Searching for Wage Growth: Policy Responses to the Robot Revolution*

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Abstract

The current wave of technological revolution is changing the way policies work. We examine the growth and distributional implications of three policies: cuts to the corporate tax rate, increases in education spending, and increases in infrastructure investment. "Robot" capital does indeed make a big difference: the trickle-down effects of corporate tax cuts on unskilled wages are attenuated, and the relative merits of investment in infrastructure and especially in education are higher. For plausible calibrations, infrastructure investment and corporate tax cuts tend to dominate investment in education in the traditional economy, but in the "robot" economy infrastructure investment dominates corporate tax cuts, while investment in education tends to produce the highest welfare gains of all. General equilibrium effects are important: in our baseline calibration, partial equilibrium rates of return always give the wrong welfare rankings.

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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. And now a new wave of innovation associated with ever-faster computers, more effective machine learning and artificial intelligence algorithms, and pervasive digitalization presages a new industrial revolution that may have even greater macroeconomic repercussions.[1]

The macroeconomic literature on this new industrial revolution, including our own earlier work, emphasizes the implications of improvements in technology for growth, labor markets, and the distribution of income. In Berg, Buffie, and Zanna (2018) we modify the canonical neoclassical growth model by introducing (i) poor hand-to-mouth consumers and (ii) "robot" capital that differs from traditional capital in its degree of substitutability with human labor. Our main results are robust to various assumptions about how automation may transform the labor market: automation is always good for growth and bad for equality.

In this paper we ask a different question: how do the effects of policy differ in this new economy with "robot" capital?[2] We examine the growth and distributional implications of three policies: cuts to the corporate tax rate, increases in education spending, and increases in infrastructure investment. We examine how different assumptions about the elasticity of substitution between "robot" capital and labor change the results compared to a model that assumes "robot" capital has the same elasticity of substitution with labor as does traditional capital (and which thus reduces to a model with just one type of capital). To enable straightforward policy comparisons, we assume that each policy is financed by an equivalent increase in lump-sum taxation of capitalists/skilled workers.

In keeping with the empirical evidence for the U.S. and other industrial countries, and to be able to discuss inequality, we allow for two types of agents: capitalists/skilled workers who save and invest, and low-skill workers who live check-to-check. We calibrate to the United States and assume an open capital account. U.S. borrowing is large enough to affect the world market interest rate.[3]

We capture the implications of public investment in infrastructure capital and education through simple modifications. Infrastructure shifts the production function; as in for example Aschauer

[1]See Grace and others (2018) for a survey of AI professionals on evolving capacities, and Susskind (2020) for a recent comprehensive discussion.

[2]By "robot" we mean the combination of computers, AI, big data, digitalization, networks, sensors and servos that are emphasized in the literature on the "new machine age."

[3]The configuration of the labor market — with robots substituting only for unskilled labor — is one of the four models analyzed in Berg, Buffie, and Zanna (2018) and probably the most relevant model for the near term. The earlier paper assumed a closed economy.

(1989), it increases total factor productivity. We assume that the supply of skilled labor responds to increases in public spending on higher education but is inelastic with respect to the skill premium, following the evidence in Autor (2014) and Murphy and Topel (2016).

There is a burgeoning literature on the implications of the current technological revolution for growth, employment, wages, and inequality. For example 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.[4]

The "tasks" approach to analyzing technological change yields many insights about the implications of technological change for employment, wages, and output.[5] With respect to implications for how the economy reacts to policy shifts, Acemoglu and Restrepo (2019a) focus on policy towards technology itself. Acemoglu, Manera, and Restrepo (2020) is an important recent exception, analyzing implications of the US tax code for employment, wages, the labor share, and automation. They find that the US tax system is biased against labor and in favor of capital, increasingly so in recent years. They find that reducing labor taxes, or combining automation taxes with reduced capital taxes, would increase employment much more than uniform reductions in capital taxes observed in recent years.

The papers of Sachs and coauthors—i.e., Sachs and Kotlikoff (2012) and Sachs, Benzell, and Lagarda (2015)—consider inter-generational equity and the role of inter-generational transfers in OLG models. Caselli and Manning (2019) look at long-run effects of higher levels of technology on the real wage. Like us, they exploit simple production functions. In contrast, however, they look only at long-run dynamics and assume only one type of capital, thus missing out on many important interactions of traditional and robot capital with different elasticities of substitution with (different types of) labor.

Our production function approach with two types of capital focuses attention on some key parameters while being similar enough to the standard literature to allow us to see how standard results change with the introduction of robots. This production function approach allows the four production factors to interact flexibly.[6] We find that the introduction of robots does indeed make a big difference to how policies work; old theoretical assumptions and benchmark models need to be revisited and empirical work taken with a large new grain of salt.

[4] Goolsbee (2019) discusses public policy, including the potential role of a universal basic income, but without the benefit of a formal model.

[5] See for example Acemoglu and Restrepo (2018), Acemoglu and Restrepo (2019a).

[6] For example, Acemoglu and Restrepo (2018) and Acemoglu and Restrepo (2019a) assume that the elasticity of substitution between capital and labor is close to but less than one, following the standard literature on capital-labor substitutability and the assumption that there is only one type of capital. Of course the tasks approach has great advantages in other contexts; for example it lends itself to the analysis of more granular labor-market issues that are not our concern here.

In the case of cuts in corporate income taxes cuts (CTC), standard Cobb-Douglas and CES models readily deliver standard results: a lower tax rate encourages capital deepening, partly financed by capital inflows, and the marginal product of labor rises as a result and labor benefits. 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 wage increases for low-skilled workers become very small or even negative.

Infrastructure investment 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. Capital grows more under our baseline calibration, and even with more pessimistic assumptions about the rate of return to infrastructure investment, GDP growth is higher than with CTC. The larger increase in unskilled wages with infrastructure investment relative to CTC becomes more salient as robot capital becomes more substitutable with unskilled labor, because with corporate tax cuts unskilled wages may even fall in real terms, while they rise substantially in all runs with infrastructure investment.

Even starker implications of new technologies, and bigger contrasts with CTC, emerge for investment in education. Wage inequality is lower, and growth higher, dramatically so with more highly substitutable robot capital. Education investment gives an especially strong boost to accumulation of robot capital, due to both the large decrease in unskilled labor that competes with robots and the increase in the supply of complementary skilled labor. If robot capital is substitutable enough, even traditional capital grows more with education than with CTC, as the increase in complementary skilled labor and robots outweighs the direct effect of lower corporate tax rates.

The welfare ranking across policies depends on the social discount factor and the weight on distributional objectives, as well as the parameters of the production function. Overall, we find that for plausible calibrations, II dominates CTC, the more so the less the future is discounted in the social welfare function. IE tends to produce the highest welfare gains of all, especially when: (i) the elasticity of substitution between traditional capital and labor is low, because education alleviates the skilled-labor constraint that is even more salient when robots substitute highly for unskilled labor; (ii) there are explicit distributional objectives, because of the positive effect of education on unskilled wages; and (iii) the discount factor is high. This last result highlights an important methodological point, which is that these rankings depend on general equilibrium features, notably here the positive effect of higher education expenditures on capital accumulation, which takes time to emerge and which is not revealed through an comparison of (partial equilibrium) rates of return across investments.

These welfare rankings also depend on robots, that is on the degree of substitutability between robot capital and unskilled labor. Absent explicit distributional objectives, the key driver of relative welfare effects is that IE benefits strongly, and CIT and IT weakly, from highly substitutable robot capital. As we will see, IE spurs especially large increases robot capital while supplying more complementary skilled labor, while the robots attenuate the effect of rising labor scarcity on capital accumulation. Thus in our calibration II delivers more welfare that IE in traditional production functions, and CTC tends to do so as well. But IE tends to produce more welfare than II and CTC as robot capital becomes more substitutable with unskilled labor.

Our simple models omit many policy-relevant considerations. And some key assumptions, for example about the efficacy with which additional education investments will produce labor that is complementary to robots, are worth closer examination. The broad outlines of our main results are likely to be robust, however. The new technology-related skepticism about the trickle-down effects of corporate tax cuts, and the more positive distributional effects of infrastructure and education investment, are driven by the simple underlying forces we model. The general lesson is that more detailed analyses should take the implications of new technologies into account.

