e and S and between $J(\bullet)$ and L are independent of variations in K_b.

[23] We used our factor shares in calculating σ_{sl}.

[24] McAdam and Willman (2018) estimate more general versions of the 4-factor production function in Krusell and others (2000b) with different nesting structures. The specification $Q = F\{K_b, J[K_e, H(L,S)]\}$ gives the best overall fit with the data, but $Q = F[G(K_b, K_e), H(L,S)]$ comes in a close second. The EOS between the two capital stocks (equipment and structures) and labor services is much lower than in Krusell et al., ranging from 0.53 to 0.65, while σ_{sl} equals 2.34 in the 3-level production function and 2.10 in the 2-level production function.

in our preferred model, but our qualitative results and the policy rankings for GDP, real wages, etc., are completely robust.

B. Estimation

In this sub-section, we show that the calibrated values of the elasticities of substitution—i.e., "σ_i" for $i = 1, 2, 3$—are in line with econometric estimates that best fit the data, given the baseline production function of our model. We also show that our estimate of σ_2 (EOS between L and Z) is greater than 2 and features a positive trend over recent decades, suggesting increasing substitutability between low-skill labor and "robots", as technology has evolved. Moreover, we argue that our baseline specification of the production function performs better empirically than two most plausible alternatives of production functions.

Stylized Facts on Capital and Labor

We proceed to look at some stylized facts of the series that will be used for the estimation, starting with the stocks, prices, and depreciation rates of ICT and non-ICT equipment (Figure 1). In the ICT category we include Communications, Software, PCs, Terminals, Semiconductors, and Storage devices. The rest are listed as non-ICT capital and these categories cover both residential and non-residential capital.[25]

The stock of ICT capital has increased exponentially since the 2000s; its price has declined, falling below that of non-ICT capital. These patterns could be driven by a technological "revolution", but also by other factors related to increased competition, economies of scale, and improved production processes. The price of non-ICT capital, instead, remained constant from the 1980s until the 2000s, and since then it has experienced a moderate increase. Moreover, the depreciation rate for ICT capital has increased from the early 1980s, which could be explained by the even higher competition in the ICT world combined with changes in consumers' preferences.[26] At the same time, the increase in this rate, after the 2000s, could reflect some technological advancements related to smartphone technologies, software, cloud computing, and faster internet connections, among others.

On labor market data, the non-routine category captures jobs that involve tasks that need problem-solving, creativity, and complex decision-making (Figure 2).[27] The routine vs non-routine tasks are aggregated categories of occupations following Eden and Gaggl (2018) based

[25] All the details on the data are available in the Online Appendix II. Capital data come from Bureau of Economic Analysis (BEA).

[26] The figure for the depreciation rates is available in the Online Appendix II.

[27] Labor data are from the Current Population Survey (CPS) by the U.S. Bureau of Labor Statistics (BLS). For reference see Flood and others (2021). In the non-routine category, we include managers in various jobs and high qualified professionals, i.e., lawyers, economists, engineers, computer systems analysts and scientists, researchers, teachers, artists, technicians, and developers ("Managerial, Professional, and Technical") together

on Acemoglu and Autor (2011). For this labor category, total employment has increased over time, particularly during the last decade, as rapid technological advancements have required problem-solving and/or technical skills."Managerial, Professional, and Technical" jobs seem to have led this increase in employment, while "Services" and other groups have plateaued since mid-2010s.[28] On the other hand, routine labor has been relatively stable in the last decades. There has been, however, a small increase in the specific category of "Operatives/Laborers," hinting that manual labor and the related routine tasks have not become obsolete. Some sectors and industries still rely on these, as they cannot be easily automated or outsourced.

Real wages show similar increasing paths for both non-routine and routine labor. In the case of wages for non-routine labor, the increase is driven by wages in "Managerial, Professional, and Technical" and "Services" jobs, given the higher demand for skilled labor, especially for "new tech" skills, and a smaller supply of specialized jobs. In the routine group, similar real wages increases are found for Administrative tasks/jobs. These aggregated outcomes, however, mask important differences across occupations for both wages and employment.

The Empirical Approach and Estimates of the Elasticities of Substitution

We estimate the elasticities of substitution of factors of production, including between "robots" and low-skill labor, following the approach by Eden and Gaggl (2018) and using U.S. data for the period 1967-2020. In the literature, these parameters have been mostly calibrated. For our estimation, we use the following proxies: ICT capital for "robot" capital (Z) and non-ICT for other capital (K); while routine labor and non-routine labor for low-skill (L) and high-skill labor (S).[29]

For the estimation, we follow a step approach that makes use of three equations associated with the first-order conditions (FOCs) of the firm's problem described above. More specifically, recall our CES production function of the model, which corresponds to our baseline:

$$F[H(S,K),V(L,Z)] \tag{22}$$

where $F(\bullet)$ is a CES in the top tier

$$F(\bullet) = [\iota_1 H^{\varepsilon_1} + \iota_2 V^{\varepsilon_1}]^{\frac{1}{\varepsilon_1}}, \tag{23}$$

with nurses, police-persons, cooks, waiters, and guides ("Services"). In the routine category, we include instead "Sales, and Administrative" jobs, which are salespersons (in different sectors), cashiers, and clerks (in different sectors), and "Production, and Operatives and Laborers" which covers repairers, carpenters, drivers, and garbage collectors. A check including "Technical, Sales, and Administrative (201-400)" entirely in the non-routine has also been performed and our outcomes are robust, see also Appendix II.

[28]The figures for employment and wages by occupation categories are available in the Online Appendix II.

[29]In Eden and Gaggl (2018), "automation" is driven by both cheaper ICT capital and an exogenous process that increases the demand for robots.

with $\iota_1 = a^{\frac{1}{\sigma_1}}$, $\iota_2 = (1-a)^{\frac{1}{\sigma_1}}$, and $\varepsilon_1 = \frac{\sigma_1 - 1}{\sigma_1}$; and $V(\bullet)$ and $H(\bullet)$ are, in turn, nested CES aggregators:

$$V(\bullet) = [\kappa_1 L^{\varepsilon_2} + \kappa_2 Z^{\varepsilon_2}]^{\frac{1}{\varepsilon_2}} \tag{24}$$

$$H(\bullet) = [\gamma_1 S^{\varepsilon_3} + \gamma_2 K^{\varepsilon_3}]^{\frac{1}{\varepsilon_3}} \tag{25}$$

with $\kappa_1 = e^{\frac{1}{\sigma_2}}$, $\kappa_2 = (1-e)^{\frac{1}{\sigma_2}}$, $\varepsilon_2 = \frac{\sigma_2 - 1}{\sigma_2}$, $\gamma_1 = g^{\frac{1}{\sigma_3}}$, $\gamma_2 = (1-g)^{\frac{1}{\sigma_3}}$, and $\varepsilon_3 = \frac{\sigma_3 - 1}{\sigma_3}$.

Using the FOCs, we can derive the following equations:

$$ln\left(\frac{\theta_z}{\theta_l}\right) = ln\left(\frac{\gamma_1}{\gamma_2}\right) + \varepsilon_2 ln\left(\frac{k_z}{l_l}\right), \tag{26}$$

$$ln\left(\frac{\theta_k}{\theta_s}\right) = ln\left(\frac{\kappa_1}{\kappa_2}\right) + \varepsilon_3 ln\left(\frac{k_k}{l_s}\right), \tag{27}$$

and

$$ln\left(\frac{\theta_H}{\theta_V}\right) = ln\left(\frac{\iota_1}{\iota_2}\right) + \varepsilon_1 ln\left(\frac{H}{V}\right), \tag{28}$$

where θ_z, θ_k, θ_s, and θ_l are the income shares of Z, K, S, and L, respectively, and l_l, l_s, k_z, and k_k are the corresponding labor and capital variables normalized by aggregate labor or capital. Moreover, θ_h and θ_v are the inputs' shares in the top-tier CES function and H and V the outcomes from equations (24) and (25).

Given equations (26), (27), and (28), we implement the estimation in a few steps. First, we estimate equation (26) to obtain $ln\left(\frac{\gamma_1}{\gamma_2}\right)$ and ε_2. Second, using equation (27) we estimate $ln\left(\frac{\kappa_1}{\kappa_2}\right)$ and ε_3. Finally, the two inputs V and H are used in equation (28) to extract $ln\left(\frac{\iota_1}{\iota_2}\right)$ and ε_1. These estimates are all by OLS and from these we calculate the elasticities of substitution, i.e., "σ_i" for $i = 1,2,3$, and their confidence bands. Note that this strategy targets the trends in the relative income shares of capital and labor.[30] To retrieve the elasticities of substitution (EOS) we are interested in, we use the facts

$$EOS(L,Z) = \sigma_2 = \frac{1}{1-\varepsilon_2}, \tag{29}$$

$$EOS(S,K) = \sigma_3 = \frac{1}{1-\varepsilon_3}, \tag{30}$$

and

$$EOS(H,V) = \sigma_1 = \frac{1}{1-\varepsilon_1}. \tag{31}$$

[30]The series on the left-hand side (LHS) and right-hand side (RHS) of each nesting are shown in the Online Appendix II. We treat the results of the estimations as stylized facts or parameters' estimates. Some of these series failed cointegration tests, as looking at the (augmented) Dickey-Fuller t test, we cannot reject non-stationarity in the residuals, e.g., in the variable related to the first nesting $V(L,Z)$ and for the top tier.

The estimates for our baseline production function are presented in Tables 2 and 3.[31] The latter also shows the so-called Hicks-EOS, based on the equation in Sato (1967), which is calculated holding other inputs and output constant and is a harmonic mean of the relevant elasticities, with weights given by combinations of factor shares.[32] Hence, it always lies between the lowest and highest values of the relevant elasticities.

Our estimate of σ_2, the the EOS between ICT capital/“robots” (Z) and low-skill/routine labor (L), is 2.54, which suggests high substitution between these factors of production. Interestingly, this elasticity has increased over time, as shown in Figure 3. By construction ICT capital seems to be mostly directed to substitute routine/low-skilled workers, compared to non-routine workers. This measure aims to capture a broader definition of “robots” (which includes waves of AI), as pointed out in the introduction, rather than specifically very last generation of automation such as LLMs, which may impact labor categories in different ways and become more relevant, in general, in the future.

The EOS between non-ICT capital (K) and non-routine/high-skill labor (S), σ_3, is the smallest in the baseline and corresponds to 0.32. Looking at the Hicks-EOS, this low substitutability is also present between ICT/“robot" capital (Z) and non-routine/high-skill labor (S), with a corresponding elasticity of 0.52. However, all together, these estimates suggest that non-routine/high-skill labor (S) is less substitutable than routine/low-skill labor (L) with respect to ICT capital/“robot" (Z). In addition, our results reveal that non-ICT capital (K) is not a close substitute to routine/low-skill labor (L), since the EOS is 0.39. Last, for the baseline production function, we are also able to estimate the EOS between $H(S,K)$ and $V(L,Z)$, obtaining that σ_1 =0.36.

Alternative Production Functions

Any choice of nested production function makes implicit assumptions about the relationship between the various elasticities of substation. Our preferred specification assumes that the elasticity of substitution between S and L (or Z) is similar to that between K and L. In order to confront this and other such implicit assumptions with the data, we also estimate alternative production functions (see Online Appendix II for details). Alternative A is the production function of Eden and Gaggl (2018),[33]

$$F\{K,G[L,W(S,Z)]\} \tag{32}$$

[31]The standard errors are as in Eden and Gaggl (2018). However if we use robust standard errors or bootstrapped standard errors, to limit possible heteroskedasticity and small sample bias, the results are very similar. The Online Appendix II provides more details as well as the Cobb-Douglas case instead of CES in the top tier nesting.

[32]see Footnote 20 for more details

[33]Where the outer nest is Cobb-Douglas and we equate K_s (structures) with K and K_e (equipment) with Z. This specification is similar to the one in Krusell and others (2000a).

Alternative A forces the elasticity of substitution between L and S to be similar to that between L and Z, which may be counterfactual. We thus test also alternative B:

$$F\{K, J[S, V(L, Z)]\}. \tag{33}$$

The main takeaway of this exercise is that our baseline production function in equation (22) is the most plausible specification. The salient empirical drawback of the alternatives A and B is that the EOS between K and the function $G(\bullet)$ or $J(\bullet)$ are smaller than zero (around -0.13). This leaves some of the Hicks-EOS undefined for these specifications. To give these specifications some chance, we instead arbitrarily assume Cobb-Douglas for the outer nesting to see what the data say about the rest of the elasticities.

Regarding some of the key elasticities of substitution, we find that our estimate for σ_2, the the EOS between ICT capital/“robots" (Z) and routine/low-skill labor (L), is above 2 across specifications. On the other hand, the EOS between non-ICT capital (K) and non-routine/high-skill labor (S), σ_3, is smaller in the baseline specification (0.32) compared to the estimate of alternative B. Similarly, the EOS between ICT capital/“robots" (Z) and non-routine/high-skill labor (S) is (much) lower, under the baseline specification, than the estimates under the other two alternatives.

Overall, the estimation exercise helps us impose some discipline for the calibration of the elasticities of substitution. Our model-based analysis will use reasonable ranges of values for these elasticities that are in line with our estimates, as we will show next in the policy experiments.

V. Policy Experiments

We now examine what happens in our model economy when corporate taxes are cut and government spending on infrastructure and education are increased, all financed by reductions in transfers to the skilled worker/capitalist. We present a mix of analytical and numerical results for all three policies, comparing the results for our “robot” economy to traditional formulations with only one type of capital. The analytical results presume small (i.e., differential) changes, but prove an accurate guide to the numerical results for large changes.

A. Corporate Tax Cuts (CTC)

We examine the effects of a corporate tax cut ($dx < 0$), with transfers T_t adjusting continuously according to (16).

The Long-Run Outcome: Analytical Results

Across steady states,

$$r = \frac{\rho}{1-x} + \delta$$

and

$$\hat{r} = \mathfrak{n}\frac{dx}{1-x}, \tag{34}$$

where

$$\mathfrak{n} \equiv \frac{\rho}{\rho + \delta(1-x)} < 1,$$

$\rho = \left(\frac{1-\beta}{\beta}\right)$, and a circumflex over a variable indicates a logarithmic differential ($\hat{r} = \frac{dr}{r}$). After making use of (34), equations (2) - (3) and (5) can be solved for K, Z, Q, w_l, and w_s as a function of x. Straightforward algebra yields

$$\hat{w}_l = \frac{(\sigma_2 - \sigma_1)\alpha_z\theta_s + (\sigma_1 - \sigma_3)\chi_k\theta_s - \mathfrak{p}(\theta_k + \theta_z)}{\theta_s\mathfrak{m}}\left(\mathfrak{n}\frac{dx}{1-x}\right), \tag{35}$$

$$\hat{w}_s = -\frac{(\sigma_2 - \sigma_1)\alpha_z(1-\theta_s) + (\sigma_1 - \sigma_3)\chi_k\theta_l + \sigma_1(\theta_k + \theta_z)}{\theta_s\mathfrak{m}}\left(\mathfrak{n}\frac{dx}{1-x}\right), \tag{36}$$

$$\hat{K} = -\frac{\sigma_3\mathfrak{q}}{\theta_s\mathfrak{m}}\left(\mathfrak{n}\frac{dx}{1-x}\right) > 0, \tag{37}$$

$$\hat{Z} = \hat{K} - \frac{(\sigma_2 - \sigma_1)\alpha_l\mathfrak{m} + (\sigma_1 - \sigma_3)\chi_s\mathfrak{q}}{\theta_s\mathfrak{m}}\left(\mathfrak{n}\frac{dx}{1-x}\right) = -\frac{\sigma_2\mathfrak{p}}{\theta_s\mathfrak{m}}\left(\mathfrak{n}\frac{dx}{1-x}\right) > 0, \tag{38}$$

and

$$\hat{Q} \quad = \theta_k\hat{K} + \theta_z\hat{Z} = -\frac{\theta_k\sigma_3\mathfrak{q} + \theta_z\sigma_2\mathfrak{p}}{\theta_s\mathfrak{m}}\left(\mathfrak{n}\frac{dx}{1-x}\right) > 0, \tag{39}$$

where

$$\mathfrak{m} \equiv \mathfrak{q} + \mathfrak{p}\frac{\theta_l}{\theta_s}, \quad \mathfrak{p} \equiv \sigma_3\chi_k + \sigma_1\chi_s, \quad \text{and} \quad \mathfrak{q} \equiv \sigma_2\alpha_z + \sigma_1\alpha_l \tag{40}$$

are composite parameters, satisfying $\mathfrak{m} > 0$, $\mathfrak{p} > 0$, and $\mathfrak{q} > 0$; θ_j is the cost share of factor j evaluated at the initial steady state; χ_k and χ_s are the cost shares of K and S in the composite input H; and α_l and α_z are the cost shares of L and Z in the composite input V. These cost shares satisfy

$$\chi_k = \frac{\theta_k}{\theta_k + \theta_s}, \quad \chi_s = \frac{\theta_s}{\theta_k + \theta_s}, \quad \alpha_l = \frac{\theta_l}{\theta_l + \theta_z}, \quad \text{and} \quad \alpha_z = \frac{\theta_z}{\theta_l + \theta_z}.$$

To make sense of the solutions, consider first the outcome for a standard non-nested CES production function. When $\sigma_i = \sigma, \forall i$,

$$\hat{w}_l = \hat{w}_s = -\frac{\theta_k + \theta_z}{\theta_s + \theta_l}\left(\mathfrak{n}\frac{dx}{1-x}\right) > 0,$$

$$\hat{K} = \hat{Z} = -\frac{\sigma}{\theta_s + \theta_l}\left(\mathfrak{n}\frac{dx}{1-x}\right) > 0,$$
$$\hat{Q} = -\sigma\frac{\theta_k + \theta_z}{\theta_s + \theta_l}\left(\mathfrak{n}\frac{dx}{1-x}\right) > 0.$$

The solutions here agree with the claims made by proponents of business tax cuts. Capital deepening increases real wages of low- and high-skill workers by the same percentage amount, while the labor shares in GDP, $\hat{w}_l - \hat{Q}$ and $\hat{w}_s - \hat{Q}$, rise or fall depending on whether $\sigma \lesseqgtr 1$.[34]

But these results, and the empirical evidence cited in support of them, pertain to a world that is disappearing. Empirical estimates informed by post-2000 data argue that ongoing advances in automation and decades of skill-biased technological change have already transformed the U.S. economy into one where today $\sigma_2 >> \sigma_1$ and possibly $\sigma_1 > \sigma_3$. (See the discussion in the next section.) This radically alters the distributional effects of capital deepening. Easy substitution between "robots" and low-skill labor ($\sigma_2 >> \sigma_1$) combined with relatively limited substitution between traditional capital and high-skill labor (small σ_3) make the slope of the marginal product of Z schedule much flatter than the slope of the marginal product of K schedule. The response of "robot" investment to the tax cut is much more elastic therefore than the response of traditional investment: in (38), both $\sigma_2 > \sigma_1$ and $\sigma_1 > \sigma_3$ help push $\hat{Z}$ above $\hat{K}$. Moreover, increases in Z have sharply asymmetric effects on the demand for low- vs. high-skill labor. From (35) and (36), it is possible to deduce that

$$\hat{w}_s > 0 \quad \text{iff} \quad \underbrace{\sigma_1(\theta_k + \chi_k\theta_l) - \sigma_3\chi_k\theta_l}_{\text{Impact of K}\uparrow} + \underbrace{\alpha_z[\sigma_2(\theta_k + \theta_l + \theta_z) - \sigma_1\theta_k]}_{\text{Impact of Z}\uparrow} > 0 \tag{41}$$

and

$$\hat{w}_l > 0 \quad \text{iff} \quad \underbrace{\sigma_3\chi_k\frac{1-\theta_l}{\theta_s}}_{\text{Impact of K}\uparrow} - \underbrace{\alpha_z\left(\sigma_2 - \frac{\sigma_1}{\theta_k + \theta_s}\right)}_{\text{Impact of Z}\uparrow} > 0. \tag{42}$$

[34] Council of Economic Advisors (2017b) calculates expected long-run wage increases following a corporate tax cut based on the Cobb-Douglas assumption of constant labor shares. Hassett and Hubbard (2002) and Council of Economic Advisors (2017a) also argue that all skill levels are likely to benefit equally from the CTC.