The rest of the paper is organized as follows. In section II, we describe the model, including the technology that allows traditional capital, robot capital, high-skill workers and low-skill workers interact flexibly. In section III, we discuss the three policy experiments—i.e., corporate tax cuts, investing in infrastructure, and investing in education. For each experiment, we provide some long-run analysis, including analytical results, and transition analysis. We also present the welfare comparative analysis of these policies. Finally, section IV 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). In order 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.[7] Because open-economy considerations may increase the growth effects of corporate tax cuts, we also introduce an open capital account: agents view the world interest rate as parametric, but we allow aggregate borrowing to influence this rate.[8]

[7]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.

[8]For this argument, see for example the open letter from nine macroeconomists to Treasury Secretary Mnuchin, both in the Wall Street Journal, November 27, 2017.

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

$$f_t = [ew_{l,t}^{1-\sigma_2} + (1-e)r_{z,t}{}^{1-\sigma_2}]^{1/(1-\sigma_2)} \tag{2}$$

and

$$h_t = [gw_{s,t}^{1-\sigma_3} + (1-g)r_{k,t}{}^{1-\sigma_3}]^{1/(1-\sigma_3)} \tag{3}$$

are sub-cost functions dual to the composite inputs $H(\bullet)$ and $V(\bullet)$ whose elasticity of substitution is denoted by σ_1; σ_2 corresponds to the elasticity of substitution between low-skill labor L_t and robots 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 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:

$$K_t = \mathbb{C}_h h_{r_k} \frac{Q_t}{G_{t-1}^{\eta}}, \qquad Z_t = \mathbb{C}_f f_{r_z} \frac{Q_t}{G_{t-1}^{\eta}}, \tag{4}$$

and

$$L_t = \mathbb{C}_f f_{w_l} \frac{Q_t}{G_{t-1}^{\eta}}, \qquad S_t = \mathbb{C}_h h_{w_s} \frac{Q_t}{G_{t-1}^{\eta}}, \tag{5}$$

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. In the case of S_t, there is also an empirical justification for treating supply as exogenous: the share of college-educated workers has changed very little in response to the large increase in the skill premium since 1980 (Autor, 2014; Murphy and Topel, 2016).

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

$$K_{a,t-1} = K_t + Z_t, \tag{6}$$

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 $K_{a,t-1}$.[9]

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

$$1 = \frac{\mathbb{C}(w_{s,t}, r_{k,t}, w_{l,t}, r_{z,t})}{G_{t-1}^{\eta}}. \tag{7}$$

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

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

[9]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.

subject to

$$C_t + I_{a,t} + \Gamma(I_{a,t}, K_{a,t-1}) + (1+i_{t-1})B_{t-1} = w_{s,t}L_{s,t} + T_t + B_t + [r_{z,t}(1-x_t) + \delta x_t]Z_t + [r_{k,t}(1-x_t) + \delta x_t](K_{a,t-1} - Z_t), \quad (8)$$

$$K_{a,t} = I_{a,t} + (1-\delta)K_{a,t-1}, \quad (9)$$

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 (8),

$$\Gamma(I_{a,t}, K_{a,t-1}) = \frac{v}{2}\left(\frac{I_{a,t}}{K_{a,t-1}} - \delta\right)^2 K_{a,t-1}, \quad (10)$$

which captures adjustment costs incurred in changing the aggregate capital stock.

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

$$C_t^{-1/\tau} = \lambda_{1,t}, \quad (11)$$

$$r_{k,t} = r_{z,t} = r_t, \quad (12)$$

$$\lambda_{1,t}\left[1 + v\left(\frac{I_{a,t}}{K_{a,t-1}} - \delta\right)\right] = \lambda_{2,t}, \quad (13)$$

and the co-state equations

$$\lambda_{1,t} = \beta(1+i_t)\lambda_{1,t+1}, \quad (14)$$

and

$$\lambda_{2,t} = \beta\lambda_{2,t+1} + \beta\lambda_{1,t+1}\left[(r_{t+1} - \delta)(1 - x_{t+1}) + \frac{v}{2}\left(\frac{I_{a,t+1}}{K_{a,t}} - \delta\right)^2\right], \quad (15)$$

where $\lambda_{1,t}$ and $\lambda_{2,t}$ are multipliers attached to the constraints (8) and (9). Equations (14)-(15) can be consolidated into two familiar Euler equations. On an optimal path, consumption satisfies

$$\left(\frac{C_{t+1}}{C_t}\right)^{1/\tau} = \beta(1+i_t) \quad (16)$$

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

$$\frac{(r_{t+1} - \delta)(1 - x_{t+1}) + 1 + v\left(\frac{I_{a,t+1}}{K_{a,t}} - \delta\right) + \frac{v}{2}\left(\frac{I_{a,t+1}}{K_{a,t}} - \delta\right)^2}{1 + v\left(\frac{I_{a,t}}{K_{a,t-1}} - \delta\right)} = 1 + i_t. \quad (17)$$

The representative saver views the world market interest rate as parametric when solving the optimization problem defined in (II.B) - (9). 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

$$i_t = \rho e^{\mu\left(\frac{B_t}{B}-1\right)}, \quad \mu > 0, \tag{18}$$

where $\rho = \left(\frac{1-\beta}{\beta}\right)$ and B corresponds to the initial value of B_t—the value at the initial steady state. We vary μ to accommodate different views about the elasticity of capital flows.

C. The Government

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:

$$T_t = x_t(r_t - \delta)K_{a,t-1} - I_{g,t} - I_{s,t}. \tag{19}$$

D. Debt Accumulation and the Current Account Deficit

Substituting for T_t in (8) (and recognizing that $r_{z,t} = r_{k,t} = r_t$) produces the following accounting identity that links debt accumulation (left-hand side) to the current account deficit (right-hand side):

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

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, in turn, 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.

Public investment ($I_{g,t}$, $I_{s,t}$), infrastructure capital (G_t), and the supply of skilled labor will not change until Sections 4 and 5. For the time being, equations (1) - (20) constitute the complete model.

[10] We thus sidestep the controversial direct distributional effects of the recent U.S. tax reform.

III. 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.[11]

A. Corporate Tax Cuts (CTC)

We examine the effects of a corporate tax cut ($dx < 0$), with transfers T_t adjusting continuously according to (19).

The Long-Run Outcome: Analytical Results

Across steady states,

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

and

$$\hat{r} = \mathfrak{n}\frac{dx}{1-x}, \tag{22}$$

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 (22), equations (4) - (5) and (7) can be solved for K, Z, Q, w_l, and w_s as a function of x. Straightforward algebra yields

$$\hat{w}_l = \frac{(\sigma_2 - \sigma_1)\alpha_z\theta_s + (\sigma_1 - \sigma_3)\chi_k\theta_s - \mathfrak{p}(\theta_k + \theta_z)}{\theta_s\mathfrak{m}}\left(\mathfrak{n}\frac{dx}{1-x}\right), \tag{23}$$

$$\hat{w}_s = -\frac{(\sigma_2 - \sigma_1)\alpha_z(1-\theta_s) + (\sigma_1 - \sigma_3)\chi_k\theta_l + \sigma_1(\theta_k + \theta_z)}{\theta_s\mathfrak{m}}\left(\mathfrak{n}\frac{dx}{1-x}\right), \tag{24}$$

[11] The analytical results are derived from differences across steady states. For this long-run analysis, we drop the time sub-index.

$$\hat{K} = -\frac{\sigma_3 \mathfrak{q}}{\theta_s \mathfrak{m}} \left(\mathfrak{n} \frac{dx}{1-x} \right) > 0, \tag{25}$$

$$\hat{Z} = \hat{K} - \frac{(\sigma_2 - \sigma_1)\alpha_l \mathfrak{m} + (\sigma_1 - \sigma_3)\chi_s \mathfrak{q}}{\theta_s \mathfrak{m}} \left(\mathfrak{n} \frac{dx}{1-x} \right) = -\frac{\sigma_2 \mathfrak{p}}{\theta_s \mathfrak{m}} \left(\mathfrak{n} \frac{dx}{1-x} \right) > 0, \tag{26}$$

and

$$\hat{Q} \quad = \theta_k \hat{K} + \theta_z \hat{Z} = -\frac{\theta_k \sigma_3 \mathfrak{q} + \theta_z \sigma_2 \mathfrak{p}}{\theta_s \mathfrak{m}} \left(\mathfrak{n} \frac{dx}{1-x} \right) > 0, \tag{27}$$

where

$$\mathfrak{m} \equiv \mathfrak{q} + \mathfrak{p} \frac{\theta_l}{\theta_s}, \quad \mathfrak{p} \equiv \sigma_3 \chi_k + \sigma_1 \chi_s, \quad \text{and} \quad \mathfrak{q} \equiv \sigma_2 \alpha_z + \sigma_1 \alpha_l \tag{28}$$