Investment in traditional capital increases the demand for both types of labor, provided that $\sigma_1 > \frac{\sigma_3\chi_k\theta_l}{\theta_k+\chi_k\theta_l}$. By contrast, investment in "robots" strengthens the demand only for skilled labor as long as $\sigma_2 > \frac{\sigma_1\theta_k}{\theta_k+\theta_l+\theta_z}$. When $\theta_k = 0.36$ and $\theta_s = 0.40$, demand for low-skill labor decreases if

$$\sigma_2 > \frac{\sigma_1}{\theta_k+\theta_s} \approx 1.3\sigma_1.$$

This condition is virtually certain to hold. Econometric estimates of σ_1 cluster between 0.4 and 1, with our own being close to the lower bound. Less is known about σ_2, but all the evidence points to a number north of two, including our estimates.

"robot" capital has been reported to count for a maximum of 11 percent of the aggregate capital stock for the U.S. but the import of $\sigma_2 > 2$ and $\hat{Z} >> \hat{K}$ shows that they punch far above their weight. Consequently, it is quite possible that capital deepening will *reduce* the real wage paid to low-skill labor. And even if w_l increases, wage inequality is sure to worsen and the income share of low-skill labor to fall. The weighted average wage

$$\omega = \frac{L}{L+S}w_l + \frac{S}{L+S}w_s$$

rises by the same amount as in the case of a non-nested CES production function:

$$\hat{\omega} = \frac{\theta_s\hat{w}_s + \theta_l\hat{w}_l}{\theta_s+\theta_l} = -\frac{\theta_k+\theta_z}{\theta_s+\theta_l}\left(\mathfrak{n}\frac{dx}{1-x}\right). \tag{43}$$

But

$$\hat{w}_s > \hat{w}_l \quad \text{iff} \quad (\sigma_2-\sigma_1)\alpha_z > (\sigma_3-\sigma_1)\chi_k, \tag{44}$$

and the income share for low-skill labor, $\hat{w}_l - \hat{Q}$, declines when

$$(\sigma_2-\sigma_1)\alpha_z\theta_s + \mathfrak{p}\theta_z(\sigma_2-1) + \sigma_3\theta_k(\mathfrak{q}-1) > 0, \tag{45}$$

where, to repeat, $\mathfrak{p} \equiv \sigma_3\chi_k + \sigma_1\chi_s$ and $\mathfrak{q} \equiv \sigma_2\alpha_z + \sigma_1\alpha_l$.

Both conditions hold comfortably for believable parameter values, for an economy with $\sigma_2 >> \sigma_1$ and $\sigma_1 > \sigma_3$. The likelihood that corporate tax cuts will boost growth without exacerbating inequality is slim to none.

The Long-Run and Transition Outcomes: Numerical Results

Equations (7), (13), (14), and (20) comprise the core dynamic system. The system has two state variables, $K_{a,t-1}$ and B_{t-1}, and two jump variables, C_t and $I_{a,t}$. As usual, the stationary equilibrium is saddle-point stable. We solve for the global nonlinear saddle path using Dynare 4.5.7.[35]

Table 4 shows how the tax cut affects wages (w_l, w_s, and ω), capital accumulation (K and Z), and GDP (Q) in the long run. The qualitative results mirror the analytical results for small changes. With Cobb-Douglas technology (the canonical production functions), GDP and both wages increase 4 percent. The 4 percent figure for GDP is exactly equal to the gain that nine prominent economists claim "a conventional approach to economic modeling suggests" (Wall Street Journal, November 27, 2017).[36]

Adding this new form of capital for"robots" to "the conventional approach to economic modeling" brings a mix of good and bad news. The good news is the growth impact of CTC is increasing in the value of σ_2. In runs with $\sigma_1 = \sigma_3 = 1$ and $\sigma_2 = 3 - 5$, GDP increases another 1-1.7 percentage points. The bad news appears in the column for wages of low-skill workers w_l: as σ_2 rises to 1.5 and above, capitalists and high-skill, high-wage workers reap a disproportionate share of the gains at the expense of low-wage workers. The total labor share (θ) also declines with σ_2. In all cases the decline is accounted for by the decrease in the income share of low skill workers (θ_L).

Figure 4 depicts the transition path to the new steady state, in the "robot" economy ($\sigma_2 = 3$ and $\sigma_1 = \sigma_3 = 0.5$). The run has an optimistic bias in that highly elastic capital flows limit the rise in the interest rate to seven basis points. Nevertheless, the speed of adjustment is very slow. The increase in GDP is a paltry 1.1 percent at $t = 10$; even at $t = 20$, the gain is only 1.75 percent. Increases in real wages are also quite small, in particular for low-skill workers: 0.1 percent at $t = 10$ and 0.2 percent at $t = 20$. And since real wages for high-skill workers increase by 2.1 percent at $t = 10$ and 3.5 percent at $t = 20$, then the transition analysis reveals that the wage gap between low- and high-skill workers widens over time. Therefore, CTC increase wage inequality.

B. Investment in Infrastructure (II)

In this section we examine the impact of "robot" capital on investment in infrastructure and compare the results to those for the CTC. To have a proper apple-to-apple comparison with the CTC, we impose fiscal equivalence on the the two policy instruments. The cut in transfers that

[35] We find the full nonlinear solution to this system with perfect foresight, using the Newton-type method implemented in the Dynare. For details, see Juillard (1996)

[36] Council of Economic Advisors (2017b) predict a long-run increase in GDP and corresponding increases in average wages of 3 to 5 percent based on back-of-the-envelope calculations using the neoclassical model with Cobb-Douglas technology.

previously offset the loss in corporate tax revenue at $t=1$ now finances an increase in $I_{g,t}$, viz.:

$$dI_g = dT|_{t=1} = -(r-\delta)K_a dx|_{t=1},$$

which can be rewritten as

$$\hat{I}_g = -\frac{\theta_k+\theta_z}{\xi_g}\left(\mathfrak{n}\,dx|_{t=1}\right), \tag{46}$$

where $\theta_k+\theta_z = rK_a/Q$ and $\xi_g \equiv I_g/Q$.[37]

The Long-Run Outcome: Analytical Results

Across steady states, equations (2) - (3) and (5) give

$$\hat{\omega} = \frac{1}{\theta_s+\theta_l}\left(\eta\hat{G}\right) > 0, \tag{47}$$

$$\hat{w}_l = \frac{\mathfrak{p}}{\theta_s\mathfrak{m}}\left(\eta\hat{G}\right) > 0, \qquad \hat{w}_s = \frac{\mathfrak{q}}{\theta_s\mathfrak{m}}\left(\eta\hat{G}\right) > 0, \tag{48}$$

$$\hat{K} = \frac{\sigma_3\mathfrak{q}}{\theta_s\mathfrak{m}}\left(\eta\hat{G}\right) > 0, \qquad \hat{Z} = \frac{\sigma_2\mathfrak{p}}{\theta_s\mathfrak{m}}\left(\eta\hat{G}\right) > 0, \tag{49}$$

and

$$\hat{Q} = \left(\frac{\theta_k\sigma_3\mathfrak{q}+\theta_z\sigma_2\mathfrak{p}}{\theta_s\mathfrak{m}}+1\right)\left(\eta\hat{G}\right) > 0, \tag{50}$$

where recall that $\mathfrak{m} \equiv \mathfrak{q}+\mathfrak{p}\frac{\theta_l}{\theta_s}$, $\mathfrak{p} \equiv \sigma_3\chi_k+\sigma_1\chi_s$, and $\mathfrak{q} \equiv \sigma_2\alpha_z+\sigma_1\alpha_l$.

II always increases the average real wage and the real wages for low-and high-skill labor. Naturally, the size of the wage gains depends on the net return on infrastructure R_g. To link the solutions to R_g, note that

$$\frac{\partial Q}{\partial G} = R_g+\delta_g = \eta\frac{Q}{G} = \eta\frac{\delta_g}{\xi_g},$$

and, using (46), that

$$\eta\hat{G} = -(\theta_k+\theta_z)\frac{R_g+\delta_g}{\delta_g}\left(\mathfrak{n}dx\right), \tag{51}$$

as $\hat{G}=\hat{I}_g$ in the long run. After substituting for $\eta\hat{G}$, the solutions in (47) - (50) can be directly compared to their counterparts in (35) - (39) and (43). Straightforward algebra yields

[37] The fiscal equivalence at $t=1$ does not hold subsequently, as the tax base evolves endogenously across experiments. It turns out that output rises more with II than CTC, so the required reduction in transfers is smaller as a share of GDP after $t=1$ with infrastructure investments, as we will see. In a more general model with costly financing, this would only magnify the differences observed in the current setup.

$$\hat{\omega}|_{\text{II}} > \hat{\omega}|_{\text{CTC}} \quad \text{iff} \quad R_g > R_g^{\diamond} = \left(\frac{x}{1-x}\right)\delta_g, \tag{52}$$

$$\hat{w}_l|_{\text{II}} > \hat{w}_l|_{\text{CTC}} \quad \text{iff} \quad R_g > R_g^{+} = \left\{1 - \frac{\theta_s\left[(\sigma_2-\sigma_1)\alpha_z - (\sigma_3-\sigma_1)\chi_k\right]}{\mathfrak{p}x\left(\theta_k+\theta_z\right)}\right\}\left(\frac{x}{1-x}\right)\delta_g, \tag{53}$$

$$\hat{w}_s|_{\text{II}} > \hat{w}_s|_{\text{CTC}} \quad \text{iff} \quad R_g > R_g^{\#} = \left[1 + \frac{\theta_l}{x\left(\theta_k+\theta_z\right)}\left(1 - \frac{\mathfrak{p}}{\mathfrak{q}}\right)\right]\left(\frac{x}{1-x}\right)\delta_g, \tag{54}$$

$$\left(\hat{w}_s - \hat{w}_l\right)|_{\text{II}} > \left(\hat{w}_s - \hat{w}_l\right)|_{\text{CTC}} \quad \text{iff} \quad R_g > R_g^{*} = \left[\frac{1}{(1-x)(\theta_k+\theta_z)} - 1\right]\delta_g. \tag{55}$$

The comparisons in (52)-(55) provide three important takeaways:

- *Labor across the skill spectrum benefits more from II than from CTC.* A small positive return on the order of 3 percent satisfies the condition in (52) when $x = 0.40$ and $\delta_g = 0.04$. Assuming $(\sigma_2 - \sigma_1)\alpha_z > (\sigma_3 - \sigma_1)\chi_k$, the condition in (52) also suffices for II to increase the low-skill wage more than the CTC. The condition in (54) is more involved. On inspection, however, it is also satisfied by a low R_g. For a depreciation rate of 4 percent ($\delta_g = 0.04$) and the values of the cost shares, the tax rate ($x_{old} = 0.40$), and the *ranges* of the elasticities of substitution—satisfying $\sigma_2 > \sigma_1$, and $\sigma_1 \geq \sigma_3$—provided in Table 1, the maximum value of threshold for the return on infrastructure $R_g^{\#}$ is 5 percent.

- *Although labor gains more from an increase in II than from the comparable CTC, wage inequality is still likely to worsen—more so for larger values of* σ_2. The CTC increases the after-tax return on traditional capital and "robot" capital by the same amount. So also does an increase in the stock of infrastructure. Unlike the CTC, however, II directly and symmetrically increases the productivity of low- and high-skill labor. Hence the asymmetric effect of capital deepening on the productivity of low- vs. high-skill labor determines the impact on the skill premium. As with the CTC,

$$\hat{w}_s > \hat{w}_l \quad \text{iff} \quad (\sigma_2 - \sigma_1)\alpha_z > (\sigma_3 - \sigma_1)\chi_k.$$

- *For high rates of return, II increases wage inequality more than the CTC.* The condition in (55) is a close call in the case of the U.S. For $\theta_k + \theta_z = 0.40$, $x = 0.040$, and $\delta_g = 0.04$ (the values in Table 1), the threshold return R_g^{*} is 12.7 percent. This is nearly three percentage points above the pre-tax return on private capital—a high bar to clear. But if the estimates in the literature can be trusted, returns this high are not unusual (See calibration of R_g in Section III.)

Compare next the stimulus to private investment. The CTC would seem to enjoy an advantage here because it directly targets the return on private capital. There are countervailing factors at work, however. Owners of capital usually consume some of the tax cut, whereas the government invests every dollar of revenue saved by reducing transfers. Furthermore, as noted earlier, most empirical estimates find that the return on infrastructure—which determines the impact on the productivity of private capital—is considerably higher than the pre-tax return on private capital (Bom and Ligthart, 2014). Together these two effects are quantitatively significant. Comparing the solutions in (37), (38) and (49) brings back the condition in (55)

$$\hat{K}\big|_{\text{II}} > \hat{K}\big|_{\text{CTC}} \quad \text{and} \quad \hat{Z}\big|_{\text{II}} > \hat{Z}\big|_{\text{CTC}} \quad \text{iff} \quad R_g > R_g^* = \left[\frac{1}{(1-x)(\theta_k+\theta_z)} - 1\right]\delta_g.$$

In view of the empirical evidence that R_g often exceeds R_g^*, the presumption that CTCs are more effective than II in promoting private investment, if it exists at all, is very weak.

Finally, it is a small step from the results in hand to the conclusion that II increases GDP more than CTC. From (39) and (50),

$$\hat{Q}\big|_{\text{II}} > \hat{Q}\big|_{\text{CTC}} \quad \text{iff} \quad R_g > R_g^{\&} = \left[\frac{\sigma_3\theta_k\mathfrak{q} + \sigma_2\theta_z\mathfrak{p}}{\mathfrak{u}(1-x)(\theta_k+\theta_z)} - 1\right]\delta_g, \tag{56}$$

where $\mathfrak{u} \equiv \mathfrak{q}(\sigma_3\theta_k + \theta_s) + \mathfrak{p}(\sigma_2\theta_z + \theta_l)$, $\mathfrak{p} \equiv \sigma_3\chi_k + \sigma_1\chi_s$, and $\mathfrak{q} \equiv \sigma_2\alpha_z + \sigma_1\alpha_l$.

For believable parameter values, the threshold $R_g^{\&}$ in (56) is relatively small. To illustrate, consider the calibration in Table 1, once more, including the *ranges* of the elasticities of substitution—satisfying $\sigma_2 > \sigma_1$, and $\sigma_1 \geq \sigma_3$—and the initial tax rate ($x_{old} = 0.40$). For a depreciation rate of 4 percent ($\delta_g = 0.04$), the maximum value for $R_g^{\&}$ is 4 percent, while the minimum value is negative. II is better at increasing growth than CTC as long as infrastructure capital pays a small positive return.

The Long-Run and Transition Outcomes: Numerical Results

Tables 5 and 6 collect numerical results for the long run. The fiscally-equivalent increase in II equals 1.5 percent of initial GDP and the set of runs is the same is the same as for the CTC. In Table 5, infrastructure pays a return of 10 percent, the same as the pre-tax return on private capital. The return in Table 6 is 15 percent, at the low end of the returns for core capital in Bom and Ligthart (2014).

As with CTC, in the case of an increase in II, high-skill labor wages (w_s), capital stocks (K and Z), and GDP (Q) grow more, and low-skill labor wages (w_l) less, in the "robot" economy compared to the Cobb-Douglas case (Tables 5 and 6). Again as with CTC, for the "robot" production functions, low values of σ_1 and σ_3 cause the fixed supply of skilled labor to bite sooner. This raises high-skill labor wages more, but chokes off the increase in traditional and hence total capital and thus GDP growth, and depresses the growth of low-skill labor wages even more.

In a Cobb-Douglas economy and a fortiori in the “robot” economy, then, II dominates CTC, as we knew from the analytical results. The new information in Tables 5 and 6 concerns *how much* bigger the numbers are compared to those for the CTC in Table 4. When R_g equals 15 percent (Table 6), the difference is of course even starker. The CTC wins only one unimportant contest. Recall that II increases the private capital stock more or less than the CTC depending on whether R_g is above or below R_g^* in (V.B). For the current calibration of the model, based on U.S. data, $R_g^* = 12.7$ percent. This is halfway between the values of R_g postulated in Tables 5 and 6, so the increases in the capital stock in Table 4 are bigger than in Table 5 but smaller than in Table 6.