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 $\sigma_i = \sigma$, $\forall i$,

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

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

and

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

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 income shares of GDP, $\hat{w}_l - \hat{Q}$ and $\hat{w}_s - \hat{Q}$, rise or fall depending on whether $\sigma \lesseqgtr 1$.[12]

[12]For example, Council of Economic Advisors (2017b) calculate expected long-run wage increases following a corporate tax cut based on the Cobb-Douglas assumption of constant labor shares. Going back to Hall and Jorgenson (1967) and Jorgenson (1963), assessments of the effects of corporate tax cuts often start with a model based on a Cobb-Douglas production function, such that the long-run elasticity of the desired capital stock to the

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 $\sigma_1 > \sigma_3$. (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 ($\sigma_1 > \sigma_3$) 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 (26), 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 (23) and (24), it is possible to deduce that

$$\hat{w}_s > 0 \quad \text{iff} \quad \underbrace{\sigma_1(\theta_k + \chi_k\theta_l) - \sigma_3\chi_k\theta_l}_{\text{Impact of K}\uparrow} + \underbrace{\alpha_z[\sigma_2(\theta_k + \theta_l + \theta_z) - \sigma_1\theta_k]}_{\text{Impact of Z}\uparrow} > 0 \tag{29}$$

and

$$\hat{w}_l > 0 \quad \text{iff} \quad \underbrace{\sigma_3\chi_k\frac{1-\theta_l}{\theta_s}}_{\text{Impact of K}\uparrow} - \underbrace{\alpha_z\left(\sigma_2 - \frac{\sigma_1}{\theta_k+\theta_s}\right)}_{\text{Impact of Z}\uparrow} > 0. \tag{30}$$

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 $\theta_s = 0.40$, as we will discuss below in the calibration, the 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. Less is known about σ_2, but all the evidence points to a number north of two. Robots are currently only 10 percent of the aggregate capital stock, but the import of $\sigma_2 > 2$ and $\hat{Z} >> \hat{K}$ is that they punch far above their weight.[13] 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

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

cost of capital is -1. See also Hassett and Hubbard (2002). Council of Economic Advisors (2017a) argue that all skill levels are likely to benefit equally.

[13] Here we equate robots with information and communication technologies (ICT) capital, as in for example Eden and Gaggl (2018) and Nordhaus (2015), though clearly this is only an approximation to the sorts of new technologies described in the introduction. In particular, industrial robots per se are not included in ICT capital.

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

$$\hat{\omega} = \frac{\theta_s \hat{w}_s + \theta_l \hat{w}_l}{\theta_s + \theta_l} = -\frac{\theta_k + \theta_z}{\theta_s + \theta_l}\left(\mathfrak{n}\frac{dx}{1-x}\right). \tag{31}$$

But

$$\hat{w}_s > \hat{w}_l \quad \text{iff} \quad (\sigma_2 - \sigma_1)\alpha_z > (\sigma_3 - \sigma_1)\chi_k, \tag{32}$$

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

$$(\sigma_2 - \sigma_1)\alpha_z \theta_s + \mathfrak{p}\theta_z(\sigma_2 - 1) + \sigma_3 \theta_k(\mathfrak{q} - 1) > 0, \tag{33}$$

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 (9), (16), (17), 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.[14]

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.[15] The discount factor, the depreciation rate, the intertemporal elasticity of substitution, and the q-elasticity of investment (Ω) all take ordinary values.[16] With respect to the other choices:

- The cost shares (θ_j) and the low- to high-skill wage ratio match the long-run return on stocks and the data on factor shares and the college wage premium in the U.S. The income share for labor, $\theta_l + \theta_s$ equals labor's share in the U.S. in 2013 and the income share for robots implies that $\frac{Z}{Z+K}$ is close to the share of ICT capital in the total capital stock (10.1 percent) reported in Nordhaus (2015). The values of θ_s, θ_l, and $\frac{w_s}{w_l}$ are jointly consistent with the date on the college wage premium and the share of hours worked by college graduates in total labor hours in 2013 in Autor (2014).

[14]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)

[15]The values assigned to I_g, I_s, η, and the depreciation rates for infrastructure and human capital are irrelevant at this point. They will be discussed in subsections B and C of this section.

[16]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 (7) and (II.B). 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 $\Omega \equiv \frac{\hat{I}_a}{\hat{q}}$.

- 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.[17]

- 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.

- 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.[18] We put more faith in the lower, micro-based estimates, but generate solutions for $\sigma_1 = 1$ as well.

- The empirical estimates in Griliches (1969), Fallon and Layard (1975), Hamermesh (1993), Krusell and others (2000), and Raval (2011) suggest that σ_3 is 20 - 60 percent smaller than σ_1. Accordingly, the runs assume either $\sigma_3 = \sigma_1$ or $\sigma_3 = 0.5\sigma_1$.

- To date, there are no econometric estimates of σ_2, the most important parameter in the model. Technology experts concur that substitution between robots 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 $\sigma_2 = 2.13$. The estimates in Acemoglu and Restrepo (2019b) also provide some guidance. Their finding that one

[17]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.

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

> robot directly eliminates 10.6 jobs suggests that σ_2 might be quite large.[19] We are reluctant, however, to pin too much on one estimate and a couple of calibration exercises. Reflecting our fuzzy priors and the probability that robots will keep getting smarter, the runs let σ_2 vary between 1.5 and 5.[20]

Table 2 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).[21]

Adding 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. In the runs with lower σ_1 and σ_3 (bottom panel of Table 2), skilled labor scarcity exerts a more powerful effect, such that output grows by less than when $\sigma_2 = 1$, accumulation of Z and especially K is reduced, and the skilled wage premium grows by even more.[22]

The labor share (θ) falls with higher σ_2 in Table 2, less so when low values of σ_3 drive higher gains for skilled workers. The fall in all cases is accounted for by the fall in the share of low-skilled workers (θ_L).

Figure 1 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

[19] 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.

[20] 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.)

[21] 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.

[22] When $\sigma_3 = 0.25$ and $\sigma_1 = 0.5$, pay cuts replace pay raises starting at $\sigma_2 = 2$.

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. Investing in Infrastructure (II)

In this section we examine the implications of the rise of the robots for the impact of investing in infrastructure (II) and compare its effects to those of the corporate tax cut (CTC). We implement public capital as a shift factor in the production function function, so that increases in G_{t-1} act like a positive TFP shock (viz equation 1). The law of motion for infrastructure capital is

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

$I_{g,t}$ (a policy variable) jumps once at $t = 1$. 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 previously offset the loss in corporate tax revenue at $t = 1$ now finances an increase in $I_{g,t}$, viz.:

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

then

$$\hat{I}_g = -\frac{\theta_k + \theta_z}{\xi_g}\left(\mathfrak{n}\, dx|_{t=1}\right), \tag{34}$$

where $\theta_k + \theta_z = \frac{rK_a}{Q}$ and $\xi_g \equiv \frac{I_g}{Q}$.[23]

We derive next some analytical results for the long run. To benchmark some of these results, as well as for the numerical transition analysis, we choose values for the initial ratio of infrastructure investment to GDP, ξ_g, and the infrastructure depreciation rate, δ_g. According to the Congressional Budget Office (2017), the figure for that ratio is 2.4 percent 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. The depreciation rate of public capital is set at 4 percent ($\delta_g = 0.04$), which is in line with the values used by the International Monetary Fund (2015) to calculate public capital stocks for high-income countries, in the recent years. Table 1 provides values for the rest of parameters.

[23]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.

The Long-Run Outcome: Analytical Results

Across steady states, equations (4) - (5) and (7) give

$$\hat{\omega} = \frac{1}{\theta_s + \theta_l}\left(\eta \hat{G}\right) > 0, \tag{35}$$

$$\hat{w}_l = \frac{\mathfrak{p}}{\theta_s \mathfrak{m}}\left(\eta \hat{G}\right) > 0, \qquad \hat{w}_s = \frac{\mathfrak{q}}{\theta_s \mathfrak{m}}\left(\eta \hat{G}\right) > 0, \tag{36}$$

$$\hat{K} = \frac{\sigma_3 \mathfrak{q}}{\theta_s \mathfrak{m}}\left(\eta \hat{G}\right) > 0, \qquad \hat{Z} = \frac{\sigma_2 \mathfrak{p}}{\theta_s \mathfrak{m}}\left(\eta \hat{G}\right) > 0, \tag{37}$$

and

$$\hat{Q} = \left(\frac{\theta_k \sigma_3 \mathfrak{q} + \theta_z \sigma_2 \mathfrak{p}}{\theta_s \mathfrak{m}} + 1\right)\left(\eta \hat{G}\right) > 0, \tag{38}$$

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 $\mathfrak{q} \equiv \sigma_2 \alpha_z + \sigma_1 \alpha_l$, satisfying $\mathfrak{m} > 0$, $\mathfrak{p} > 0$, and $\mathfrak{q} > 0$.

Clearly, from the solutions in (35) and (36), II always increases the average real wage and the real wages for low- and high-skill workers. This contrasts with the results of CTC, where some conditions associated with the elasticities of substitution and cost shares—see conditions in (29) and (30)—need to be satisfied to ensure real wages increase. In fact, recall that real wages of low-skill workers could even decline.

The extent to which II increases real wages—as well as capital, robots, and output—by more than CTC depends on the net rate of return on infrastructure R_g. In this regard, it is helpful to rewrite the solutions in (35) - (38) in terms of that rate of return. To do this, note that the marginal product of public capital satisfies

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

implying that

$$\eta = \frac{R_g + \delta_g}{\delta_g} \xi_g. \tag{39}$$

And since $\hat{G} = \hat{I}_g$ in the long run, from (34),

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

After substituting for $\eta \hat{G}$, the solutions in (35) - (38) are then expressed in terms of R_g and can be directly compared to their counterparts in (23) - (27) and (31).

Focus first on real wages. From (31) and (35),

$$\hat{\omega}|_{\text{II}} > \hat{\omega}|_{\text{CTC}} \quad \text{iff} \quad R_g > R_g^{\diamond} = \left(\frac{x}{1-x}\right)\delta_g. \tag{40}$$

Comparing the solutions for w_l produces

$$\hat{w}_l|_{\text{II}} > \hat{w}_l|_{\text{CTC}} \quad \text{iff} \quad R_g > R_g^{+} = \left\{1 - \frac{\theta_s\left[(\sigma_2-\sigma_1)\alpha_z - (\sigma_3-\sigma_1)\chi_k\right]}{\mathfrak{p}x\left(\theta_k+\theta_z\right)}\right\}\left(\frac{x}{1-x}\right)\delta_g, \tag{41}$$

where $\mathfrak{p} \equiv \sigma_3\chi_k + \sigma_1\chi_s > 0$. Assuming $(\sigma_2-\sigma_1)\alpha_z > (\sigma_3-\sigma_1)\chi_k$, the condition in (40) suffices for II to increase the low-skill wage more than the CTC.[24] In this case, $R_g > R_g^{\diamond} > R_g^{+}$.

On the other hand, comparing the solutions for w_s yields the following condition that ensures a bigger increase in w_s:

$$\hat{w}_s|_{\text{II}} > \hat{w}_s|_{\text{CTC}} \quad \text{iff} \quad R_g > R_g^{\#} = \left[1 + \frac{\theta_l}{x\left(\theta_k+\theta_z\right)}\left(1 - \frac{\mathfrak{p}}{\mathfrak{q}}\right)\right]\left(\frac{x}{1-x}\right)\delta_g. \tag{42}$$

where $\mathfrak{q} \equiv \sigma_2\alpha_z + \sigma_1\alpha_l > 0$.

This comparison of the relative increases of real wages provides important takeaways. The first one is that 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 (40), when $x = 0.40$, as calibrated before, and $\delta_g = 0.04$. The condition in (41) follows, as above, and the condition in (42), although more involved, also requires low returns on infrastructure to be satisfied. 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. And the more so for larger values of σ_2, the elasticity of substitution between low-skill labor and robots. 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, under investing in infrastructure we find that

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

[24] As discussed above, σ_2 is assumed greater than σ_1, while the evidence suggests that $\sigma_3 < \sigma_1$.

The second takeaway is that in the robot economy, it is more likely that the increase in wage inequality due to CTC is greater than that due to II. This is because robots make it more likely that II will increase low-skill labor wages more than CTC, in that the condition in (41) is weaker the larger is σ_2—since $\frac{\partial R_g^+}{\partial \sigma_2} < 0$. In contrast, the condition in (42) for high-skill labor wages to increase more with II than CTC becomes more stringent as σ_2 increases—since $\frac{\partial R_g^\#}{\partial \sigma_2} > 0$.

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, 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 (25), (26) and (37) yields

$$\hat{K}\big|_{\text{II}} > \hat{K}\big|_{\text{CTC}} \quad \text{and} \quad \hat{Z}\big|_{\text{II}} > \hat{Z}\big|_{\text{CTC}} \quad \text{iff} \quad R_g > R_g^* = \left[\frac{1}{(1-x)(\theta_k+\theta_z)} - 1\right]\delta_g. \tag{43}$$

The condition in (43) is a close call in the case of the U.S. For $\theta_K + \theta_z = 0.40$, $x = 0.40$—following Table 1—, and $\delta_g = 0.04$, the threshold R_g^* is about 12.7 percent, a value slightly above the pre-tax return on private capital (10 percent). A return of almost 13 percent is certainly a nice return. But if the estimates in the literature can be trusted, returns this high are not unusual.[25] The presumption that CTC 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 (27) and (38),

$$\hat{Q}\big|_{\text{II}} > \hat{Q}\big|_{\text{CTC}} \quad \text{iff} \quad R_g > R_g^{\&} = \left[\frac{\sigma_3\theta_k\mathfrak{q} + \sigma_2\theta_z\mathfrak{p}}{\mathfrak{u}(1-x)(\theta_k+\theta_z)} - 1\right]\delta_g, \tag{44}$$

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 (44) 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. Therefore, II is better at increasing growth than CTC as long as infrastructure capital pays a small positive return.

[25] In their comprehensive survey, Bom and Ligthart (2014) find the average rate of return on core capital to be in the range of 17 to 19 percent.

What difference does the introduction of robots make to investment and growth? Robots matter equally for the impact of both CTC and II on investment, as can be seen from the absence of σ_2 in (43). The implications for growth, on the other hand, are not clear, given that the effect of higher values of σ_2 on the condition in (44) is ambiguous. We will investigate this in the numerical analysis.

The Long-Run and Transition Outcomes: Numerical Results

Tables 3 and 4 collect numerical results for the long run. In these tables, the fiscally-equivalent increase in II equals 1.5 percent of initial GDP, and the calibration follows Table 1 as in the analysis of CTC. As explained before, the initial investment in infrastructure is assumed to be 4 percent of GDP, and the depreciation rate of public capital is set at 4 percent. In Table 3, infrastructure pays a return of 10 percent, the same as the pre-tax return on private capital. The return in Table 4 is 15 percent, at the low end of the returns for core capital in Bom and Ligthart (2014).[26]

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 3 and 4). 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 3 and 4 concerns *how much* bigger the numbers are compared to those for the CTC in Table 2. When R_g equals 15 percent (Table 4), 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 (43). 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 3 and 4, so the increases in the capital stock in Table 2 are bigger than in Table 3 but smaller than in Table 4.

Robots amplify the greater wage inequality-inducing effects of CTC relative to II (Table 5). As σ_2 increases, the 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

[26]To match these rates of return, the elasticity η is adjusted according to equation (39), and given ξ_g and δ_g.

corresponding values in the Cobb-Douglas economy ($\sigma_i = 1, \forall i$) are 10.6 and 4.0 percentage points.[27] 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.[28]

Figure 2 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 2. 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.

The elasticity of the interest rate to capital flows μ also plays a 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. Investing in Education (IE)

Public investment in higher education I_s increases the supply of education capital S_u, according to the stock accumulation equation:

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

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

[28] 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.

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:

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

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

As in the II analysis, we first derive some analytical results for the long run. To benchmark some of these results, as well as for the numerical transition analysis, we calibrate the initial ratio of education investment to GDP, $\xi_s \equiv \frac{I_s}{Q}$, and the depreciation rate, δ_s. This ratio is set at 1.3 percent, the value in the U.S. in 2017, and the depreciation rate at 3 percent. Three percent is a common choice for δ_s 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). For the rest of parameters, we use the values listed in Table 1.