“Robot" capital amplifies the greater wage inequality-inducing effects of CTC relative to II (Table 7). As σ_2 increases, high-skill labor wages increasingly outpace low-skill labor wages, and output increasingly outpaces total wages, for both CTC and II, and the difference in percentage points is about the same for the same value of σ_2. However, the much higher levels of low-skill wage and output growth with II vs CTC, at all values of σ_2, make the differences much more important in CTC than II. For example, when $\sigma_2 = 5$, low-skill wages grow by only 0.7 percentage points with CTC and 7.0 percentage points with II (and $R_g = 0.15$), whereas the corresponding values in the Cobb-Douglas economy ($\sigma_i = 1, \forall i$) are 10.6 and 4.0 percentage points.[38] The evolution of the labor share θ is as with CTC: the higher is σ_2, the greater the fall in the labor share, again accounted for by the share of low-skilled labor θ_L.[39]

Figure 5 compares impulse responses for II and the CTC. The comparison strongly favors II, but there are surprises, both quantitative and qualitative, stemming from the large gaps between the red dotted and blue bold lines in the paths for K and Z. The CTC stimulates private investment from the outset. II, however, exerts conflicting effects in the short/medium run. Growth in the stock of infrastructure increases future income of capitalists and high-skill labor. This creates an incentive for owners of capital to smooth the path of consumption by temporarily reducing investment. On the other hand, the positive impact of infrastructure on the productivity of capital and the desire to minimize adjustment costs encourage an immediate increase in investment. Aided by large capital inflows, the positive pull of the long-run fundamentals dominates the consumption-smoothing motive in Figure 5. But while K and Z increase continuously, they increase very slowly compared to the paths for the CTC. Across steady states, the increase in the private capital stock $(K+Z)$ equals 75 percent of the increase induced by the CTC. The gaps on the transition path are much smaller for a long time. The slow pace of private capital accumulation, in turn, slows growth of GDP, national income (NI), and the high-skill labor wage. At the 20-year horizon, the gains in GDP and NI are only 57 percent and 46 percent higher than on the path for the CTC. And in the case of the high-skill labor wage, it takes twenty-seven years for the gap to become positive.

[38] These results are for $\sigma_1 = \sigma_3 = 1$.

[39] In the CES case, the income share of skilled labor rises, but the unskilled share falls by even more, so the total share still declines.

The elasticity of the interest rate to capital flows μ plays a critical role in the transition analysis. New capital inflows reach 11 percent of GDP and prevent the interest rate from rising more than twenty basis points. With less elastic capital flows, growth of the private capital stock is slower and the large positive effects of II on wages and real output take even longer to materialize. When $\mu = 0.60$, K and Z do not increase until year ten and another eight years elapse before w_s rises above the path associated with the CTC.

C. Investment in Education (IE)

As in the preceding two sections, we first derive analytical results for the long run.

The Long-Run Outcome: Analytical Results

Solve the steady-state versions of equations (2) - (3) and (5) yet again, this time with S varying exogenously. Naturally, w_l rises and w_s falls

$$\hat{w}_l = \frac{\theta_l + \theta_s \psi}{\theta_l \mathfrak{m}} \left(\hat{S}\right) > 0 \quad \text{and} \quad \hat{w}_s = -\frac{\theta_l + \theta_s \psi}{\theta_s \mathfrak{m}} \left(\hat{S}\right) < 0, \tag{57}$$

where $\psi = \frac{w_l}{w_s} < 1$ and, to repeat, $\mathfrak{m} \equiv \mathfrak{q} + \mathfrak{p}\frac{\theta_l}{\theta_s} > 0$, $\mathfrak{p} \equiv \sigma_3 \chi_k + \sigma_1 \chi_s > 0$, and $\mathfrak{q} \equiv \sigma_2 \alpha_z + \sigma_1 \alpha_l > 0$. The changes in w_l and w_s cancel out in the solution for the weighted-average wage, leaving only the effect of a higher employment share for skilled workers:[40]

$$\hat{\omega} = \underbrace{\frac{\theta_s}{\theta_s + \theta_l}\hat{w}_s + \frac{\theta_l}{\theta_s + \theta_l}\hat{w}_l}_{=0} + \frac{\theta_s}{\theta_s + \theta_l}(1 - \psi)\hat{S} = \frac{\theta_s}{\theta_s + \theta_l}(1 - \psi)\hat{S}.$$

The solutions for the capital stocks and GDP are

$$\hat{K} = \frac{\sigma_1 (\theta_l \chi_s + \theta_s) + (\sigma_2 - \sigma_1)\theta_s \alpha_z - \sigma_3 (\theta_l \chi_s + \theta_s \psi)}{\theta_s \mathfrak{m}} \left(\hat{S}\right), \tag{58}$$

$$\hat{Z} = \frac{\sigma_2 \theta_l + (\sigma_2 - \sigma_1)\psi \alpha_l \theta_s - \psi \theta_l \mathfrak{p}}{\theta_l \mathfrak{m}} \left(\hat{S}\right), \tag{59}$$

$$\hat{Q} = \frac{\mathfrak{q} - \psi \mathfrak{p}}{\mathfrak{m}} \left(\hat{S}\right). \tag{60}$$

We follow the same game plan as in the analysis of II. That is, we re-express the solutions in (57) - (60) in terms of fiscally-equivalent increases in investing in education (IE) and com-

[40] The zero-profit condition gives $\theta_s \hat{w}_s + \theta_l \hat{w}_l = 0$.

pare them with the CTC solutions in (35) - (39), underscoring the role of the rate of return to investment in education R_s. This yields (see Appendix):

$$\hat{\omega}\big|_{\text{IE}} > \hat{\omega}\big|_{\text{CTC}} \quad \text{iff} \quad R_s > R_s^{\diamond} = \left(\frac{x}{1-x}\right)\delta_s, \tag{61}$$

$$\hat{w}_l\big|_{\text{IE}} > \hat{w}_l\big|_{\text{CTC}} \quad \text{if} \quad (i)\ (\sigma_2-\sigma_1)\alpha_z > (\sigma_3-\sigma_1)\chi_k \ \text{and}\ (ii)\ R_s > R_s^{+} = \left[\frac{\theta_l \mathfrak{p}(1-\psi)}{(1-x)(\theta_l+\theta_s\psi)} - 1\right]\delta_s, \tag{62}$$

for real wages and

$$\hat{K}\big|_{\text{IE}} > \hat{K}\big|_{\text{CTC}} \quad \text{if} \quad (i)\ \sigma_1 \geq \sigma_3 \ \text{and}\ (ii)\ R_s > R_s^{*} = \left[\frac{\sigma_3}{(1-x)(\theta_k+\theta_z)} - 1\right]\delta_s, \tag{63}$$

$$\hat{Z}\big|_{\text{IE}} > \hat{Z}\big|_{\text{CTC}} \quad \text{if} \quad (i)\ \sigma_2 > \sigma_1\left[1+\frac{\theta_l+\theta_z}{\theta_s}\left(\frac{\mathfrak{p}}{\sigma_1}\right)\right] \ \text{and}\ (ii)\ R_s > R_s^{'} = \left[\frac{\mathfrak{p}(1-\psi)}{(1-x)(\theta_k+\theta_z)} - 1\right]\delta_s, \tag{64}$$

$$\hat{Q}\big|_{\text{IE}} > \hat{Q}\big|_{\text{CTC}} \quad \text{iff} \quad R_s > R_s^{\&} = \left[\frac{(\theta_k\sigma_3\mathfrak{q}+\theta_z\sigma_2\mathfrak{p})(1-\psi)}{(1-x)\,(\mathfrak{q}-\psi\mathfrak{p})\,(\theta_k+\theta_z)} - 1\right]\delta_s, \tag{65}$$

for capital stocks and real output.

Each of the conditions in (61), (62), and (65) are weak for empirically plausible values of σ_1, σ_2, σ_3, and the factor cost shares. For the calibration values in Table 1, the conditions in (61) and (62) are satisfied by R_s >2 percent, while the range of maximum threshold values for R_s^* and $R_s^{\&}$ are 3.2-9.5 percent and 0-1.8 percent, respectively.[41] We may safely conclude that IE increases the low-skill wage, the average wage, and GDP more than CTC. The impact on the non-robot capital stock is less clear as R_s^* in (63) is sensitive to the value of σ_3. When $\sigma_3 = 0.5$, traditional capital is virtually certain to increase more than with CTC ($R_s^* = 3.2$ percent). For $\sigma_3 = 1$, it is a close call; in the numerical results presented shortly, IE wins by a small margin.

Turning to the condition in (64), there is a strong presumption, bordering on certainty, that IE increases "robot" capital more than the comparable CTC. For the discussed calibration, the threshold return $R_s^{'}$ in condition (ii) is only 1.8-3.2 percent. Condition (i) requires $\sigma_2 = 1.6\sigma_1$ when $\sigma_1 = \sigma_3$ and θ_l, θ_z, and θ_s take their base case values. This barely fails when $\sigma_1 = \sigma_3 = 1$ and $\sigma_2 = 1.5$. In all of the other runs in Table 1, it holds comfortably.

Substitutable "robot" capital increases the advantages of IE over CTC. First, it makes it even more likely that growth in low-skill wages and "robot" capital is higher under IE than CTC. We can see this from the observation that the higher σ_2, the less stringent are the conditions (i) in (62) and (64), for $\hat{w}_l|_{\text{IE}} > \hat{w}_l|_{\text{CTC}}$ and for $\hat{Z}\big|_{\text{IE}} > \hat{Z}\big|_{\text{CTC}}$—conditions (ii) are not affected, since R_s^+, and $R_s^{'}$ do not depend on σ_2. The high-skill labor wage ($\hat{w}_s$), on the other hand, will fall more as σ_2 rises, as can be deduced from (57). Regarding the average wage ($\hat{\omega}$) and traditional

[41] In the calculation of the threshold returns R_s^+, $R_s^{'}$, and $R_s^{\&}$, we did not consider the combination $\sigma_2 = 1.5$ and $\sigma_1 = \sigma_3 = 0.5$, because it implies $w_s < w_l$ across steady states for IE.

capital ($\hat{K}$), the relative ranking is not affected by a higher σ_2, since the conditions in (61) and (63) are invariant to this elasticity—$R_s^{\diamond}$ and R_s^{*} do not depend on σ_2.

The effect of “robots"—increasing σ_2—on the ranking condition for GDP in (65) is less clear. But it is possible to prove that

$$\frac{\partial R_s^{\diamond}}{\partial \sigma_2} < 0 \quad \text{iff} \quad \sigma_3 > \left[\frac{\theta_l(\theta_k+\theta_s) - \psi\theta_s(\theta_l+\theta_z)}{\psi\theta_k}\right]\sigma_1, \tag{66}$$

which is likely to hold for plausible parameter values. For instance, for the parameter values of the cost shares and the inverse of the skill premium reflected in Table 1, the necessary and sufficient condition in (66) reduces to $\sigma_3 > 0.49\sigma_1$, which is satisfied for the parametrizations of the elasticities of substitution from that Table, as long as $\sigma_3 < \sigma_1$. Thus, “robots" makes it more likely that IE will increase growth more than CTC.

Both IE and CTC promote capital deepening. However, IE specifically promotes “robot” capital, all the more so as substitutability with unskilled labor rises, as the reduction in the supply of unskilled labor stimulates the accumulation of “robot” capital. At the same time, overall wages and growth benefit from highly substitutable “robot” capital with IE, because the larger supply of skilled labor alleviates the key constraint to overall capital accumulation and growth.

The Long-Run and Transition Outcomes: Numerical Results

Table 8 reports results for the long-run impact of an increase in IE equal to 1.5 percent of initial GDP (fiscally-equivalent to the change in transfers associated with the CTC). What immediately catches the eye are the huge numbers in the columns for w_l, GDP, and Z. The low-skill labor wage w_l increases most when σ_2 is low. Although, as we learned from the analytical results, these increases of w_l are always bigger than the increases in the high-skill labor wage w_s—which in fact always declines—across the σ_2 spectrum. For the other variables, though, the advantage derives mainly from the interaction of IE with higher values of σ_2—indeed traditional capital K grows less under IE than CTC in a Cobb-Douglas economy, while the advantage for output is relatively modest.

One word, scarcity, explains the out-sized increases in the low-skill labor wage. The supply of low-skill labor decreases 25 percent in the long run. The supplies of high-skill labor and traditional capital, complementary inputs that enhance the productivity of low-skill labor, increase 25 percent and 7 - 21 percent, respectively. Thus the supply curve shifts far to the left and the demand curve far to the right in the market for low-skill labor. To eliminate the large ex-ante increase in excess demand, the low-skill labor wage rises 24 - 47 percent (Table 8).

Easy substitution between “robot” capital and low-skill labor explains the other eye-catching numbers, as foreshadowed in the analytical results. IE stimulates investment in traditional capital by increasing the supply of skill labor. Less obviously, it also *strongly* stimulates investment in “robots". This reflects two important implications of robots and labor being strong gross substitutes in production, as we explain next.

First, the productivity of “robots" increases sharply when the supply of low-skill labor contracts. Second, the marginal product of “robots" a much greater incentive to invest in “robots" than in traditional capital. The big upward shift in the flat MPZ schedule excites a prolonged investment boom that increases the supply of “robot” capital by 69 - 196 percent when σ_2 increases from 3 to 5 (Table 8). Moreover, potent knock-on effects magnify the sizable direct contribution to GDP. The stupendous increase in the supply of “robots" sustains investment in traditional capital by minimizing the decrease in low-skill labor services. As a result, the numbers for K and $K+Z$ are much greater in Table 8 than in Tables 4, 5, and 6, even though the return on IE is only 7 percent vs. 10 percent (pre-tax) for private capital and 10 - 15 percent for II. The disparity in the impact on total investment is so great that IE often delivers gains in GDP 3-8 percentage points larger than those from II, which pays a return of 15 percent: outside of the the run for $\sigma_1 = \sigma_3 = 1$, the average increase in GDP in Table 8 is 14.5 percent vs. 9.3 percent in Table 6.

The impact of IE on the labor share contrasts with the other policies. In the non-robot economy, IE leaves the total labor share constant (of course—the economy is Cobb-Douglas). But IE dramatically increases the share going to unskilled labor, including that accruing to those unskilled workers who become skilled through education. As σ_2 increases above 1, the total and unskilled labor shares falls, as with the other policies but more so. Even when $\sigma_2 = 5$, however, the overall effect is that IE increases the unskilled labor share by at least four percentage points (from 20 percent to 24-24.4 percent).[42]

Figure 6 presents the transition dynamics for IE and CTC for σ_2 = 3, $\sigma_1 = \sigma_3 = 0.5$, and $R_s = 0.07$. The most striking result is that the long-run advantage we saw for IE with respect to the accumulation of traditional capital does not emerge for several decades. The initial direct impulse from the CTC eventually runs into a scarcity of skilled labor, but this takes a long time. Output is nonetheless higher from the beginning, and increasingly so, with IE, due to the more rapid growth in “robots" and human capital.

In sum, then, increased spending on education raises low-skill labor wages, GDP, and capital stocks much more than fiscally-equivalent cuts in corporate profits taxes or increases in public infrastructure investment in the “robot” economy. At the same time, by increasing the supply of skilled labor it reduces the skill premium and high-skill wages.

The strong results on the effectiveness of education spending comes with a caveat. In calibrating the parameter ϕ that governs the translation of education spending to the quantity of skilled labor, we used estimates of the rate of return to education spending from an empirical litera-

[42]When calculating the average increase in Table 6, we exclude the runs where NA appears in Table 8.

ture based on historical data. This assumes going forward that education produces skills that complement "robots" at historical rates. But sustaining the historical level of "targeting" may be hard to realize as technology continues to evolve. Frey (2019) argues that new technologies are likely to complement and not replace most skilled workers as conventionally defined. On the other hand, Brynjolfsson and Mitchell (2017) argue that effects of new AI technologies are more complex and not easy to characterize in terms of their relation to levels of education. Perhaps along these lines, Beaudry, Green, and Sand (2013) suggest that technological progress began to drive a falling skilled wage premium after 2000.[43]

VI. Social Welfare

The pre-tax return on private capital and the returns on II and IE all exceed the private time preference rate. Consequently, the initial equilibrium is sub-optimal: there is too much spending on consumption relative to investment, both public and private. The degree of under-investment increases further if, in addition, the social time preference rate (social discount factor) is lower (higher) than the private time preference rate (private discount factor).

For now, we put distributional considerations to one side. The social welfare function is simply

$$SW = \sum_{t=0}^{\infty} \beta_{sp}^{t} \frac{{c_t}^{1-1/\tau}}{1-1/\tau}, \tag{67}$$

where β_{sp} is the social discount factor and $c \equiv C + w_t L_t$ is aggregate consumption.

In very general terms, β_{sp} should take the value a benevolent social planner would choose, acting on behalf of society writ large. This requires a judgment specifically about whether the private discount factor is too low.

The position of policy makers is clear. In both developed and less developed countries, the social discount factor used to calculate the cost-benefit ratio for public sector projects is usually much higher than the private discount factor. HM Treasury (2003) recommends, for example, $\beta_{sp} = 0.965$ - 0.98.

Although theory cannot tell us whether 0.97 is a sensible number for β_{sp}, it does provide cogent arguments for $\beta_{sp} > \beta$. In Sen (1967)'s isolation paradox, private saving is suboptimal because individuals would be willing to enter into a social contract that required everyone to save more. Feldstein (1964) and Baumol (1965) reach the same conclusion more quickly by appealing to the notion that economic development is partly a public good; if the premise is granted,

[43]To repeat, we assume in calibrating the model that the marginal value of ϕ equals its average value in the data. An alternative, more flexible specification would allow ϕ to vary with Z.

then the social time preference rate "must be adminstratively determined as a matter of public policy [because] the market cannot express the 'collective' demand for investment to benefit the future" (Feldstein (1964), pp. 362, 365).

A. The Benchmark Case ($\sigma_2 = 3$)

The welfare rankings depend on the social discount factor and all three elasticities of substitution. To organize the analysis, we first present in Figure 7 results for $\sigma_2 = 3$, our best educated guess for the true value of σ_2. We do not take a position on the right values for other parameters. As noted earlier, econometric estimates have yet to decide whether substitution between traditional capital and labor services is best described by Cobb-Douglas technology or a CES function with low elasticities of substitution. Accordingly, we carry out runs for both $\sigma_1 = \sigma_3 = 1$ and $\sigma_1 = \sigma_3 = 0.5$. The value for the other key parameters, β_{sp}, is in the eye of the policy beholder. In the figure, the lowest value of the social discount factor equals the private discount factor (0.943), while the higher values correspond to those favored in the project evaluation literature (0.97 - 0.99). The CTC reduces revenue by one percent of GDP at $t = 0$.[44]

Some of the pairwise welfare rankings in Figure 7 depend on the coordinates of the run. One ranking, however, is completely robust: II *always* dominates the CTC. This result is baked in. The direct return on infrastructure is the same as for private capital. But while the private sector consumes part of the tax cut, the government invests every dollar. Moreover, crowding-in of private capital is 75 percent as large as with the CTC. Ipso facto, II is more effective than the CTC in reducing underinvestment. The result that the red line is always above the blue line is not specific to the calibration of the model and was fully predictable from inspection of Tables 4 and 5.