The Long-Run Outcome: Analytical Results

Solve the steady-state versions of equations (4) - (5) and (7) yet again, this time with S varying exogenously. Naturally, w_l rises and w_s falls

$$\hat{w}_l = \frac{\theta_l + \theta_s \psi}{\theta_l \mathfrak{m}} \left(\hat{S}\right) > 0 \quad \text{and} \quad \hat{w}_s = -\frac{\theta_l + \theta_s \psi}{\theta_s \mathfrak{m}} \left(\hat{S}\right) < 0, \tag{45}$$

where $\psi = \frac{w_l}{w_s} < 1$ and recall that $\mathfrak{m} \equiv \mathfrak{q} + \mathfrak{p}\frac{\theta_l}{\theta_s} > 0$, $\mathfrak{p} \equiv \sigma_3 \chi_k + \sigma_1 \chi_s > 0$, 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:[29]

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

The solutions for the capital stocks and GDP are

$$\hat{K} = \frac{\sigma_1(\theta_l \chi_s + \theta_s) + (\sigma_2 - \sigma_1)\theta_s \alpha_z - \sigma_3(\theta_l \chi_s + \theta_s \psi)}{\theta_s \mathfrak{m}} \left(\hat{S}\right), \tag{46}$$

$$\hat{Z} = \frac{\sigma_2 \theta_l + (\sigma_2 - \sigma_1)\psi \alpha_l \theta_s - \psi \theta_l \mathfrak{p}}{\theta_l \mathfrak{m}} \left(\hat{S}\right), \tag{47}$$

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

and

$$\hat{Q} = \frac{\mathfrak{q} - \psi\mathfrak{p}}{\mathfrak{m}} \left(\hat{S}\right). \tag{48}$$

We follow the same game plan as in the analysis of II. That is, we re-express the solutions in (45) - (48) in terms of fiscally-equivalent increases in investing in education (IE) and compare them with the CTC solutions in (23) - (27). When comparing these solutions, we will derive conditions that depend on the rate of return to investment in education R_s, the elasticities of substitution, and the factor cost shares.

Analogous to (34) the fiscally-equivalent increase in I_s is

$$\hat{I}_s = -\frac{\theta_k + \theta_z}{\xi_s} \left(\mathfrak{n}dx\right), \tag{49}$$

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 (49) yields

$$\hat{S} = -\left(\phi \frac{S_u}{S}\right) \frac{\theta_k + \theta_z}{\xi_s} \left(\mathfrak{n}dx\right). \tag{50}$$

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

$$R_s + \delta_s = (1-\psi)\theta_s \frac{\delta_s}{\xi_s} \left(\phi \frac{S_u}{S}\right). \tag{51}$$

Using this expression and (50) gives

$$\hat{S} = -\left[\frac{\theta_k + \theta_z}{(1-\psi)\theta_s}\right] \frac{R_s + \delta_s}{\delta_s} \left(\mathfrak{n}dx\right). \tag{52}$$

Substituting for $\hat{S}$ in (45) and (47) - (48) and comparing the solutions to those for the CTC yields the following conditions for wages:[30]

$$\hat{\omega}|_{\text{IE}} > \hat{\omega}|_{\text{CTC}} \quad \text{iff} \quad R_s > R_s^{\diamond} = \left(\frac{x}{1-x}\right)\delta_s \tag{53}$$

and

$$\hat{w}_l|_{\text{IE}} > \hat{w}_l|_{\text{CTC}} \quad \text{if} \quad (i)\ (\sigma_2-\sigma_1)\alpha_z > (\sigma_3-\sigma_1)\chi_k \text{ and } (ii)\ R_s > R_s^{+} = \left[\tfrac{\theta_l \mathfrak{p}(1-\psi)}{(1-x)(\theta_l+\theta_s\psi)} - 1\right]\delta_s, \tag{54}$$

for capital and robots

$$\hat{K}\big|_{\text{IE}} > \hat{K}\big|_{\text{CTC}} \quad \text{if} \quad (i)\ \sigma_1 \geq \sigma_3 \text{ and } (ii)\ R_s > R_s^{*} = \left[\frac{\sigma_3}{(1-x)(\theta_k+\theta_z)} - 1\right]\delta_s \tag{55}$$

and

$$\hat{Z}\big|_{\text{IE}} > \hat{Z}\big|_{\text{CTC}} \quad \text{if} \quad (i)\ \sigma_2 > \sigma_1\left[1+\tfrac{\theta_l+\theta_z}{\theta_s}\left(\tfrac{\mathfrak{p}}{\sigma_1}\right)\right] \text{ and } (ii)\ R_s > R_s^{'} = \left[\tfrac{\mathfrak{p}(1-\psi)}{(1-x)(\theta_k+\theta_z)} - 1\right]\delta_s, \tag{56}$$

and for output

$$\hat{Q}\big|_{\text{IE}} > \hat{Q}\big|_{\text{CTC}} \quad \text{iff} \quad R_s > R_s^{\&} = \left[\frac{(\theta_k\sigma_3\mathfrak{q}+\theta_z\sigma_2\mathfrak{p})(1-\psi)}{(1-x)\,(\mathfrak{q}-\psi\mathfrak{p})\,(\theta_k+\theta_z)} - 1\right]\delta_s, \tag{57}$$

where, to repeat, $\mathfrak{p} \equiv \sigma_3\chi_k + \sigma_1\chi_s > 0$ and $\mathfrak{q} \equiv \sigma_2\alpha_z + \sigma_1\alpha_l > 0$.

All of the conditions in (53)-(55) are weak for empirically plausible values of σ_1, σ_2, σ_3, and the factor cost shares. To see this, consider the calibration in Table 1, including the *ranges* of the elasticities of substitution—satisfying $\sigma_2 > \sigma_1$, and $\sigma_1 \geq \sigma_3$—, the initial tax rate ($x_{old} = 0.40$), and the inverse of the skill premium $\left(\psi = \frac{w_l}{w_s}\right)$. For $\delta s = 0.03$, the conditions (i) in (53) and (54) are satisfied, while the maximum values for the thresholds $R_s^{\diamond}$, R_s^{+}, and R_s^{*} correspond to 2, -1.8 and 9.5 percent, respectively. [31]This hints that returns on investing in education do not have to be exorbitant to be above these thresholds. We then may safely conclude that IE increases the low-skill wage, the average wage, and the private capital stock more than CTC.

Although there is a strong presumption that IE increases robot capital more than the comparable CTC, this result is not guaranteed. Condition (ii) in (56) is virtually certain to hold—for the discussed calibration, the maximum value of the threshold $R_s^{'}$ is 3.3 percent. Condition (i), however, 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.

[30]Note that we do not state a condition for $\hat{w}_s$. From (45), we know that $\hat{w}_s < 0$, *always*, under IE; while from (29) we learned that CTC can induce $\hat{w}_s > 0$. That is, CTC is more likely to increase high-skill wages more than IE.

[31]In the calculation of the thresholds $R_s^{\diamond}$, R_s^{+}, R_s^{*}, $R_s^{'}$, and $R_s^{\&}$, we do not consider the combinations $\sigma_2 = 1.5$ and $\sigma_1 = \sigma_3 = 0.5$, and $\sigma_1 = 0.5$ and $\sigma_3 = 0.25$ for any σ_2, since they imply $w_s < w_l$ across steady states, for IE.

Clearly this requirement is not satisfied if $\sigma_2 = 1.5$ and $\sigma_1 = 1$, one of the parametrizations of Table 1.

The condition in (57), which serves to rank the impact on GDP, is more complicated and harder to evaluate. Once more, if we consider the values for the cost shares and the elasticities of substitution—satisfying $\sigma_2 > \sigma_1$, and $\sigma_1 \geq \sigma_3$—from Table 1 and $\delta s = 0.03$, we find that the maximum value of the return threshold $R_s^{\&}$ is about 1.8 percent. Given this, it seems very likely that IE will have a bigger positive impact on GDP than CTC.

As expected, IE also reduces wage inequality relative to CTC. We know that if the condition in (32) holds, then $\hat{w}_s > \hat{w}_l$, which means that CTC increases wage inequality. For IE, in contrast, the results in (45) imply that $\hat{w}_l > \hat{w}_s$, regardless of the structural parameters values. Hence, IE decreases wage inequality.

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 (54) and (56), 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 (45). Regarding the average wage ($\hat{\omega}$) and traditional capital ($\hat{K}$), the relative ranking is not affected by a higher σ_2, since the conditions in (53) and (55) 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 (57) is less clear. But it is possible to prove that

$$\frac{\partial R_s^{\diamond}}{\partial \sigma_2} < 0 \quad \text{iff} \quad \sigma_3 > \left[\frac{\theta_l(\theta_k + \theta_s) - \psi\theta_s(\theta_l + \theta_z)}{\psi\theta_k}\right]\sigma_1, \tag{58}$$

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 (58) 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 make 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

We calculated the long-run impact of an increase in investment on education of 1.5 percent of GDP, which is fiscally-equivalent to the change in transfers associated with CTC. As explained before, we set the initial ratio of this investment to GDP equal to 1.3 percent $\left(\frac{I_s}{Q} = 0.013\right)$ and the depreciation rate at 3 percent ($\delta_s = 0.3$). For the rate of return on education, we pick a value of 7 percent ($R_s = 0.07$), following Gennaioli and others (2011).[32] The rest of parameters values are the same as those used under the CTC experiment, which are listed in Table 1.

Table 6 reports the results, while again Table 5 facilitates easy comparison between the IE and CTC policy experiments. 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 6).

Easy substitution between robots 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 (MPZ) schedule is very flat. In general equilibrium, therefore, IE creates 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 6). 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

[32] To match this rate of return, the parameter ϕ is adjusted according to equation (51).

decrease in low-skill labor services. As a result, the numbers for K and $K+Z$ are much greater in Table 6 than in Tables 2, 3, and 4, 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 6 is 14.5 percent vs. 9.3 percent in Table 4.

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).[33]

Figure 3 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 robot 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 literature 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.[34]

[33]When calculating the average increase in Table 4, we exclude the runs where NA appears in Table 6.

[34]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.

IV. 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.

Ranking the alternative investment programs requires policymakers to specify values for the social discount factor (β_{sp}) and the weight (s) attached to distributional objectives. For now, we put distributional concerns to one side. The social welfare function is simply

$$SW = \sum_{t=0}^{\infty} \beta_{sp}^{t} \frac{{c_t}^{1-1/\tau}}{1-1/\tau}, \tag{59}$$

where $c \equiv C + w_t L_t$ 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, $\beta_s = .965$ - $.98$.

Although theory cannot tell us whether 0.97 is a sensible number for β_s, it does provide cogent arguments for $\beta_s > \beta$. In Sen's (1967) 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, 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 4 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 - .99). The CTC reduces revenue by one percent of GDP at $t = 0$.[35]

Some of the pairwise welfare rankings in Figure 4 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 2 and 3.

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.

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 5 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 ($\beta_{sp} = 0.97$).

[35] Postulating a smaller tax cut than in Section III 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 6 disappears when the tax cut and the fiscally-equivalent increase in IE are smaller.)

Robots clearly matter. 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

$$SW = \sum_{t=0}^{\infty} \beta_s^t \frac{(c_t + \zeta w_t L_o)^{1-1/\tau}}{1-1/\tau}, \quad \zeta > 0, \tag{60}$$

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 (60) 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 (60) misses the large consumption gain of this group, the welfare ranking, taken on its own terms, is biased against IE.

We start in Figure 6 by repeating the runs in Figures 4 and 5 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.

Our first result is that, for the benchmark economy, the welfare rankings change dramatically when real income of the poor enters the social welfare function with even a *small* weight. In Figure 6, 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 $\beta_{sp} = 0.97$.[36]

The difference robots make also itself depends on the weight attached to distributional concerns (Figures 7 for the Cobb-Douglas economy and 8 for the CES case). First, the impact of higher values of σ_2 on the welfare gain for II, CTC, and especially IET changes from positive to negative as ζ rises from 0 to 0.25 to 0.50. This reflects the fact that higher values of σ_2 are good for private capital accumulation and growth but bad for real wages of the poor. Thus, for all three policies, even a small amount of concern for distributional implies that the welfare welfare gains are lower in the robot economy. While the large impact on IE visually dominates the figures, the effects on the other policies are themselves significant. The welfare gain from CTC, for example, is 17.6 percent lower when $\sigma_2 = 5$ than when $\sigma_2 = 1$, in the Cobb-Douglas economy with $\beta_{sp} = 0.943$ and $\zeta = 0.50$ (Figure 7).

The trade-off is much more acute for IE: when $\zeta = 0$ policymakers do not care particularly about the poor and the strong positive impact of σ_2 on the private capital stock ensures a strong positive relationship between σ_2 and social welfare. For $\zeta > 0$, however, higher values of σ_2 have two effects going in different directions: the higher private capital stock and GDP still increases social welfare, but the adverse distributional consequences of sharper declines in the low-skill wage reduce it. At $\zeta = 0.50$, the smaller-gains-for-the-poor effect is far stronger and high values of σ_2 significantly reduce the welfare gain from IE relative to II and the CTC. With these effects, IE still dominates the CTC and still claims first place in six of the eight runs, settling for a tie with II or second place only when $\zeta = 0.25$ in the Cobb-Douglas economy (Figure 7).

V. Conclusion

A new wave of AI-based automation seems to be underway. Much has been made of the potential growth and distributional implications of a new wave of AI-based automation. A common though not universal conclusion is that such an innovation is likely to be good for incomes, at least in the long run, but unevenly, with capital owners and skilled workers likely to benefit more. And the transition, which may take decades, is may well be very tough, particularly for unskilled workers.

Less appreciated is the fact that this wave of automation may change the way the economy reacts to policies. Here, we implement the minimal necessary modifications to a standard neoclassical growth model calibrated to the U.S.: we introduce a second type of capital, "robots", which are close substitutes for a large part of the labor force. And we introduce two types

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

of agents—low-skilled hand-to-mouth workers and high-skilled savers—to address parsimoniously the fundamental distributional issues of the labor share and wage inequality.

We then examine the implications of three policies: corporate tax cuts (CTC), increases in public investment in infrastructure (II), and increases in public investment in education (IE). These three policies nicely explore the underlying dynamics of technological change in our model, with CTC promoting both traditional and robot capital, II acting as a productivity shifter for the entire production function, and IE shifting labor from unskilled to skilled.

The introduction of robots can indeed make a big difference to how policies work. In the case of cuts in corporate income taxes, such as those in a stylized version of the corporate tax cut enacted in the U.S. in 2019, we show that standard models readily deliver the sorts of 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.[37]

If, instead, we assume that robot capital is highly substitutable with low-wage workers, and skilled labor and traditional capital are reasonably close substitutes ($\sigma_3 = 1$), 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 substitute for unskilled labor to allow more capital deepening before fixed labor supplies drive the marginal product of capital down, while this same feature keeps unskilled wages from rising as much or, in some cases, at all. II follows similar patterns: unskilled labor wages rise less and skilled labor wages more for higher values of σ_2. For both CTC and II, the labor share falls as σ_2 increases.

Now comparing II and CTC, labor across the skill spectrum benefits more from II than CTC. Capital grows more with II under our baseline calibration with the rate of return to infrastructure of 15 percent. Even if we assume a return of 10 percent, and as a result capital grows less with II than CTC, GDP growth is still higher than with CTC. The larger increase in unskilled labor wages with II relative to CTC becomes more salient at higher values of σ_2, because with the CTC unskilled labor wages may even fall in real terms, while they rise substantially in all runs with II.

Starker implications of new technologies, and bigger contrasts with CTC, emerge for IE. Wage inequality is lower, and GDP growth higher, with IE, dramatically so with higher values of σ_2. Not surprisingly, IE that increases the supply of skilled labor and reduced the supply of unskilled labor powerfully increases unskilled and reduces skilled labor wages, an effect that is attenuated, but by no means eliminated, at higher values of σ_2. IE gives an especially strong boost to accumulation of robot capital. This results from the large increase in unskilled labor wages, and the decrease in complementary skilled labor wages. Growth of traditional capital

[37] As explained in the main text, we abstract from many important factors in the particular case of the U.S. corporate tax cuts of 2019 to focus on the basics.

is lower with IE with Cobb-Douglas technology. With high enough values of σ_2, however, the increase in complementary skilled labor and robots outweighs the direct effect of lower corporate tax rates, and even traditional capital grows more with IE than with CTC. Despite the increase in the low-skilled wage and the income share going to (current and previously) low-skilled workers , the large growth in capital implies a fall in the total labor share, the more so with higher values of σ_2.

The welfare ranking across policies depends on the values that policymakers assign to the social discount factor and the weight on distributional objectives. Overall, for plausible calibrations, II dominates CTC, the more so the less the future is discounted in the social welfare function. IE tends to produce the highest welfare gains of all, especially when the elasticity of substitution between traditional capital and labor is low, there are explicit distributional objectives, and the discount factor is high.