The ranking of IE is less robust. In a partial equilibrium analysis, IE would finish dead last because its direct return is three percentage points lower than the returns on private capital and infrastructure. In the general equilibrium analysis undertaken here, IE's much bigger positive impact on the aggregate capital stock can and often does reverse the partial equilibrium welfare ranking. The general equilibrium welfare gains take time to materialize and are much larger when the elasticity of substitution between traditional capital and labor services is low. IE scores best therefore when σ_1 and σ_3 are small and β_{sp} is large. For $\sigma_1 = \sigma_3 = 1$, the welfare gain produced by IE is smaller than the gain for II and does not overtake the gain for the CTC until $\beta_{sp} = 0.97$. But when $\sigma_1 = \sigma_3 = 0.5$, IE dominates the CTC everywhere except at $\beta_{sp} = \beta$ (where it ties) and beats II once $\beta_{sp} > 0.957$ — a value judged to be too low in the project evaluation literature.

[44]Postulating a smaller tax cut than in Section V allows us to compare results for IE with those for II and CTC when $\sigma_1 = \sigma_3 = 0.5$ and σ_2 is low. (The NA problem in Table 8 disappears when the tax cut and the fiscally-equivalent increase in IE are smaller.)

B. The “robot" Economy is Different

Our welfare analysis thus far has assumed our best-guess value of σ_2. We are ultimately interested, however, in the extent to which the introduction of a pervasive new set of automation technologies makes a difference to how we should think about the impact of policies. In Figure 8 we let σ_2 range from low values associated with standard Cobb-Douglas and CES production functions up to five. The social discount factor equals either the private discount factor ($\beta_{sp} = 0.943$) or the recommended value in the project evaluation literature ($\beta_{sp} = 0.97$).

“Robot" capital clearly matters. Most notably, the welfare effects of II (slightly), CTC, and especially IE rise with σ_2. This reflects the fact that the accumulation of infrastructure capital, traditional capital, and skilled labor all increase the return to and thus accumulation of complementary “robot” capital, allowing the the fixed overall labor supply to bind more gradually. The effect is particularly strong for IE because it helps relieve the scarcity of skilled labor and, by reducing the supply of unskilled labor, provides an especially strong boost to “robot” capital investment. Because the effect is so much stronger for IE, the rankings of policies can reverse in the “robot” economy. In particular, except when $\sigma_1 = \sigma_3 = 1$ and β_{sp} =0.943, IE becomes preferred to CTC with high enough σ_2. And IE does better than even II in the CES economy with $\sigma_2 > 1.5$ and $\beta_{sp} = 0.97$.

C. Incorporating Distributional Concerns

Short of building a more disaggregated model with additional heterogenous agents, we use real income of low-wage workers as a proxy for policymakers’ distributional objective. Now

$$SW = \sum_{t=0}^{\infty} \beta_{sp}^t \frac{(c_t + \zeta w_t L_o)^{1-1/\tau}}{1-1/\tau}, \quad \zeta > 0, \tag{68}$$

where $1+\zeta$ equals the marginal rate of substitution between consumption of the poor and the non-poor in social welfare.

The distributional metric in (68) is reasonable but not without problems. Obviously, it ignores changes in the distribution of income within the saving class — a diverse group that includes struggling middle-class households with few assets, affluent professionals, and the uber rich. Worse, it does not correctly measure the consumption gain of the poor in the case of IE. More IE enables some workers who are poor and low-skill ex ante to become high-skill and non-poor ex post. Because $w_t L_o$ in (68) misses the large consumption gain of this group, the welfare ranking, taken on its own terms, is biased against IE.

We start in Figure 9 by repeating the runs in Figures 7 and 8 for the benchmark calibration with $\sigma_2 = 3$, now including positive values for ζ in the second and third columns. The bias against

IE arguably calls for for high values of ζ in order to compensate. However, the fact that the model does not track changes in the overall distribution of income suggests caution, and we thus restrict the analysis to cases where ζ =0.25 and 0.50.

Figure 9 shows that the welfare rankings change *dramatically* when real income of the poor enters the social welfare function with even a *small* weight. In the benchmark economy, IE strongly dominates the CTC and beats II in three of the four runs with $\zeta > 0$. The welfare ranking is ambiguous only in the run for $\sigma_1 = \sigma_3 = 1$ and $\zeta = 0.25$, where IE runs a close second to II before pulling ahead at $\beta_{sp} = 0.97$.[45]

VII. Conclusion

The introduction of “robot" capital makes a big difference to how policies work. In the case of cuts in corporate income taxes, such as in the corporate tax cuts (CTC) enacted in the U.S. in 2019, we show that "traditional" economy models deliver growth and wage growth forecasts touted by advocates of the tax cut: lower tax rates encourage capital deepening, partly financed by capital inflows, and the marginal product of labor rises as a result. If, instead, we assume that “robot” capital is highly substitutable with low-wage workers, which is also in line with our empirical estimates (where σ_2 is greater than 2), then long-run GDP growth is higher, but wages of low-skilled workers increase very little or even fall. The basic intuition is that the “robots”, as per our broad definition, substitutes for unskilled labor to allow more capital deepening, and this before fixed labor supplies drive the marginal product of capital down. This same feature keeps unskilled wages from rising as much or, in some cases, at all. Investment in Infrastructure (II) follows similar patterns: unskilled labor wages rise less and skilled labor wages more for higher values of σ_2, which represent substitutability of low skilled labor with “robot” capital. For both CTC and II, the labor share falls as σ_2 increases. But while the impact on wage inequality is similar in the two cases, the quantitative impact on wage growth is very different. Labor across the skill spectrum benefits much more from II than from CTC; most notably, in sharp contrast to the CTC, wage gains for low-skill labor remain large as σ_2 rises from 1.5 to 5.

Investment in Education (IE) is highly affected by adoption of these new technologies, in bigger contrasts with CTC. Wage inequality is lower and GDP growth higher—dramatically so for high values of substitutability (our σ_2). As expected, the increase in the supply of skilled labor reduces the skilled wage. Surprisingly, however, IE *greatly* increases the real wage despite stimulating spectacular growth in the supply of “robot” capital; real wage gains for low-skill workers range from 25 to 47 percent (in the long run) vs. -1.2 to 3.4 percent for the CTC and 4.1 to 8.5 percent for II.

[45] This near-dominance of IE is all the more notable given the negative bias towards IE in our measurement of social welfare.

The welfare rankings across policies depend on the values that policymakers assign to the social discount factor and the weight they give on the distributional objectives. Overall, for plausible calibrations, II dominates the CTC. This is even more so when the future is discounted less in the social welfare function. Moreover, IE tends to produce the highest welfare gains of them all, especially when: the elasticity of substitution between traditional capital (non-robot) and labor is low, there are explicit distributional objectives, and the discount factor is high. Absent explicit distributional objectives, the key driver of relative welfare effects is that IE benefits strongly, and CTC and IT weakly, from highly substitutable “robot” capital. Thus II delivers larger welfare gains than IE in traditional production functions; CTC tends to do so as well. But once “robot” capital becomes highly substitutable with unskilled labor, IE overtakes both II and CTC in the welfare ranking.

These welfare rankings depend on the elasticities of substitution, especially σ_2. The introduction of “robot" capital as a distinct factor of production measured by ICT capital means that empirical estimates from the literature are not directly comparable.[46] Extracting data on the capital and labor stocks, and wages and rates of return, that correspond to our production function, we infer the elasticities implied by this data for our specification, as well as for two different CES production functions with different nesting structures. We conclude that our preferred specification is indeed the most empirically plausible, and both for this baseline and reasonable alternative nestings, σ_2 is above than 2, lending broad support to the most important assumption we make in this paper.

Our main results are likely to be robust to the inevitable wide-ranging caveats. There are of course many factors relevant to these policy questions that our simple model does not capture. And some key assumptions, for example about the efficacy with which additional IE will produce labor that is complementary to “robots", merit closer examination.[47] Critically though, the new technology-related skepticism about the trickle-down effects of CTC, and the more positive effects of II and IE, are driven by the simple underlying forces we model.

This same simplicity leaves a large research agenda. An important general lesson is that richer analysis of the payoff to policies such as those we examine here need to consider the implications of increasing automation. The specific results of our paper, of course, may depend on the exact modeling of the technological change (and initial indications are that Large Language Models model, such as ChatGPT, may look somewhat different), but the underlying results remain: general equilibrium effects are first-order, traditional production functions give the wrong answer, and partial equilibrium rates of return may give the wrong welfare rankings.

[46] Again, Eden and Gaggl (2018) is an exception.

[47] Results with much lower returns to IE are available on request. Surprisingly, the case for IE remains strong even if its direct return is only 30 to 40 percent as high as the direct returns on II and private capital, *provided* policymakers care a little bit about helping the poor.

Appendix

A. Derivation of Equations for Long-Run Comparisons between CTC and IE

To compare the long-run solutions between IE and CTC, we re-express the solutions in (57) - (60) in terms of fiscally-equivalent increases in IE and compare them with the CTC solutions in (35) - (39). When comparing these solutions, we focus on the dependence on the rate of return to investment in education R_s. Analogous to (46) the fiscally-equivalent increase in I_s is

$$\hat{I}_s = -\frac{\theta_k + \theta_z}{\xi_s}\left(\mathfrak{n}dx\right), \tag{69}$$

where $\xi_s = \frac{I_s}{Q}$. Across steady states,

$$\hat{S} = \phi \frac{S_u}{S}\hat{S}_u = \phi \frac{S_u}{S}\hat{I}_s,$$

since $\hat{S}_u = \hat{I}_s$, which combined with (69) yields

$$\hat{S} = -\left(\phi \frac{S_u}{S}\right)\frac{\theta_k + \theta_z}{\xi_s}\left(\mathfrak{n}dx\right). \tag{70}$$

The return to investment in education R_s depends primarily on ϕ and the skill premium $\frac{1}{\psi}$. To see this, use the marginal product of education capital:

$$\frac{\partial Q}{\partial S_u} = R_s + \delta_s = (w_s - w_l)\frac{dS}{dS_u} = (1-\psi)\theta_s \phi \frac{Q}{S}$$

to deduce that

$$R_s + \delta_s = (1-\psi)\theta_s \frac{\delta_s}{\xi_s}\left(\phi \frac{S_u}{S}\right). \tag{71}$$

Using this expression and (70) gives

$$\hat{S} = -\left[\frac{\theta_k + \theta_z}{(1-\psi)\theta_s}\right]\frac{R_s + \delta_s}{\delta_s}\left(\mathfrak{n}dx\right). \tag{72}$$

Substituting for $\hat{S}$ in (57) and (59) - (60) and comparing the solutions to those for the CTC yields the conditions in (61)-(65).

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VIII. Tables and Figures

Table 1. Base Case Calibration

Parameter	Value	Definition
β	0.94	Discount factor
δ	0.06	Depreciation rate of private capital
τ	0.5	Intertemporal elasticity of substitution
Ω	2	q-elasticity of investment
θ_k	0.36	Capital's cost share evaluated at the initial steady state
θ_z	0.04	Robots's cost share evaluated at the initial steady state
θ_s	0.4	High-skill labor's cost share evaluated at the initial steady state
θ_l	0.2	Low-skill labor's cost share evaluated at the initial steady state
$\frac{w_l}{w_s}$	0.5	Inverse of the skill premium
x_{old}	0.4	Initial corporate profits tax rate
x_{new}	0.36	After-cut corporate profits tax rate
μ	0.1, 0.6	Elasticity to capital flows
$\frac{B}{Q}$	0.4	Net debt-to-GDP ratio
σ_1	0.5, 1	Elasticity of substitution between the composite inputs $H(\bullet)$ and $V(\bullet)$
σ_2	1.5, 3, 5	Elasticity of substitution between low-skill labor and robots
σ_3	0.25, 0.5, 1	Elasticity of substitution between high-skill labor and traditional capital
δ_g	0.04	Depreciation rate of infrastructure
ξ_g	0.04	Ratio of infrastructure investment to GDP
R_g	0.10, 0.15	Return on infrastructure investment net of depreciation
η	0.10, 0.15	Elasticity of output with respect to insfrastructure
δ_s	0.03	Depreciation rate of education capital
ξ_s	0.013	Ratio of investment in education to GDP
R_s	0.07	Return on investment in education net of depreciation
ϕ	0.5	Input-output coefficient that links education capital to the supply of skilled labor

Notes: See the calibration discussion in the main text. The values for η and ϕ are derived from the values assigned to other parameters.

Table 2. Estimated coefficients for the baseline

VARIABLES	(1) ln(θ_z/θ_l)	(2) ln(θ_k/θ_s)	(3) Top tier ln(θ_h/θ_v)
ln(k$_z/l_l$)	0.607***		
	(0.006)		
ln(k$_k/l_s$)		-2.111**	
		(0.964)	
ln(h/v)			-1.778***
			(0.0530)
Constant	-1.812***	-29.73**	8.740***
	(0.063)	(11.74)	(0.00779)
Observations	54	54	54
R-squared	0.994	0.084	0.956
ε_2	0.607 [0 .593, 0.620]		
γ_1	0.140 [0.126, 0.157]		
ε_3		-2.111 [-4.045, -0.177]	
κ_1		0.000 [0.000, 0.002]	
ε_1			-1.778 [-1.884, -1.672]
ι_1			0.999 [0.9998, 0.999]

Table 3. EOS and Hicks-EOS for the baseline compared to calibration

	Parameters	**EOS and Hicks-EOS**	**Calibration**
EOS(S,Z)		0.52	
EOS(L,Z)	σ_2	**2.542 [2.457, 2.631]**	**1, 1.5, 3, 5**
EOS(S,K)	σ_3	**0.321 [0.198, 0.849]**	**0.25, 0.5, 1**
EOS(K,L)		0.39	
EOS(Z,K)		0.47	
EOS(L,S)		0.41	
EOS [H(S,K),V(Z,L)]	σ_1	**0.356 [0.347, 0.375]**	**0.5, 1**

Note: in parentheses 95% confidence intervals. For details on the variables and the alternative production functions, see Online Appendix II.

Table 4. Long-run impact of a reduction in the corporate profits tax

Canonical Production Functions:

	w_l	w_s	ω	GDP	K	Z	$K+Z$	θ	θ_l
σ_i = 0.5	3.9	3.9	3.9	1.9	4.9	4.9	4.9	61.2	20.4
σ_i = 1	4.0	4.0	4.0	4.0	10.2	10.2	10.2	60.0	20.0

Robots Production Functions:

	$\sigma_1 = \sigma_3 = 0.5$								
σ_2	w_l	w_s	ω	GDP	K	Z	$K+Z$	θ	θ_l
1.5	2.1	4.8	3.9	2.4	5.4	12.6	6.1	60.9	19.9
3	0.3	5.8	3.9	2.8	5.9	20.1	7.3	60.6	19.5
5	–1.2	6.5	3.9	3.2	6.3	26.1	8.3	60.4	19.1

	$\sigma_1 = \sigma_3 = 1$								
σ_2	w_l	w_s	ω	GDP	K	Z	$K+Z$	θ	θ_l
1.5	3.4	4.3	4.0	4.3	10.5	14.9	11.0	59.8	19.8
3	2.1	5.0	4.0	5.0	11.3	26.8	12.9	59.4	19.4
5	0.7	5.7	4.1	5.7	12.1	38.7	14.8	59.1	19.1

	$\sigma_1 = 1, \sigma_3 = 0.5$								
σ_2	w_l	w_s	ω	GDP	K	Z	$K+Z$	θ	θ_l
1.5	1.7	5.0	3.9	2.4	5.5	12.0	6.2	60.9	19.9
3	0.6	5.6	3.9	2.9	5.8	21.2	7.4	60.6	19.6
5	–0.6	6.2	3.9	3.3	6.1	30.1	8.5	60.4	19.2

	$\sigma_1 = 1.69, \sigma_3 = 0.67$, as in Krusell and others (2000b)								
σ_2	w_l	w_s	ω	GDP	K	Z	$K+Z$	θ	θ_l
1.5	2.0	4.9	3.9	3.1	7.4	12.4	7.9	60.5	19.8
3	1.1	5.4	4.0	3.6	7.7	23.3	9.3	60.2	19.5
5	0.2	5.9	4.0	4.2	8.0	35.5	10.8	59.9	19.2

Notes: Figures in percent. The corporate profits tax rate is reduced from 27 to 20 percent. Numerical solutions. Calibration explained in the main text and Table 1. w_l and w_s are the wage of unskilled and skilled labor and ω the average wage. θ and θ_L are the labor share and the low-skilled labor share, respectively.

Table 5. Long-run impact of an increase in infrastructure investment ($R_g = 0.10$)

Canonical Production Functions:

	w_l	w_s	ω	GDP	K	Z	$K+Z$	θ	θ_l
σ_i = 0.5	7.7	7.7	7.7	6.1	3.8	3.8	3.8	60.9	20.3
σ_i = 1	7.7	7.7	7.7	7.7	7.7	7.7	7.7	60.0	20.0

Robots Production Functions:

	$\sigma_1 = \sigma_3 = 0.5$								
σ_2	w_l	w_s	ω	GDP	K	Z	$K+Z$	θ	θ_l
1.5	6.2	8.4	7.7	6.5	4.1	9.5	4.6	60.9	20.0
3	4.8	9.1	7.7	6.8	4.5	15.1	5.5	60.5	19.6
5	3.6	9.7	7.7	7.1	4.7	19.6	6.2	60.3	19.4
	$\sigma_1 = \sigma_3 = 1$								
σ_2	w_l	w_s	ω	GDP	K	Z	$K+Z$	θ	θ_l
1.5	7.3	7.9	7.7	7.9	7.9	11.1	8.2	59.9	19.9
3	6.2	8.5	7.7	8.5	8.5	19.9	9.6	59.6	19.6
5	5.2	9.1	7.8	9.1	9.1	28.6	11.0	59.3	19.3
	$\sigma_1 = 1, \sigma_3 = 0.5$								
σ_2	w_l	w_s	ω	GDP	K	Z	$K+Z$	θ	θ_l
1.5	5.9	8.5	7.7	6.5	4.2	9.1	4.7	60.7	19.9
3	5.0	9.0	7.7	6.8	4.4	15.8	5.6	60.5	19.7
5	4.1	9.5	7.7	7.2	4.6	22.4	6.4	60.3	19.4
	$\sigma_1 = 1.69, \sigma_3 = 0.67$, as in Krusell and others (2000b)								
σ_2	w_l	w_s	ω	GDP	K	Z	$K+Z$	θ	θ_l
1.5	6.1	8.5	7.7	7.0	5.6	9.3	6.0	60.4	19.8
3	5.5	8.8	7.7	7.4	5.8	17.3	7.0	60.2	19.6
5	4.8	9.2	7.7	7.9	6.1	26.2	8.1	59.9	19.4

Notes: Figures in percent. $\delta_g = 0.04$ and the initial $\frac{I_g}{Q} = 0.04$ in all runs. The increase in I_g, in percent of initial GDP, yields the same fiscally-equivalent change in transfers as in Table 4. w_l and w_s are the wage of unskilled and skilled labor and ω the average wage. θ and θ_L are the labor share and the low-skilled labor share, respectively.

Table 6. Long-run impact of an increase in infrastructure investment
($R_g = 0.15$)

Canonical Production Functions:

	w_l	w_s	ω	GDP	K	Z	$K+Z$	θ	θ_l
σ_i = 0.5	10.5	10.5	10.5	8.3	5.1	5.1	5.1	61.2	20.4
σ_i = 1	10.6	10.6	10.6	10.6	10.6	10.6	10.6	60.0	20.0

Robots Production Functions:

	$\sigma_1 = \sigma_3 = 0.5$								
σ_2	w_l	w_s	ω	GDP	K	Z	$K+Z$	θ	θ_l
1.5	8.5	11.5	10.5	8.9	5.6	13.0	6.4	60.9	19.9
3	6.5	12.6	10.5	9.4	6.1	20.8	7.6	60.7	19.5
5	4.9	13.4	10.6	9.8	6.5	27.1	8.5	60.4	19.1

	$\sigma_1 = \sigma_3 = 1$								
σ_2	w_l	w_s	ω	GDP	K	Z	$K+Z$	θ	θ_l
1.5	10.0	10.9	10.6	10.9	10.9	15.4	11.4	59.8	19.9
3	8.5	11.7	10.7	11.7	11.7	27.8	13.3	59.4	19.4
5	7.0	12.5	10.7	12.5	12.5	40.3	15.3	59.0	19.0

	$\sigma_1 = 1, \sigma_3 = 0.5$								
σ_2	w_l	w_s	ω	GDP	K	Z	$K+Z$	θ	θ_l
1.5	8.1	11.7	10.5	8.9	5.7	12.5	6.4	60.9	19.9
3	6.9	12.4	10.6	9.4	6.0	22.0	7.6	60.6	19.5
5	5.6	13.1	10.6	9.9	6.3	31.3	8.8	60.4	19.2

	$\sigma_1 = 1.69, \sigma_3 = 0.67$, as in Krusell and others (2000b)								
σ_2	w_l	w_s	ω	GDP	K	Z	$K+Z$	θ	θ_l
1.5	8.4	11.6	10.6	9.6	7.7	12.8	8.2	60.5	19.8
3	7.5	12.1	10.6	10.2	8.0	24.2	9.6	60.2	19.5
5	6.5	12.7	10.6	10.8	8.3	36.9	11.2	59.9	19.2

Notes: Figures in percent. $\delta_g = 0.04$ and the initial $\frac{I_g}{Q} = 0.04$ in all runs. The increase in I_g, in percent of initial GDP, yields the same fiscally-equivalent change in transfers as in Table 4. w_l and w_s are the wage of unskilled and skilled labor and ω the average wage. θ and θ_L are the labor share and the low-skilled labor share, respectively.

Table 7. Long-run impact of CTC vs II vs IE for different values of σ_2 (σ_1 = σ_3 = 1)

Corporate Tax Cut									
σ_2	w_l	w_s	ω	GDP	K	Z	$K+Z$	θ	θ_l
1	4.0	4.0	4.0	4.0	10.2	10.2	10.2	60.0	20.0
1.5	3.4	4.3	4.0	4.3	10.5	14.9	11.0	59.8	19.8
3	2.1	5.0	4.0	5.0	11.3	26.8	12.9	59.4	19.4
5	0.7	5.7	4.1	5.7	12.1	38.7	14.8	59.1	19.1
Infrastructure Investment (R_g = 0.10)									
σ_2	w_l	w_s	ω	GDP	K	Z	$K+Z$	θ	θ_l
1	7.7	7.7	7.7	7.7	7.7	7.7	7.7	60.0	20.0
1.5	7.3	7.9	7.7	7.9	7.9	11.1	8.2	59.9	19.9
3	6.2	8.5	7.7	8.5	8.5	19.9	9.6	59.6	19.6
5	5.2	9.1	7.8	9.1	9.1	28.6	11.0	59.3	19.3
Infrastructure Investment (R_g = 0.15)									
σ_2	w_l	w_s	ω	GDP	K	Z	$K+Z$	θ	θ_l
1	10.6	10.6	10.6	10.6	10.6	10.6	10.6	60.0	20.0
1.5	10.0	10.9	10.6	10.9	10.9	15.4	11.4	59.8	19.9
3	8.5	11.7	10.7	11.7	11.7	27.8	13.3	59.4	19.4
5	7.0	12.5	10.7	12.5	12.5	40.3	15.3	59.0	19.0
Education Investment ($R_s = 0.07$)									
σ_2	w_l	w_s	ω	GDP	K	Z	$K+Z$	θ	θ_l
1	40.6	–15.7	5.4	5.4	5.4	5.4	5.4	60.0	28.0
1.5	38.1	–14.7	5.6	6.6	6.6	21.8	8.1	59.4	27.4
3	31.0	–12.0	6.1	10.0	10.0	68.7	15.8	57.9	25.9
5	23.7	–9.3	6.5	13.4	13.4	116.9	23.8	56.4	24.4

Notes: Figures in percent. $\delta_g = 0.04$, the initial $\frac{I_g}{Q} = 0.04$, $\delta_s = .03$, and the initial $\frac{I_s}{Q} = 0.013$ in all runs. The increases in I_g and I_s, in percent of initial GDP, yield the same fiscally-equivalent change in transfers as in Table 4. w_l and w_s are the wage of unskilled and skilled labor and ω the average wage. θ and θ_L are the labor share and the low-skilled labor share, respectively.

Table 8. Long-run impact of an increase in investment in education

Canonical Production Functions:

	w_l	w_s	ω	GDP	K	Z	$K+Z$	θ	θ_l
σ_i = 0.5					NA				
σ_i = 1	40.6	–15.7	5.4	5.4	5.4	5.4	5.4	60.0	28.0

Robots Production Functions:

$\sigma_1 = \sigma_3 = 0.5$

σ_2	w_l	w_s	ω	GDP	K	Z	$K+Z$	θ	θ_l
1.5					NA				
3	46.6	–18.2	4.9	13.1	13.1	136.5	25.4	55.6	26.7
5	30.7	–12.1	5.9	17.2	17.2	186.2	34.1	54.2	24.2

$\sigma_1 = \sigma_3 = 1$

σ_2	w_l	w_s	ω	GDP	K	Z	$K+Z$	θ	θ_l
1.5	38.1	–14.7	5.6	6.6	6.6	21.8	8.1	59.4	27.4
3	31.0	–12.0	6.1	10.0	10.0	68.7	15.8	57.9	25.9
5	23.7	–9.3	6.5	13.4	13.4	116.9	23.8	56.4	24.4

$\sigma_1 = 1, \sigma_3 = 0.5$

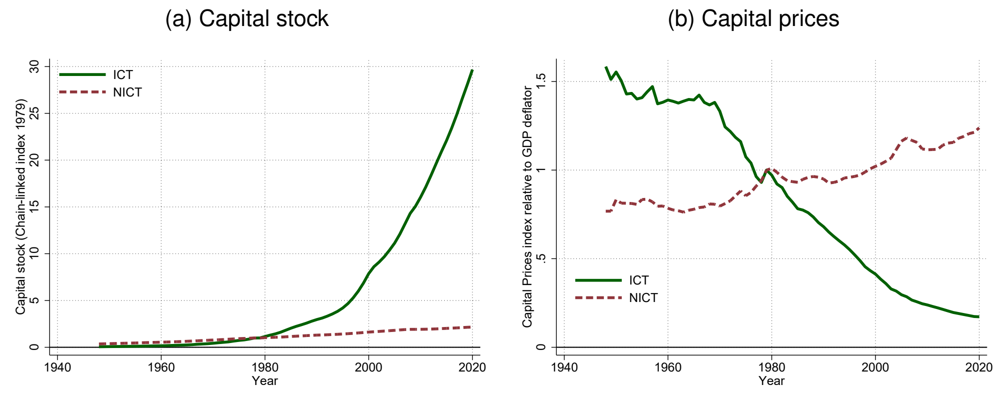
σ_2	w_l	w_s	ω	GDP	K	Z	$K+Z$	θ	θ_l
1.5	41.6	–16.0	5.4	9.5	14.5	26.3	15.7	57.7	27.1
3	33.1	–12.8	5.9	12.6	16.7	76.8	22.7	56.4	25.5
5	24.7	–9.7	6.4	15.7	18.8	126.5	29.6	55.2	24.0

$\sigma_1 = 1.69, \sigma_3 = 0.67$, as in Krusell and others (2000b)

σ_2	w_l	w_s	ω	GDP	K	Z	$K+Z$	θ	θ_l
1.5	26.0	–10.1	6.5	10.0	16.4	6.1	15.4	58.0	25.4
3	22.8	–8.8	6.7	11.8	17.5	38.7	19.6	57.2	24.6
5	18.9	–7.4	6.9	14.0	18.8	77.9	24.7	56.3	23.8

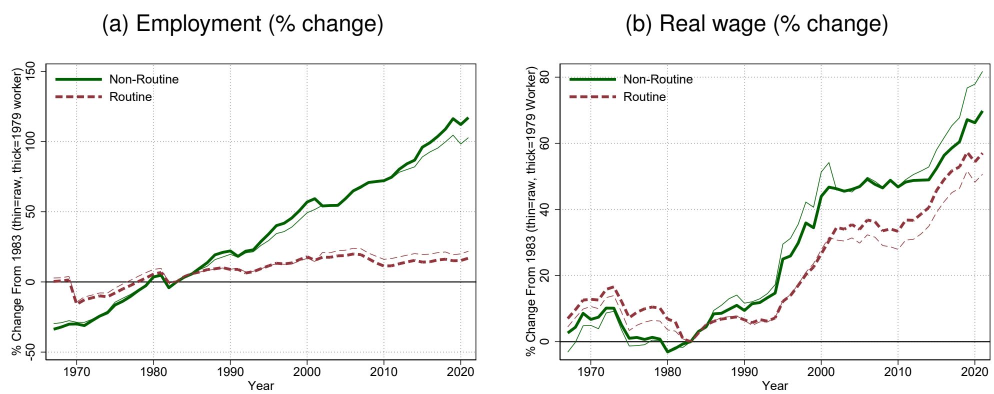
Notes: Figures in percent. $R_s = .07$, $\delta_s = .03$ and the initial $\frac{I_s}{Q} = 0.013$ in all runs. The increase in I_s, in percent of initial GDP, yields the same fiscally-equivalent change in transfers as in Table 4. NA is entered when w_s is less than w_l at the new steady state. w_l and w_s are the wage of unskilled and skilled labor and ω the average wage. θ and θ_L are the labor share and the low-skilled labor share, respectively.

Figure 1. ICT vs non-ICT capital



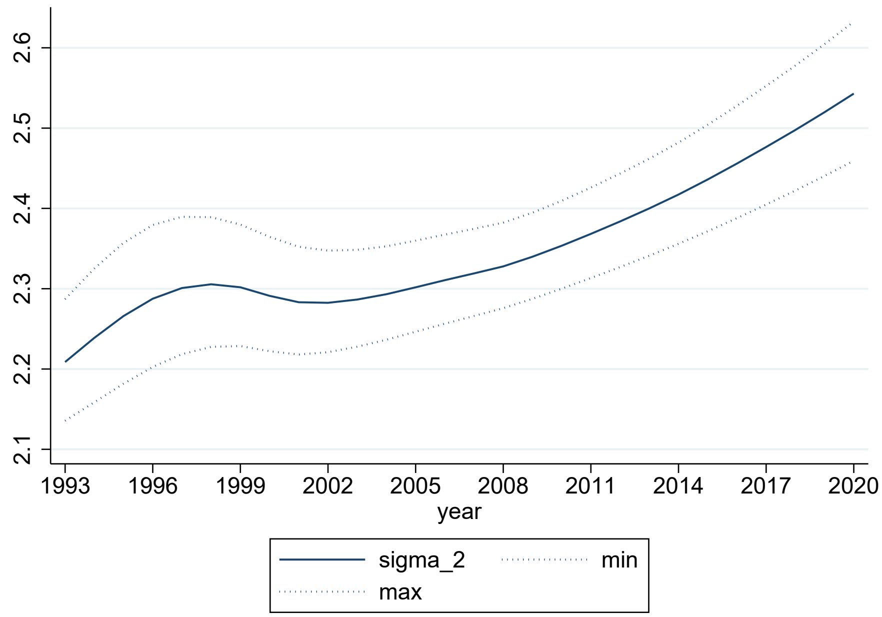
Note: NICT is non-ICT capital, which for us is regular capital (non-robot). ICT is our proxy for “robot” capital.

Figure 2. Non-Routine vs Routine labor: employment and wages



Note: Non-Routine includes "Manag./Prof./Tech." and "Service".

Figure 3. Evolution of σ_2



Note: This shows the evolution of σ_2 over time (1993-2020) by using sub-samples of data starting in 1967 end ending from 1993 to 2020, including one year at the time. The error bands are based on standard errors, as per Table 2.

Figure 4. Transition Path when the corporate profits tax falls from 27 to 20 percent

(σ_2 =3; σ_1 = σ_3 = 0.5)

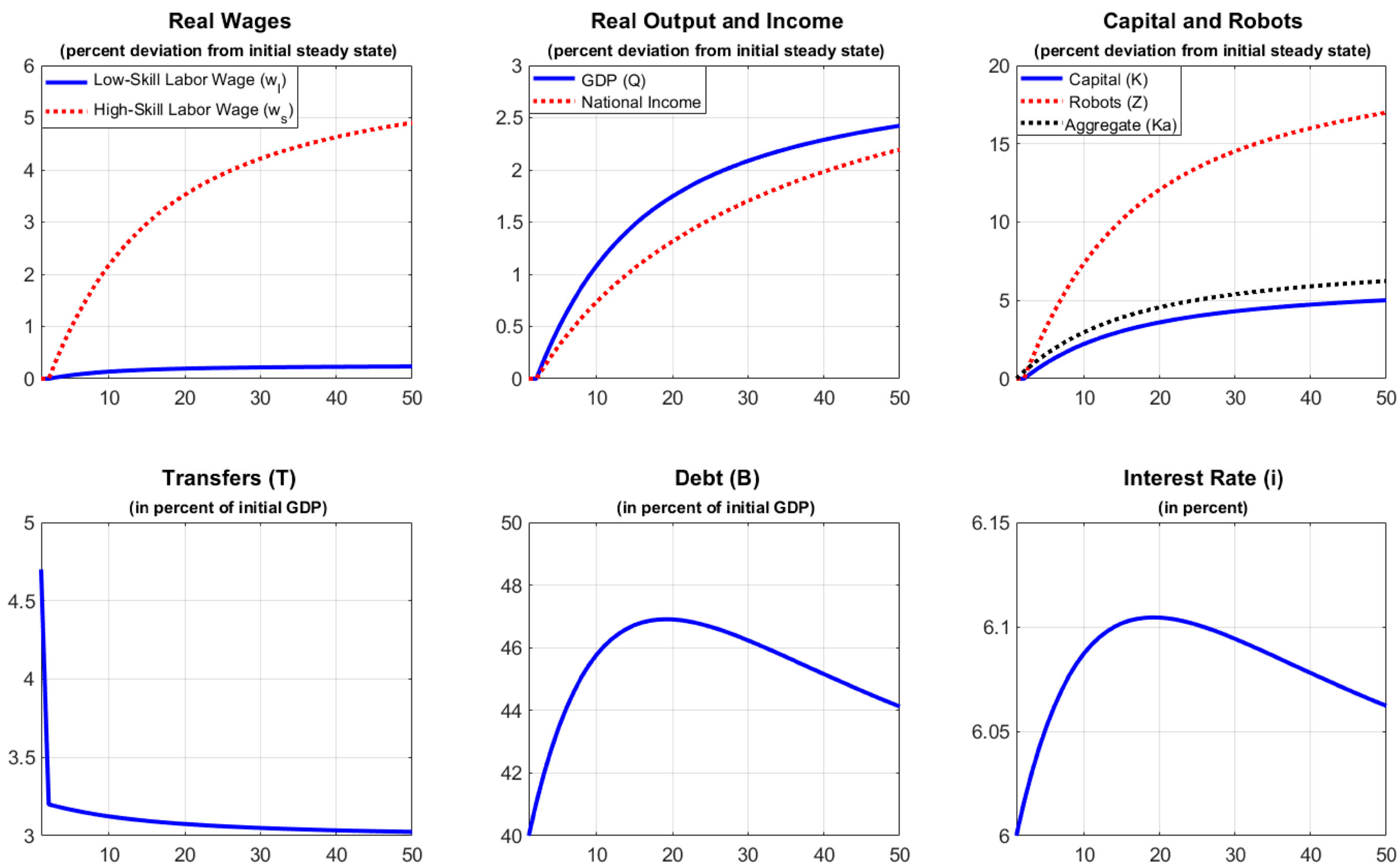


Figure 5. Corporate tax cut vs. a fiscally-equivalent increase in infrastructure investment

(Tax cut from 27 to 20 percent. σ_2 = 3, σ_1 = σ_3 = 0.5, R_g = 0.10)