These welfare rankings depend on σ_2. Absent explicit distributional objectives, the key driver of relative welfare effects is that IE benefits strongly, and CIT and IT weakly, from highly substitutable robot capital.Thus II delivers more welfare that IE in traditional production functions, and CTC tends to do so as well. But once robot capital becomes highly substitutable with unskilled labor, IE tends to produce more welfare than II and CTC.

A simple comparison of partial-equilibrium rates of returns across investments would give the wrong welfare rankings, because general equilibrium effects are important and vary with the policy and with σ_2. Perhaps the most important such effect is the especially positive effect of higher education expenditures on traditional and especially robot capital accumulation.

With respect to our specific policy conclusions, caveats are in order. There are of course many factors relevant to these policy questions that our simple models do not capture. And some key assumptions, for example about the efficacy with which additional education investments will produce labor that is complementary to robots, are worth closer examination.[38]

The broad outlines of our main results are likely to be robust, however. The new technology-related skepticism about the trickle-down effects of corporate tax cuts, and the more positive effects of infrastructure and education investment, are driven by the simple underlying forces we model.

This same simplicity leaves a large research agenda. Further work to estimate the key parameters, particularly σ_2 would be very useful. 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 the increasing automation. Empirical analyses based on historical data are likely to mislead.

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

General equilibrium effects are first-order, but traditional production functions give the wrong answer.

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VI. Tables and Figures

Table 1. Base Case Calibration

Parameter	Value	Definition
β	0.94	Discount factor
δ	0.06	Depreciation of 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	Robot'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, 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

Notes: See the calibration discussion in the main text.

Here is a version of Table 5 (comparing the different approaches) for CES too (Table 5 does CD).

Table 2. 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

percent 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
	$\sigma_1 = 0.5, \sigma_3 = 0.25$								
σ_2	w_l	w_s	ω	GDP	K	Z	$K+Z$	θ	θ_L
1.5	0.6	5.5	3.9	1.4	2.8	10.1	3.6	61.5	19.8
3	−0.9	6.3	3.9	1.7	3.0	15.9	4.3	61.3	19.5
5	−2.1	6.9	3.9	1.9	3.2	20.3	4.9	61.2	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 3. 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

Robot 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
	$\sigma_1 = 0.5, \sigma_3 = 0.25$								
σ_2	w_l	w_s	ω	GDP	K	Z	$K+Z$	θ	θ_L
1.5	5.0	8.9	7.6	5.7	2.2	7.7	2.7	61.1	19.9
3	3.8	9.6	7.6	5.9	2.3	12.0	3.3	61.0	19.6
5	2.9	10.0	7.7	6.1	2.4	15.3	3.7	60.9	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 2. 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 4. 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

Robot Production Functions:

σ_2	$\sigma_1 = \sigma_3 = 0.5$								
	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

σ_2	$\sigma_1 = \sigma_3 = 1$								
	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

σ_2	$\sigma_1 = 1, \sigma_3 = 0.5$								
	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

σ_2	$\sigma_1 = 0.5, \sigma_3 = 0.25$								
	w_l	w_s	ω	GDP	K	Z	$K+Z$	θ	θ_L
1.5	6.9	12.3	10.5	7.8	2.9	10.5	3.7	61.5	19.8
3	5.2	13.1	10.5	8.1	3.1	16.4	4.5	61.3	19.5
5	3.9	13.8	10.5	8.3	3.3	21.1	5.1	61.2	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 2. 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 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 2. 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 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

Robot Production Functions:

	$\sigma_1 = \sigma_3 = 0.5$								
σ_2	w_l	w_s	ω	GDP	K	Z	$K+Z$		
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	$K+Z$		
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	$K+Z$		
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

	$\sigma_1 = 0.5, \sigma_3 = 0.25$								
σ_2	w_l	w_s	ω	GDP	K	Z	$K+Z$		
1.5					NA				
3					NA				
5	31.6	−12.5	5.8	18.9	20.9	195.7	38.4	53.4	24.0

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 2. 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.

Table 7. Long-run impact of CTC vs II vs IE for different values of σ_2
(σ_1 = σ_3 = .5)

Corporate Tax Cut									
σ_2	w_l	w_s	ω	GDP	K	Z	$K+Z$	θ	θ_L
.5	3.9	3.9	3.9	1.9	4.9	4.9	4.9	61.2	20.4
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
Infrastructure Investment (R_g = 0.10)									
σ_2	w_l	w_s	ω	GDP	K	Z	$K+Z$	θ	θ_L
.5	7.7	7.7	7.7	6.1	3.8	3.8	3.8	60.9	20.3
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
Infrastructure Investment (R_g = 0.15)									
σ_2	w_l	w_s	ω	GDP	K	Z	$K+Z$	θ	θ_L
.5	10.5	10.5	10.5	8.3	5.1	5.1	5.1	61.2	20.4
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
Education Investment ($R_s = 0.07$)									
σ_2	w_l	w_s	ω	GDP	K	Z	$K+Z$	θ	θ_L
.5					NA				
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

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

(σ_2 =3; σ_1 = σ_3 = 0.5)

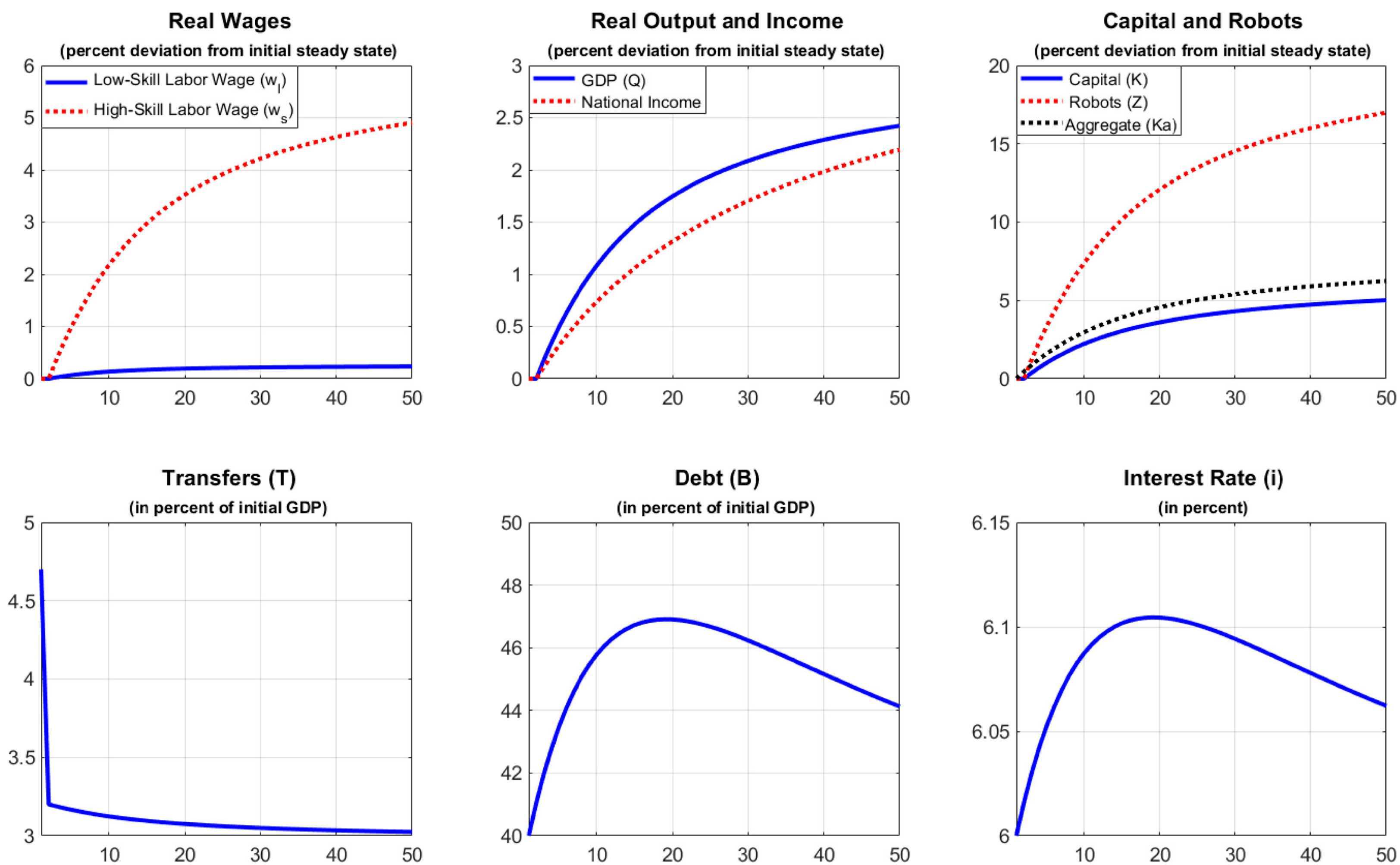

Figure 2. Corporate tax cut vs. a fiscally-equivalent increase in infrastructure investment