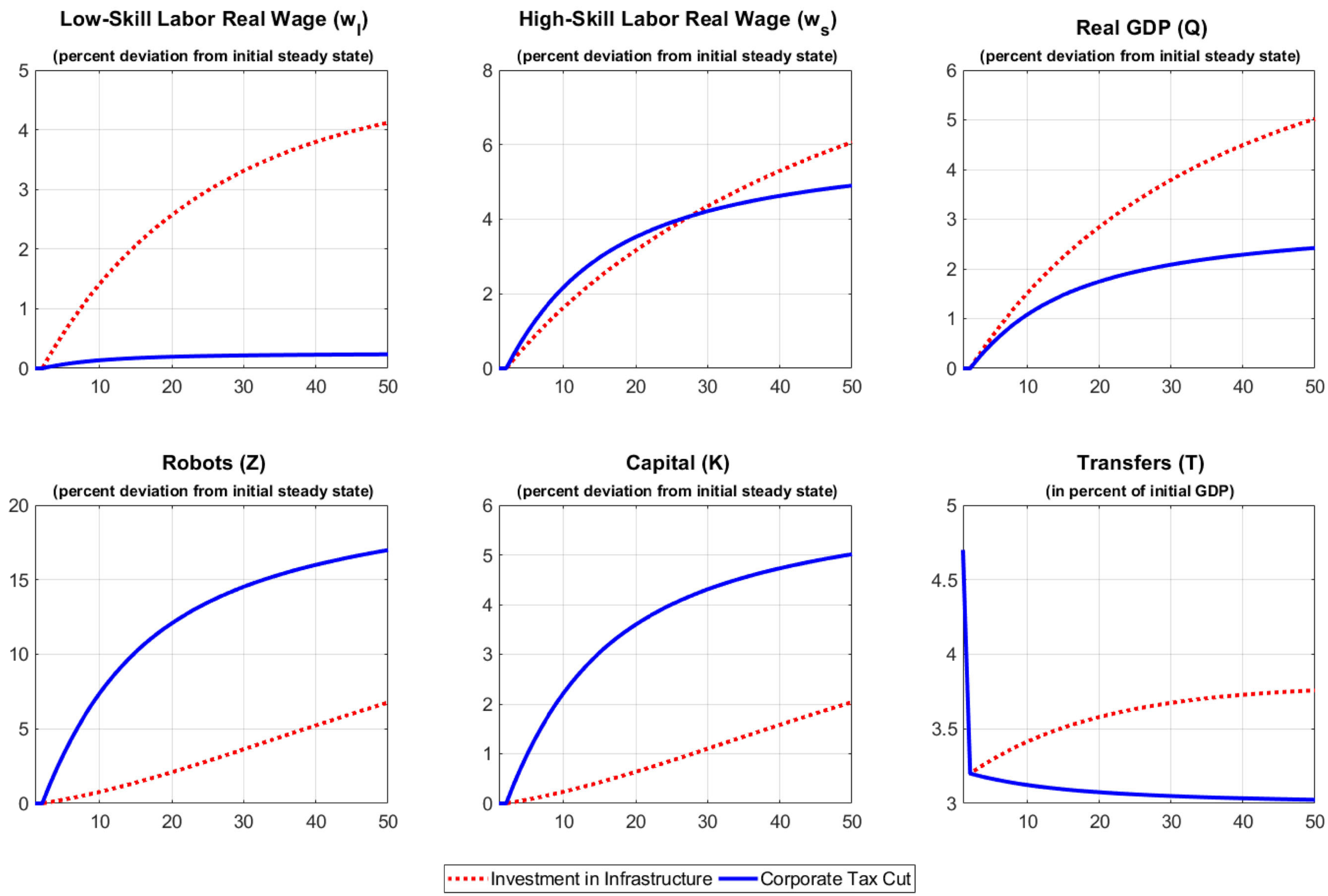


Figure 6. Corporate tax cut vs. a fiscally-equivalent increase in investment in education

(Tax cut from 27 to 20 percent. σ_2 = 3, σ_1 = σ_3 = 0.5, R_s = 0.07)

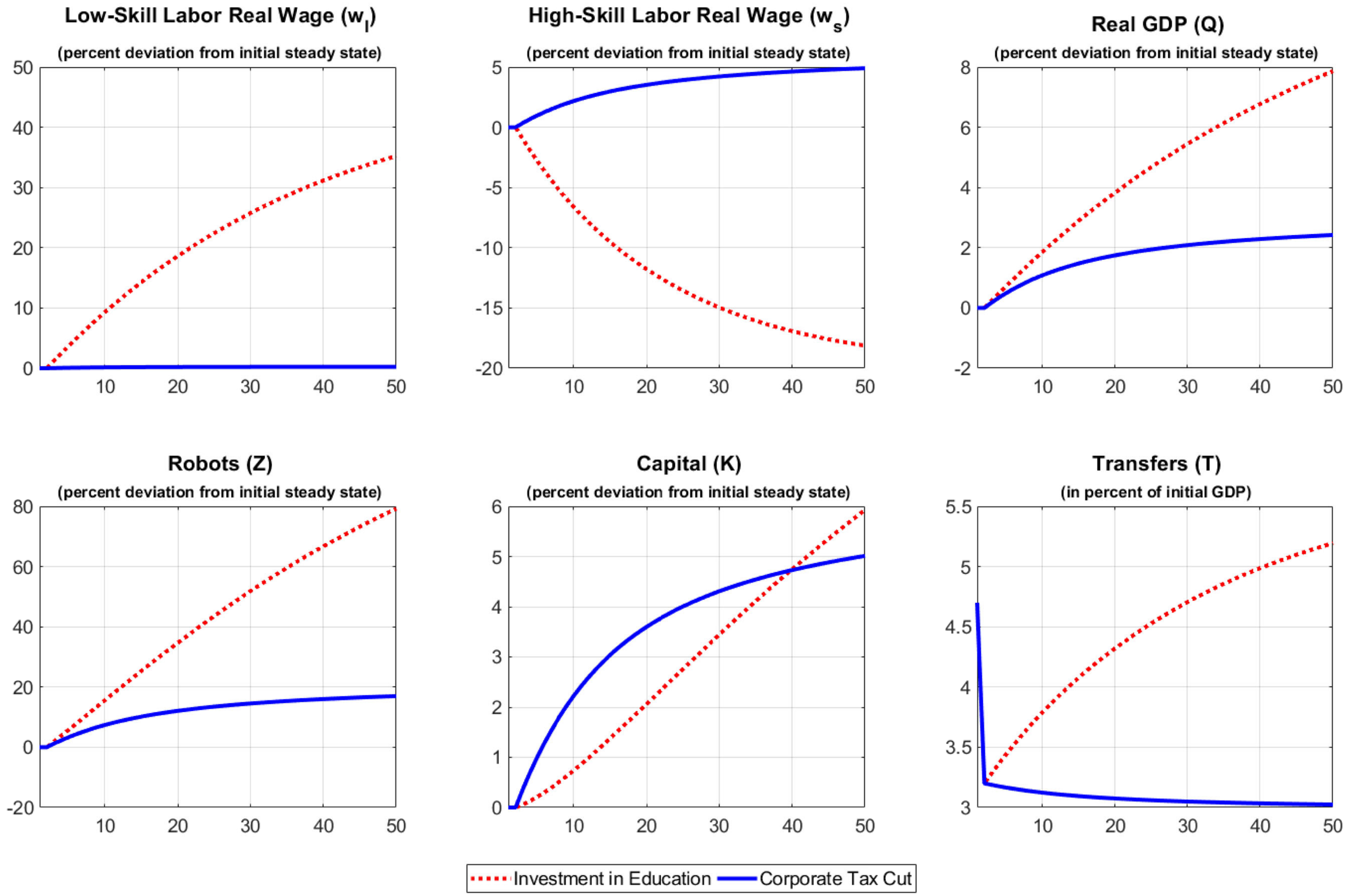


Figure 7. Welfare gains across policies:
The role of the social discount factor (β_{sp})

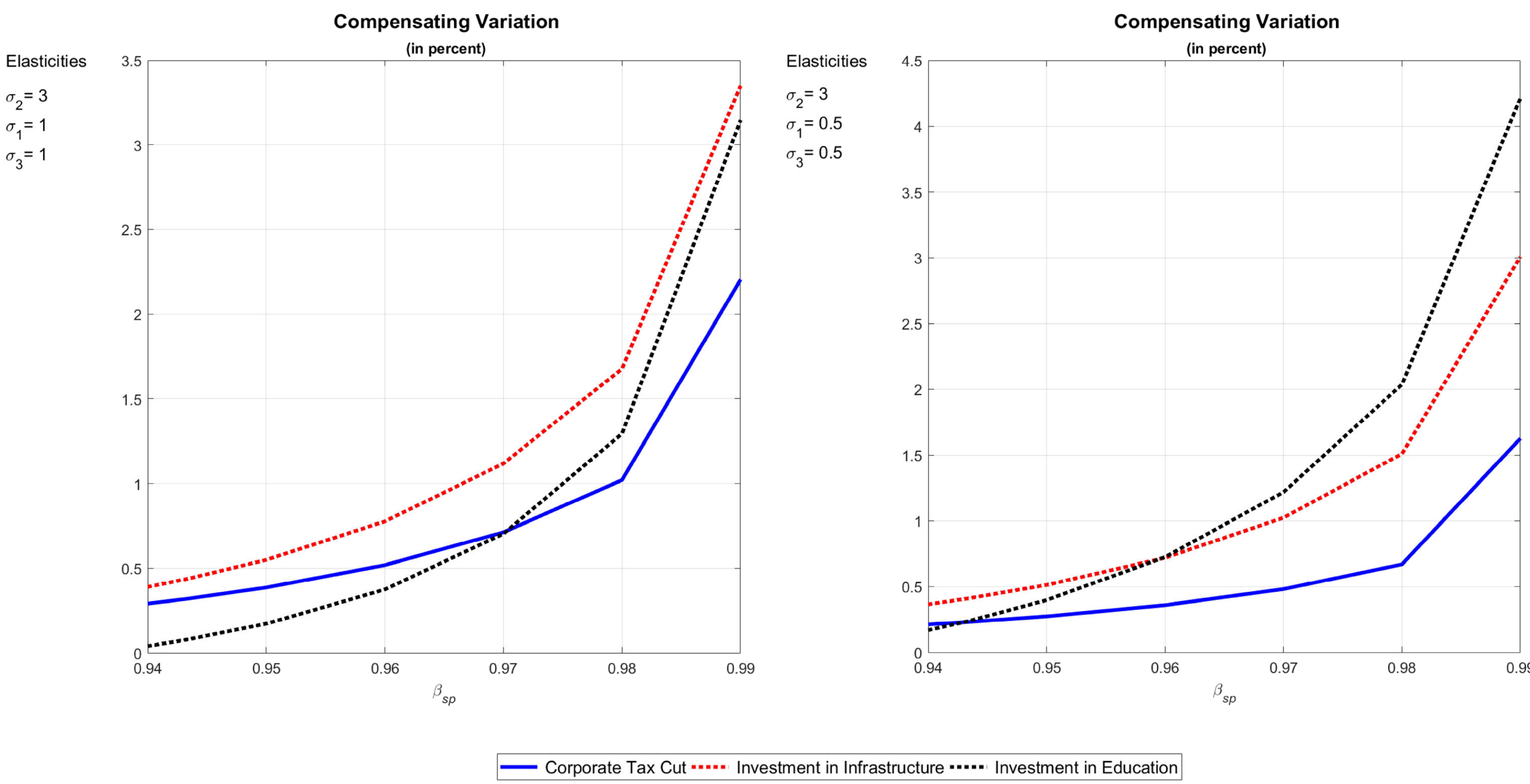


Figure 8. Welfare gains across policies:
The role of the elasticity of substitution between "robot" and low-skill labor (σ_2)

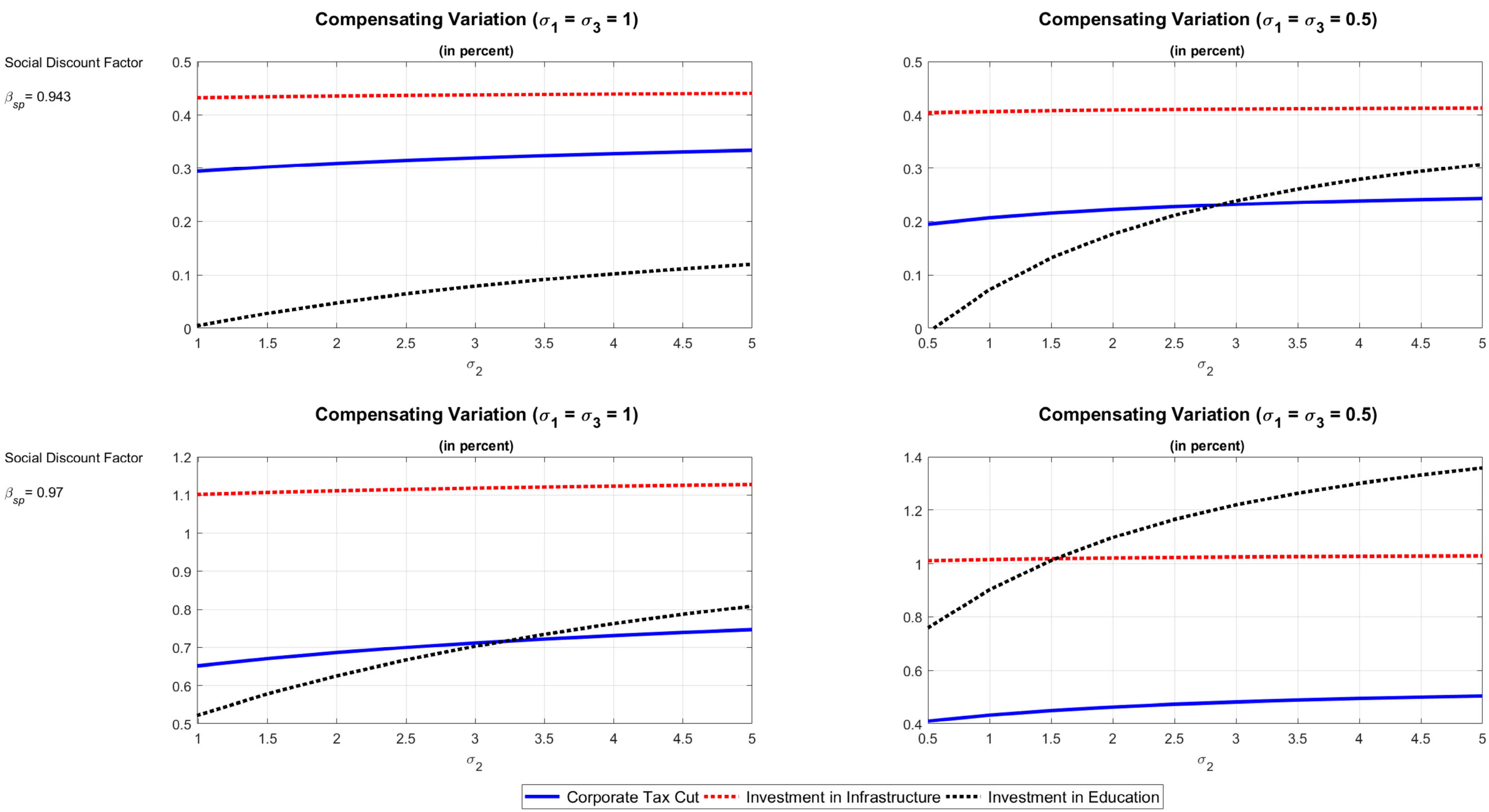
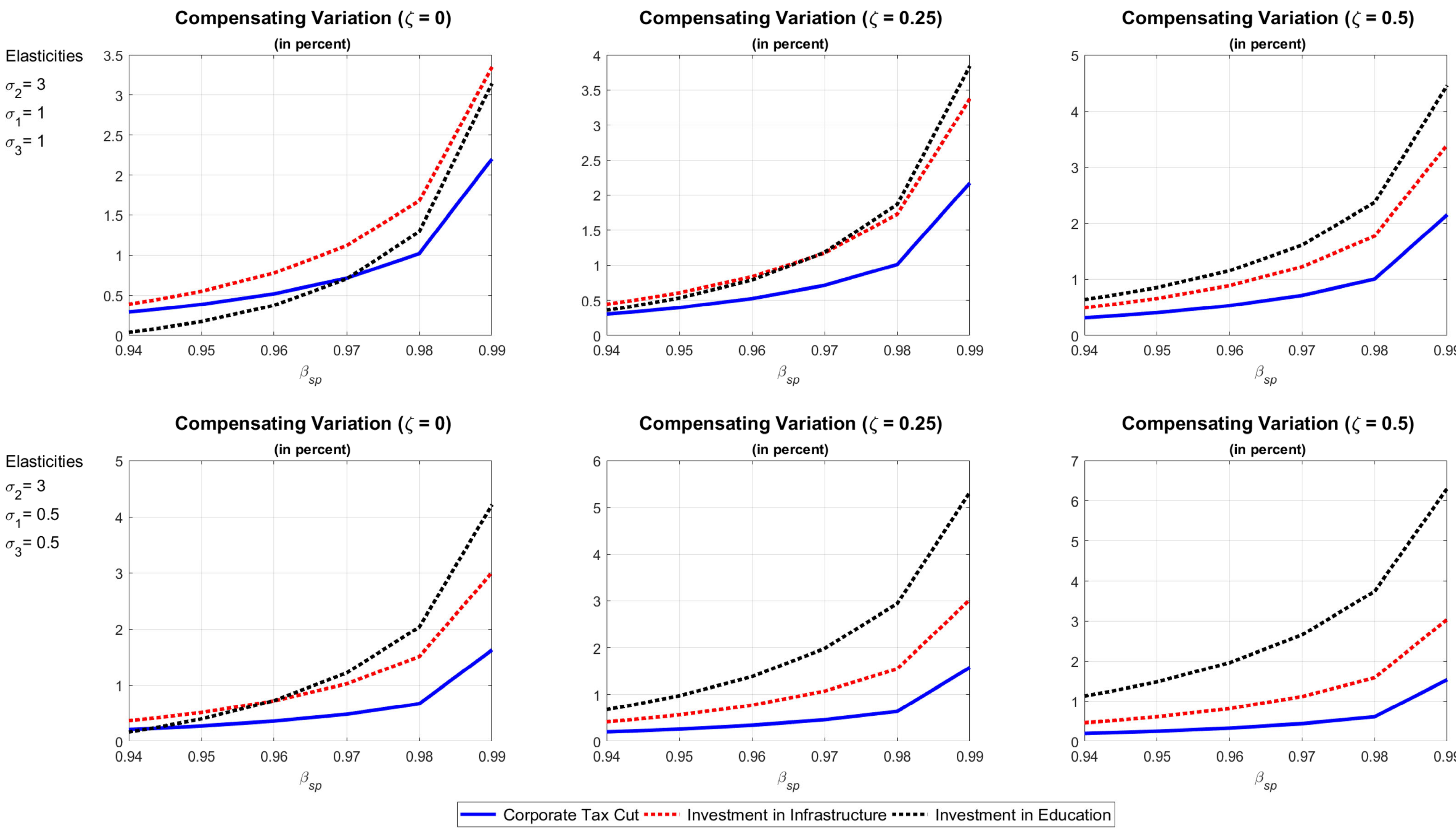


Figure 9. Welfare gains across policies: basecase with distribution (ζ)



Online Appendix I

In this appendix we present analytical and numerical results for the three-tiered CES production function $Q = F\{K, J[S, V(L,Z)]\}$. The cost function dual to the production function is

$$\bar{C} = \frac{[mr_k^{1-\sigma_1} + (1-m)f^{1-\sigma_1}]^{1/(1-\sigma_1)}}{G^\eta}, \tag{73}$$

where

$$\begin{aligned} f &= [aw_s^{1-\sigma_4} + (1-a)c^{1-\sigma_4}]^{1/(1-\sigma_4)}, \\ c &= [gw_l^{1-\sigma_2} + (1-g)r_z{}^{1-\sigma_2}]^{1/(1-\sigma_2)}, \end{aligned}$$

σ_1 is the elasticity of substitution (EOS) between traditional capital and $J(\bullet)$; σ_2 is the EOS between "robot" capital and low-skill labor; and σ_4, the new kid on the block, is the EOS between skilled labor and $V(\bullet)$.

Write the cost function as $\bar{C} = C\{r_k, f[w_s, c(w_l, r_z)]\}/G^\eta$. The market-clearing conditions for the four inputs are then

$$K = C_r Q/G^\eta, \tag{74}$$
$$Z = C_f f_c c_z Q/G^\eta, \tag{75}$$
$$L = C_f f_c c_w Q/G^\eta, \tag{76}$$
$$S = C_f f_w Q/G^\eta, \tag{77}$$

where $C_r = \partial C/\partial r_k$, $c_z = \partial c/\partial r_z$, and $f_w = \partial f/\partial w_s$.

Appendix A. Long-Run Outcome: Analytical Results

The solution procedure is the same as in the main body of the paper. After making use of the fact that (across steady states)

$$\hat{r}_k = \hat{r}_z = \frac{\rho}{\rho + \delta(1-x)} \frac{dx}{1-x}, \tag{78}$$

equations (2) - (5) and the zero-profit condition

$$1 = \frac{C(r_k, r_z, w_s, w_l)}{G^\eta} \tag{79}$$

can be solved for K, L, Q, w_s and w_l as a function of x, G, and S.

Because the production function is different, the definitions of some factor shares differ from those in the paper. Now:[48]

$$\begin{aligned}\theta_f &= \theta_s + \theta_l + \theta_z, \\ \chi_s &= \theta_s / \theta_f, \\ \chi_c &= (\theta_l + \theta_z) / \theta_f.\end{aligned}$$

A.1. Corporate Tax Cut (CTC)

The solutions for the low- and high-skill wages are

$$\hat{w}_l = \left[(\sigma_2 - \sigma_4)\alpha_z - \sigma_4 \frac{\theta_k + \theta_z}{\theta_s} \right] \frac{n}{a_2} \frac{dx}{1-x}, \tag{80}$$

$$\hat{w}_s = -[\sigma_2 \alpha_z (1-\theta_s) + \sigma_4 \alpha_l \theta_k] \frac{n}{a_2 \theta_s} \frac{dx}{1-x}, \tag{81}$$

where

$$\begin{aligned} n &\equiv \frac{\rho}{\rho + \delta(1-x)} < 1, \\ a_2 &\equiv \sigma_2 \alpha_z + \sigma_4 (\alpha_l + \theta_l / \theta_s). \end{aligned}$$

The high-skill wage always increases, while the low-skill wage decreases when σ_2 is sufficiently large relative to σ_4

$$\hat{w}_l < 0 \quad \text{iff} \quad \sigma_2 > \sigma_4 \left(1 + \frac{\theta_k + \theta_z}{\theta_s \alpha_z} \right), \tag{82}$$

and wage inequality worsens for $\sigma_2 > \sigma_4$

$$\hat{w}_s - \hat{w}_l = -\frac{(\sigma_2 - \sigma_4)\alpha_z}{a_2 \theta_s} n \frac{dx}{1-x}. \tag{83}$$

Estimates of σ_4 vary widely. If estimates on the order of 1.5 are accurate, then the low-skill wage is unlikely to decrease and wage inequality may actually diminish.[49]

[48]Note also that $\theta_l = \theta_f \chi_c \alpha_l$ and $\theta_z = \theta_f \chi_c \alpha_z$.

[49]For $\theta_k + \theta_z = .40$, $\theta_s = .20$, and $\alpha_z = .167$ — the factor shares in the paper — the condition in (10) requires $\sigma_2 > 6.99\sigma_4$.

The solutions for the two capital stocks and real output are

$$\hat{K} = -[\sigma_1(\sigma_2\chi_s\alpha_z + \sigma_4\alpha_l) + \sigma_4\sigma_2\alpha_z\chi_c]\, n\frac{dx}{1-x} > 0, \tag{84}$$

$$\hat{Z} = -\left\{\frac{\sigma_4}{a_2\theta_s}[\alpha_l(\sigma_2 - \sigma_4\theta_k) + \sigma_2\chi_s\alpha_z(1-\theta_k)] + \chi_s \frac{\sigma_2\alpha_z(1-\theta_s) + \sigma_4\alpha_l\theta_k}{a_2\theta_s}\left[1 + \frac{(\sigma_2 - \sigma_4)\chi_s\alpha_z}{a_1}\right]\right\} n\frac{dx}{1-x}, \tag{85}$$

$$\hat{Q} = -[\sigma_1\theta_k(\sigma_2\chi_s\alpha_z + \sigma_4\alpha_l) + \sigma_4\sigma_2\alpha_z(\theta_k\chi_c + \theta_l + \theta_z)]\frac{n}{a_2\theta_s}\frac{dx}{1-x} > 0, \tag{86}$$

where

$$a_1 \equiv \sigma_2\alpha_z + \sigma_4\alpha_l.$$

It is readily shown that K, Z, and Q are increasing in σ_2. [50]

A.2. Infrastructure Investment (II)

In the case of II:

$$\hat{w}_l = \frac{\sigma_4}{a_2\theta_s}\eta\hat{G} > 0, \tag{87}$$

$$\hat{w}_s = \frac{\sigma_2\alpha_z + \sigma_4\alpha_l}{a_2\theta_s}\eta\hat{G} > 0, \tag{88}$$

$$\hat{w}_s - \hat{w}_l = \frac{\sigma_2 - \sigma_4}{a_2\theta_s}\alpha_z\eta\hat{G}, \tag{89}$$

$$\hat{Q} = \left[\sigma_4\sigma_2\alpha_z\frac{\theta_l + \theta_z}{\theta_f} + (\sigma_2\chi_s\alpha_z + \sigma_4\alpha_l)(\sigma_1\theta_k + \theta_f)\right]\frac{\eta}{a_2\theta_s}\hat{G} > 0, \tag{90}$$

$$\hat{K} = [\sigma_1(\sigma_2\chi_s\alpha_z + \sigma_4\alpha_l) + \sigma_4\sigma_2\alpha_z\chi_c]\frac{\eta}{a_2\theta_s}\hat{G} > 0, \tag{91}$$

$$\hat{Z} = \sigma_4\sigma_2\frac{\eta}{a_2\theta_s}\hat{G} > 0. \tag{92}$$

The qualitative results are the same as in the paper. II increases the low-skill wage, the high-skill wage, GDP and both components of the private capital stock. Note also that, as in the paper, the condition for wage inequality to worsen ($\sigma_2 > \sigma_4$) is the same as with the CTC.

[50] $\sigma_2 > \sigma_4\theta_k$ is a weak sufficient condition for Z to increase.

Comparing the fiscally-equivalent increase in II to the CTC yields[51]

$$\hat{Q}\big|_{\text{II}} \;>\; \hat{Q}\big|_{\text{CTC}} \quad \text{iff} \quad R_g > \delta_g \left[\frac{\sigma_4\sigma_2\alpha_z\chi_c + \sigma_1\theta_k(\sigma_2\chi_s\alpha_z + \sigma_4\alpha_l)}{\Delta(\theta_k+\theta_z)(1-x)} - 1\right], \quad (93)$$

$$\hat{w}_l\big|_{\text{II}} \;>\; \hat{w}_l\big|_{\text{CTC}} \quad \text{iff} \quad R_g > \delta_g \left[\frac{x}{1-x} - \frac{(\sigma_2-\sigma_4)\alpha_z\theta_s}{\sigma_4(\theta_k+\theta_z)(1-x)}\right], \quad (94)$$

$$\hat{w}_s\big|_{\text{II}} \;>\; \hat{w}_s\big|_{\text{CTC}} \quad \text{iff} \quad R_g > \delta_g \left[\frac{\sigma_2\alpha_z(1-\theta_s) + \sigma_4\alpha_l\theta_k}{(\sigma_2\alpha_z+\sigma_4\alpha_l)(\theta_k+\theta_z)(1-x)} - 1\right], \quad (95)$$

$$(\hat{w}_s-\hat{w}_l)\big|_{\text{II}} \;>\; (\hat{w}_s-\hat{w}_l)\big|_{\text{CTC}} \quad \text{iff} \quad R_g > \delta_g \left[\frac{1}{(\theta_k+\theta_z)(1-x)} - 1\right], \quad (96)$$

$$\hat{K}\big|_{\text{II}} \;>\; \hat{K}\big|_{\text{CTC}} \quad \text{iff} \quad R_g > \delta_g \left[\frac{\sigma_2\alpha_z\theta_s + \sigma_4\alpha_l\theta_f}{(\theta_k+\theta_z)(1-x)} - 1\right], \quad (97)$$

where

$$\Delta \equiv \sigma_4\sigma_2\alpha_z\chi_c + (\sigma_2\chi_s\alpha_z + \sigma_4\alpha_l)(\sigma_1\theta_k + \theta_f).$$

II increases the low-skill wage, the high-skill wage, and GDP more than the CTC provided the return on infrastructure is not unusually low. For $\sigma_1 = .5$, $\sigma_2 = 3$, $\sigma_4 = 1.5$, and the calibration values in the paper, the threshold values of R_g that satisfy (21), (22), and (23) are .02, .016, and .036, respectively.

The conditions for II to increase wage inequality and the traditional capital stock more than the CTC are again close calls. The condition in (24) is the same as in the paper. The condition in (25) is more or less stringent than its counterpart in the paper depending on whether $\sigma_2\alpha_z\theta_s + \sigma_4\alpha_l\theta_f \gtrless 1$. As luck would have it, for the aforementioned calibration values, $\sigma_2\alpha_z\theta_s + \sigma_4\alpha_l\theta_f = 1$ — the condition in (25) and the condition in the paper deliver the same threshold value of 12.7% for R_g.

A.3. Investment in Education (IE)

For IE, we present just a couple of solutions that make it easier to understand the numerical results that follow in the next section.

From (2), (3), and 7),

$$\hat{K} \;=\; \hat{Q}, \quad (98)$$

$$\hat{Z} \;=\; (\sigma_4-\sigma_2)\frac{\chi_s}{\chi_c}\hat{w}_s + \hat{Q}. \quad (99)$$

Traditional capital always increases by the same percentage amount as GDP. Ditto for “robot” capital when $\sigma_2 = \sigma_4$.

[51] Substitute $\eta\hat{G} = -(\theta_k+\theta_z)[(R_g+\delta_g)/\delta_g]ndx$ in equations (15) - (20).

The increase in GDP depends on how much the two capital stocks and the supply of skilled labor increase. Since the increase in S is exogenous and σ_1 does not appear in (26) or (27), the solutions for K, Z, Q, w_l, and w_s are all independent of the EOS between traditional capital and the composite input $J[S,V(L,Z)]$.

APPENDIX B. LONG-RUN OUTCOME: NUMERICAL RESULTS

Tables A1-A4 report results for $\sigma_2 = 1.5$, 3, 5 when $\sigma_4 = 1.5$ and $\sigma_1 = .5$, 1. We ignore the runs for $\sigma_2 = \sigma_4 = 1.5$; they correspond to just another standard production function.

All of the qualitative results for $\sigma_2 = 3$ - 5 in the paper reappear here. The impact on the quantitative results is generally modest for CTC and II. It is significant, however, for IE: the increases in the low-skill wage and GDP and the decrease in the high-skill wage, while large in absolute terms, are much smaller than in the paper.

Table 9. Long-run impact of a reduction in the corporate profits tax from 27% to 20%.

	σ_1 = .5, σ_4 = 1.5								
σ_2	w	w_s	ω	GDP	K	Z	K+Z	θ_{LS}	θ_L
1.5	3.9	3.9	3.9	2.6	5.6	15.6	6.6	60.8	20.3
3	2.9	4.5	3.9	3.4	6.5	29.8	8.8	60.3	19.9
5	1.7	5.1	4.0	4.4	7.5	45.8	11.3	59.8	19.5

	σ_1 = 1, σ_4 = 1.5								
σ_2	w	w_s	ω	GDP	K	Z	K+Z	θ_{LS}	θ_L
1.5	4.0	4.0	4.0	4.3	10.6	15.8	11.1	59.8	19.9
3	2.9	4.6	4.0	5.2	11.5	30.0	13.4	59.3	19.6
5	1.8	5.2	4.1	6.2	12.6	46.2	15.9	58.8	19.2

$$Q = FK, H[S, J(L, Z)] / G^{\eta} \tag{100}$$

where σ_1 is the EOS between K and H (total labor services); σ_2 is the EOS between L and Z; and σ_4 is the EOS between S and J (i.e., the EOS between and high-skill and low-skill labor services).

Table 10. Long-run impact of an increase in infrastructure investment with R_g = .10.

σ_2	σ_1 = .5, σ_4 = 1.5								
	w	w_s	ω	GDP	K	Z	K+Z	θ_{LS}	θ_L
1.5	7.7	7.7	7.7	6.6	4.3	11.7	5.0	60.6	20.2
3	6.9	8.1	7.7	7.3	4.9	22.0	6.6	60.2	19.9
5	6.0	8.6	7.7	8.0	5.6	33.5	8.4	59.8	19.6

σ_2	σ_1 = 1, σ_4 = 1.5								
	w	w_s	ω	GDP	K	Z	K+Z	θ_{LS}	θ_L
1.5	7.7	7.7	7.7	8.0	8.0	11.8	8.4	59.9	19.9
3	6.9	8.2	7.7	8.6	8.6	22.2	10.0	59.5	19.7
5	6.0	8.7	7.8	9.4	9.4	33.8	11.8	59.1	19.4

R_g = .10 and δ_g = .04 in all runs. I_g increases by 1.5% of initial GDP. (I_{go} = 4% of GDP).

Table 11. Long-run impact of an increase in infrastructure investment with R_g = .15.

σ_2	σ_1 = .5, σ_4 = 1.5								
	w	w_s	ω	GDP	K	Z	K+Z	θ_{LS}	θ_L
1.5	10.5	10.5	10.5	9.1	5.8	16.2	6.9	60.8	20.3
3	9.4	11.2	10.6	10.0	6.7	30.9	9.1	60.3	19.9
5	8.1	11.9	10.6	11.1	7.8	47.6	11.8	59.8	19.5

σ_2	σ_1 = 1 , σ_4 = 1.5								
	w	w_s	ω	GDP	K	Z	K+Z	θ_{LS}	θ_L
1.5	10.6	10.6	10.6	11.0	11.0	16.4	11.5	59.8	19.9
3	9.5	11.3	10.7	12.0	11.9	31.2	13.9	59.3	19.6
5	8.2	12.0	10.7	13.1	13.0	48.1	16.6	58.8	19.1

R_g = .15 and δ_g = .04 in all runs. I_g increases by 1.5% of initial GDP. (I_{go} = 4% of GDP).

Table 12. Long-run impact of an increase in investment in education.

	σ_4 = .5								
σ_2	w	w_s	ω	GDP	K	Z	K+Z	θ_{LS}	θ_L
1.5	26.3	-10.2	6.4	6.4	6.4	6.4	6.4	60.0	26.2
3	22.9	-8.9	6.7	8.7	8.7	39.3	11.8	58.9	25.3
5	19.0	-7.4	6.9	11.4	11.4	78.7	18.1	57.6	24.3

R_s = R_{so} = .07 and δ_s = .03. Is increases by 1.5% of initial GDP. (I_{so} = 1.3% of GDP.) The income share for low-skill workers includes the income gain of workers who are low-skill ex ante and become high-skill ex post. Recall that the results are independent of the value of σ_1.

Online Appendix II

Appendix C. EOS estimations

C.1. Data

ICT assets and non-ICT assets data for the US are from Bureau of Economic Analysis (BEA) detailed fixed asset accounts.[52] The BEA reports quality adjusted prices, depreciation rates, and stocks of capital. ICT assets are defined as BEA asset codes starting with EP, EN, RD2, or RD4. The data are very granular in the industries and with a large T dimension (1948-2020). As in Eden and Gaggl (2018), in the ICT category we include Communications, Software, PCs, Terminals, Semiconductors, Storage devices. They are included in the BEA database in the equipment and intellectual property products. The rest are listed as non-ICT capital and these categories cover both residential and non-residential capital.

As for earnings and occupation, these are from the Current Population Survey (CPS) by the US Bureau of Labor Statistics (BLS). More specifically, we retrieve the data from IPUMS-CPS ASEC ("March") supplement in annual frequency (1967-2021).[53] The routine vs non-routine tasks are aggregated categories of occupations following Eden and Gaggl (2018) taken from Acemoglu and Autor (2011)). That is, we consider as non-routine workers if employed in “management, business, and financial operations occupations”, “professional, technical, and related occupations”, and “service occupations”. This category aims to capture jobs that involve tasks that need problem-solving, creativity, and complex decision-making.

Then we define routine workers as ones employed in “sales and related occupations”, “office, clerical, and administrative support occupations”, “production occupations”, “transportation and material moving occupations”, “construction and extraction occupations”, and “installation, maintenance, and repair occupations”. Farm workers are dropped.

This is mirrored in 5 major occupation categories (see in Appendix F in Eden and Gaggl (2018)), based on IPUMS-CPS codes and aggregations: Managerial and Professional (000-200); Technical, Sales, and Administrative (201-400); Service (401-470); Farming, Forestry, and Fishing (471-500); Precision Production, Craft, and Repairers (501-700); Operatives and Laborers (701-900); Non-occupational responses (900-999). The routine occupations are Sales, and Administrative (241-400), Precision Production, Craft, and Repairers (501-700), and Operatives and Laborers (701-900). The non-routine list includes instead: Managerial and Professional (000-200), Technical (201-240) and Service (401-470).[54] We hence exclude Farming, Forestry, and Fishing (471-500), and Non-occupational responses (900-999).

[52] The data can be retrieved from here: https://apps.bea.gov/national/FA2004/Details/Index.htm.

[53] The IPUMS-CPS data are available free of charge. For reference see Flood and others (2021).

[54] Using the IPUMS-CPS aggregate Technical, Sales, and Administrative (201-400) entirely in the non-routine, our results are robust.

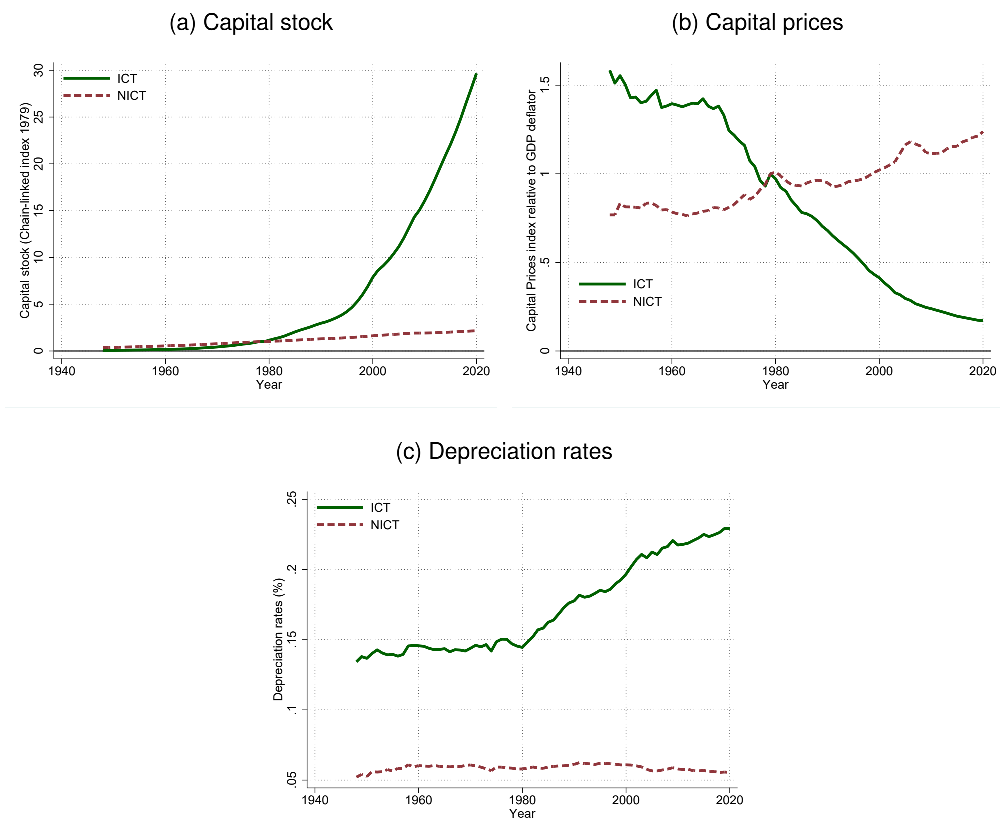
As in appendix F, we create a more balanced bins for the demographics by using other characteristics (gender, race, industry etc.) and checked with the case in which only occupation is used. The overall results are not driven by this choice also in our extended dataset up to 2020.[55][56]

[55]In 2013 there is a spike in employment due to a change in CPS weights. We interpolate the series to have a smooth variable.

[56]The steps and transformations utilized for these variables are carefully reported in Eden and Gaggl (2018).

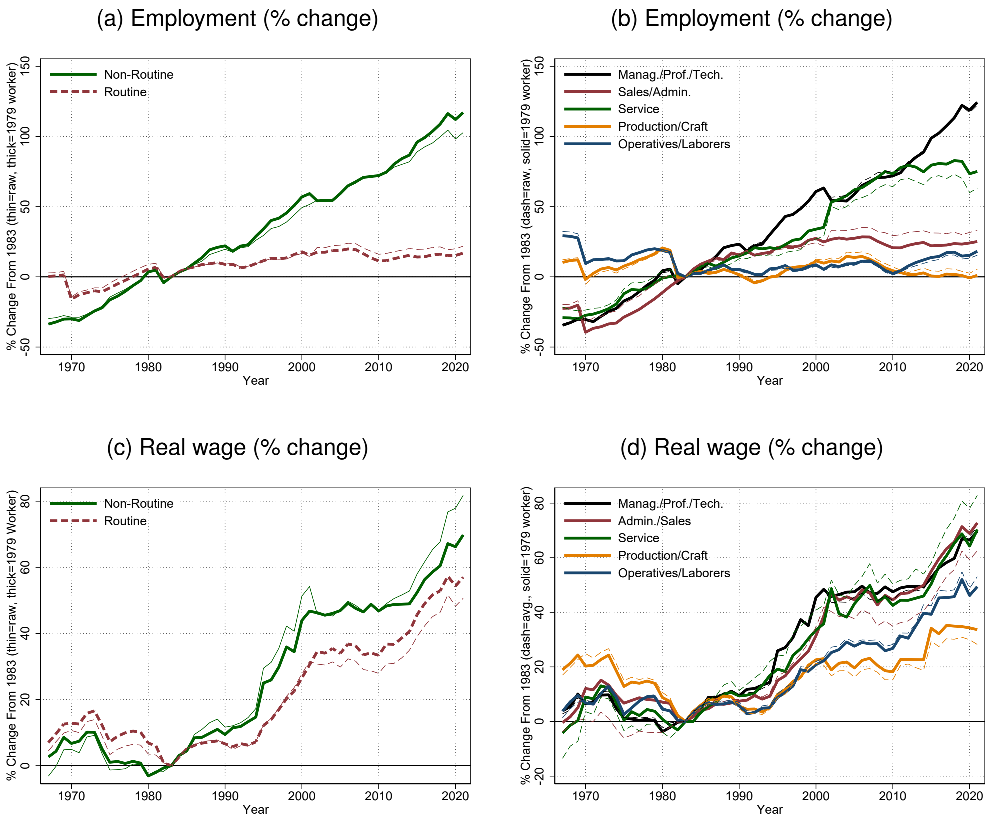
C.1.1. Capital and labor

Figure 10. ICT vs non-ICT capital



Note: NICT is non-ICT capital, which for us is regular capital (non-robot). ICT is our proxy for “robot” capital.

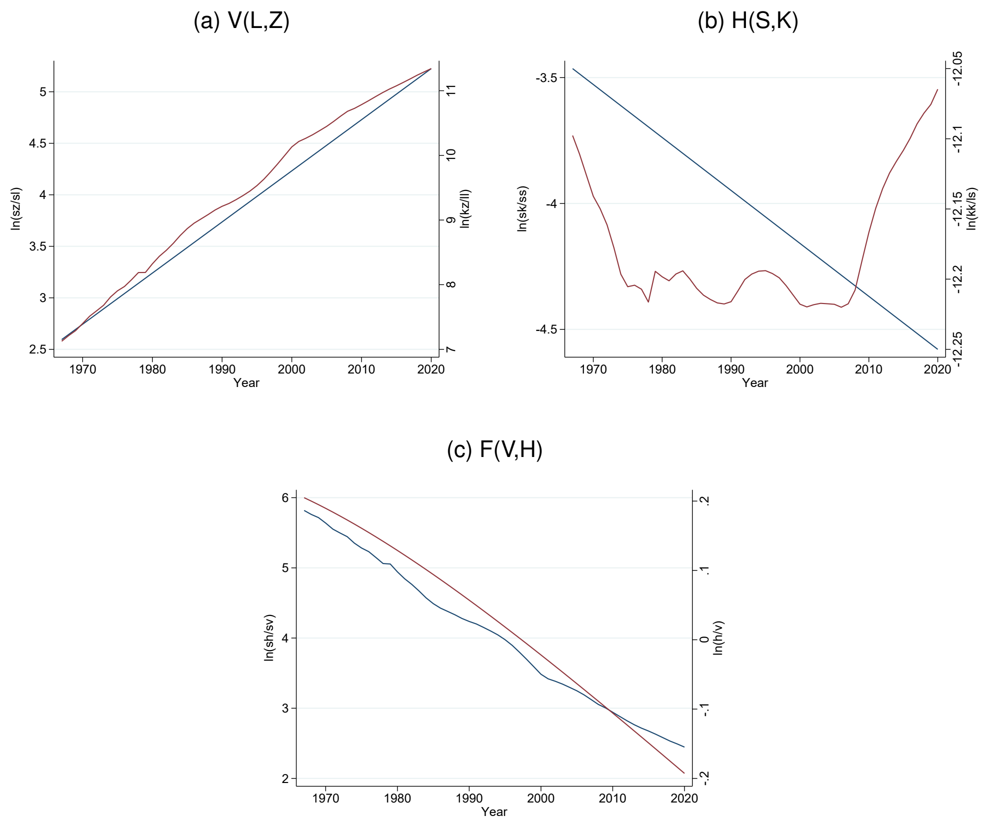
Figure 11. Non-Routine vs Routine labor: employment and wages



Note: Non-Routine includes "Manag./Prof./Tech." and "Service".

C.2. Series for the estimations

Figure 12. LHS and RHS variables for baseline estimates



Note: We plot the variables for the estimates as in Table 2 in the main text. On the y-axis on the LHS, we show the dependent variables, while on the y-axis on the RHS, we plot the regressors.

C.3. Full estimates for baseline and alternatives

Table 13. Estimated coefficients and parameters

	Baseline		
	(1)	(2)	(3)
VARIABLES	ln(θ_z/θ_l)	ln(θ_k/θ_s)	Top tier ln(θ_h/θ_v)
$\ln(k_z/l_l)$	0.607***		
	(0.006)		
$\ln(k_k/l_s)$		-2.111**	
		(0.964)	
$\ln(h/v)$			-1.778***
			(0.0530)
Constant	-1.812***	-29.73**	8.740***
	(0.063)	(11.74)	(0.00779)
Observations	54	54	54
R-squared	0.994	0.084	0.956
ε_2	0.607		
	[0.593, 0.620]		
γ_1	0.140		
	[0.126, 0.157]		
ε_3		-2.111	
		[-4.045, -0.177]	
κ_1		0.000	
		[0.000, 0.002]	
ε_1			-1.778
			[-1.884, -1.672]
ι_1			0.999
			[0.9998, 0.999]

	Alternative A		
	(1)	(2)	(3)
VARIABLES	ln(θ_z/θ_s)	ln(θ_l/θ_w)	Top tier ln(θ_k/θ_h)
$\ln(k_z/l_s)$	0.462***		
	(0.006)		
$\ln(l_l/w)$		0.610***	
		(0.006)	
$\ln(k/h)$			8.544***
			(0.135)
Constant	-0.553***	0.517***	3.848***
	(0.062)	(0.049)	(0.0163)
Observations	54	54	54
R-squared	0.990	0.994	0.987
ε_2	0.462		
	[0.449, 0.475]		
γ_1	0.365		
	[0.337,0.395]		
ε_3		0.610	
		[0.596,0.623]	
κ_1		0.626	
		[0.603, 0.649]	
ε_1			8.544
			[8.274, 8.814]
ι_1			0.979
			[0.979, 0.979]

	Alternative B		
	(1)	(2)	(3)
VARIABLES	ln(θ_z/θ_l)	ln(θ_s/θ_v)	Top tier ln(θ_k/θ_j)
$\ln(k_z/l_s)$	0.607***		
	(0.00669)		
$\ln(l_s/v)$		0.459***	
		(0.00654)	
$\ln(k/j)$			8.547***
			(0.135)
Constant	-1.812***	-0.971***	2.931***
	(0.0636)	(0.0433)	(0.0164)
Observations	54	54	54
R-squared	0.994	0.990	0.987
ε_2	0.607		
	[0.593, 0.620]		
γ_1	0.140		
	[0.126, 0.157]		
ε_3		0.459	
		[0.445, 0.471]	
κ_1		0.274	
		[0.258, 0.292]	
ε_1			8.547
			[8.277, 8.817]
ι_1			0.9494
			[0.9493, 0.9494]

Note: θ_z and θ_k are the capital shares of Z and K, and θ_s and θ_l are the income shares of S and L, respectively. θ_h and θ_v are the inputs' shares and h and v the outcomes from the inner nestings H and V. θ_w is the share of the composite W(S,Z), θ_v is the share of composite V(L,Z), θ_h is the share of the composite H(S,K), and θ_j is the share of the composite J(S,V). The labor variables are normalized by aggregate labor and the two types of capital are normalized by total capital. These are denoted by lower case 'l' and 'k'. Top tier refers to higher level of CES nesting.[57]

[57] We use simple OLS. The standard errors are as in Eden and Gaggl (2018), however if we use robust standard errors or bootstrapped standard errors, to limit possible heteroskedasticity and small sample bias, the results are very similar. For example, in the baseline, the standard error of ε_2 is 0.006, in the alternative cases is 0.007. The one of ε_1 is 0.964 while in the alternatives is 1.130 and 1.005 for robust and bootstrapped errors respectively. The full set of results is available upon request.

Table 14. The EOS with different production functions: estimated and Hicks-EOS

Model	Baseline	Alternative A	Alternative B
EOS(S,Z)	0.52	1.859 [1.814, 1.904]	2.06
EOS(L,Z)	2.542 [2.457, 2.631]	2.23	2.542 [2.457, 2.631]
EOS(S,K)	0.321 [0.198, 0.849]	<0	1.22
EOS(K,L)	0.39	<0	1.27
EOS(Z,K)	0.47	<0	1.36
EOS(L,S)	0.41	2.49	1.94
EOS[L, (S,Z)]		2.561 [2.475, 2.652]	
EOS[S, (L,Z)]			1.847 [1.801, 1.890]
EOS [H(S,K),V(Z,L)]	0.356 [0.347, 0.375]		
EOS[K, G(L,W(S,Z))]		<0	
EOS[K, J(S, V(L,Z))]			<0

Note: in parentheses 95% confidence intervals. Please note that the Hicks-EOS for Alternative B can be only calculated with Cobb-Douglas, as the EOS between K and $J(\bullet)$ is negative. Some Hicks-EOS for Alternative A also cannot be computed.

C.4. Hicks-EOS with Cobb-Douglas

We report here the EOS and Hicks-EOS imposing always Cobb-Douglas in the top tier nesting. In this case all the top tier EOS are assumed to be equal to 1. The differences are seen only in the Baseline and shown below in italics.

Table 15. Estimated and Hicks-EOS with Cobb-Douglas at top tier

Model	Baseline	Alternative A	Alternative B
EOS(S,Z)	*0.93*	1.859 [1.814, 1.904]	2.06
EOS(L,Z)	2.542 [2.457, 2.631]	2.23	2.542 [2.457, 2.631]
EOS(S,K)	0.321 [0.198, 0.849]		1.22
EOS(K,L)	*0.58*		1.27
EOS(Z,K)	*0.68*		1.36
EOS(L,S)	*0.77*	2.49	1.94

C.5. Estimating the EOS: Eden and Gaggl (2018)

Given the data on capital and labor, we compute the correspondent shares as in Eden and Gaggl (2018), just extending the dataset to 2020. We then estimate the equations based on their production function by OLS, and compute coefficients/constants 95% confidence intervals to calculate their coefficients, named in their paper σ, γ, η, and θ. These correspond to ε_2, γ_1, κ_1, and ε_3 in our setup. From this step, we compute the EOS.[58] Note that this strategy targets the trends in the relative income shares of capital Z and labor (L and S).[59]

The coefficients in Eden and Gaggl (2018), looking at the closest setup as ours (Table G.11 B.2, i.e., on chain indices), are 0.275 for ε_2 and 1.071 for ε_3, with the latter greater than one hence going against the assumptions in the production function. The constant is much larger than ours in the first step (-5.037) and even negative in the second one (-0.100).

Table 16. Our estimates (data until 2020)

VARIABLES	(1) Step 1	(2) Step 2
ε_2	0.462***	
	(0.006)	
ε_3		0.610***
		(0.006)
Constant	-0.553***	0.517***
	(0.062)	(0.049)
Observations	54	54
R-squared	0.990	0.994

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[58]The standard errors are as in Eden and Gaggl (2018), however if we use robust standard errors or bootstrapped standard errors, to limit possible heteroskedasticity and small sample bias, the results are very similar. For example, the standard deviation of gamma as in Table 1 is 0.006, in the alternative cases is 0.007. The full set of results is available upon request.

[59]By focusing on relative rather than absolute income shares and excluding non-ICT capital (K), we attribute the rise in the ICT capital/"robots" (Z) income share to automation only, allowing for part of the decline in the aggregate labor income share to reflect other factors.

Table 17. Eden and Gaggl (data until 2013) - Table G.11 B.2

VARIABLES	(1) Step 1	(2) Step 2
ε_2	0.275***	
	(0.005)	
ε_3		1.071***
		(0.004)
Constant	-5.037***	-0.100***
	(0.046)	(0.001)
Observations	47	47
R-squared	?	?

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

We report our parameters and EOS below, using 95% confidence bands. In the table, the ranges for Eden and Gaggl (2018) are instead their different options shown in Table G.11.[60] These includes the homogeneous labor model and the segmented labor market model (using either data or chain indices). The closest to our estimation is the latter.[61] Using data from 1967 to 2020 (N=54),[62] we can see that the EOS between Z and S (ICT capital and non-routine labor) is 1.859. Hence this is bigger when we extend the series to 2020: for Eden and Gaggl (2018) (data up to 2013 and N=47) is between 1.379 and 1.427. This means that over time, with some more years of data, these became more substitutable. The EOS between the (z) composite variable (a composite good as a product of W(S,Z)) and L (routine labor) is much smaller than for them (2.561 versus 8.403) but on the positive side we do find a ε_3 smaller than 1 and equal to 0.610. Eden and Gaggl (2018) are cautious of their estimated ε_3, reporting it as 1.071,[63] hence greater than 1.[64]

[60] We report here the ranges for Eden and Gaggl (2018) to cover their options shown in Table G.11. These includes the homogeneous labor model and the segmented labor market model (using either data or chain indices). For our estimates we compute 95% confidence intervals for the coefficients to calculate min and max bands for parameters and the EOS.

[61] All regressions use fitted log-linear trends as data inputs, in order to eliminate the influence of cyclical fluctuations.

[62] We start in 1967 because the two main datasets are unbalanced, i.e., capital data start in 1948 and labor data in 1967 - we also have the estimated values with the full sample (1948-2020), available upon request.

[63] In case of differentiated labor, it is equal to 1.119.

[64] The maximum value of EOS between W(S,Z) and L (in italics in the table) comes from our calculations, as it is not reported in Eden and Gaggl (2018).

Table 18. Parameters and EOS estimates

Model	ε_2	γ_1
Eden and Gaggl (data 2013)	[0.299, 0.275]	[0.005, 0.006]
Our data (2020)	0.462 [0.449, 0.475]	0.365 [0.337, 0.395]

Model	ε_3	κ_1
Eden and Gaggl (data 2013)	[0.876, 1.119]	[0.466, 0.535]
Our data (2020)	0.609 [0.596, 0.623]	0.626 [0.603, 0.649]

Model	EOS (S,Z)	EOS(L,W(S,Z))
Eden and Gaggl (data 2013)	[1.379, 1.427]	[8.039, *8.403*]
Our data (2020)	1.859 [1.814, 1.904]	2.561 [2.475, 2.652]

PUBLICATIONS

Searching for Wage Growth: Policy Responses to the “New Machine Age”
Working Paper No. WP/2024/003