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

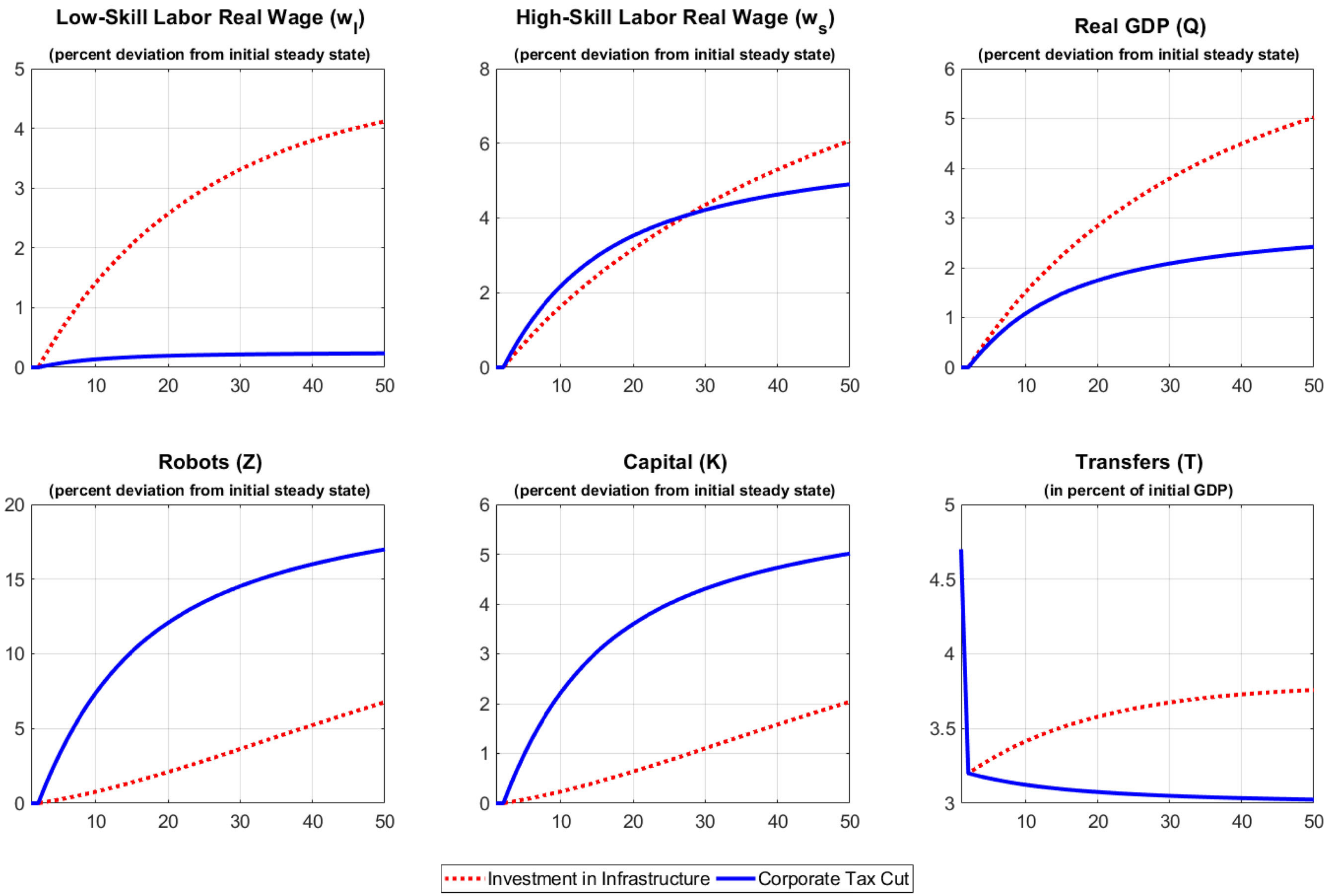

Figure 3. Corporate tax cut vs. a fiscally-equivalent increase in investment in education

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

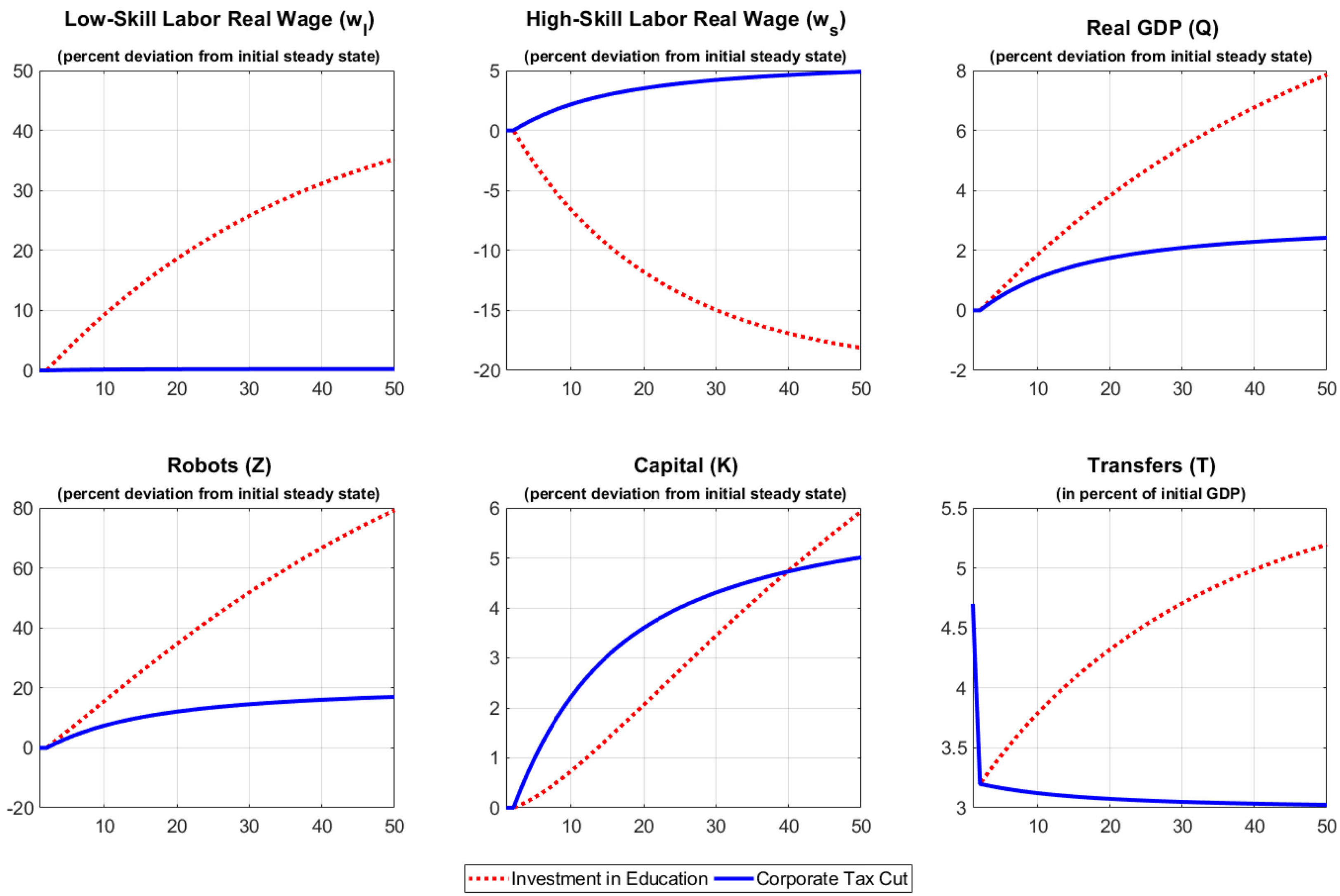

Figure 4. Welfare gains across policies:
The role of the social discount factor (β_{sp})

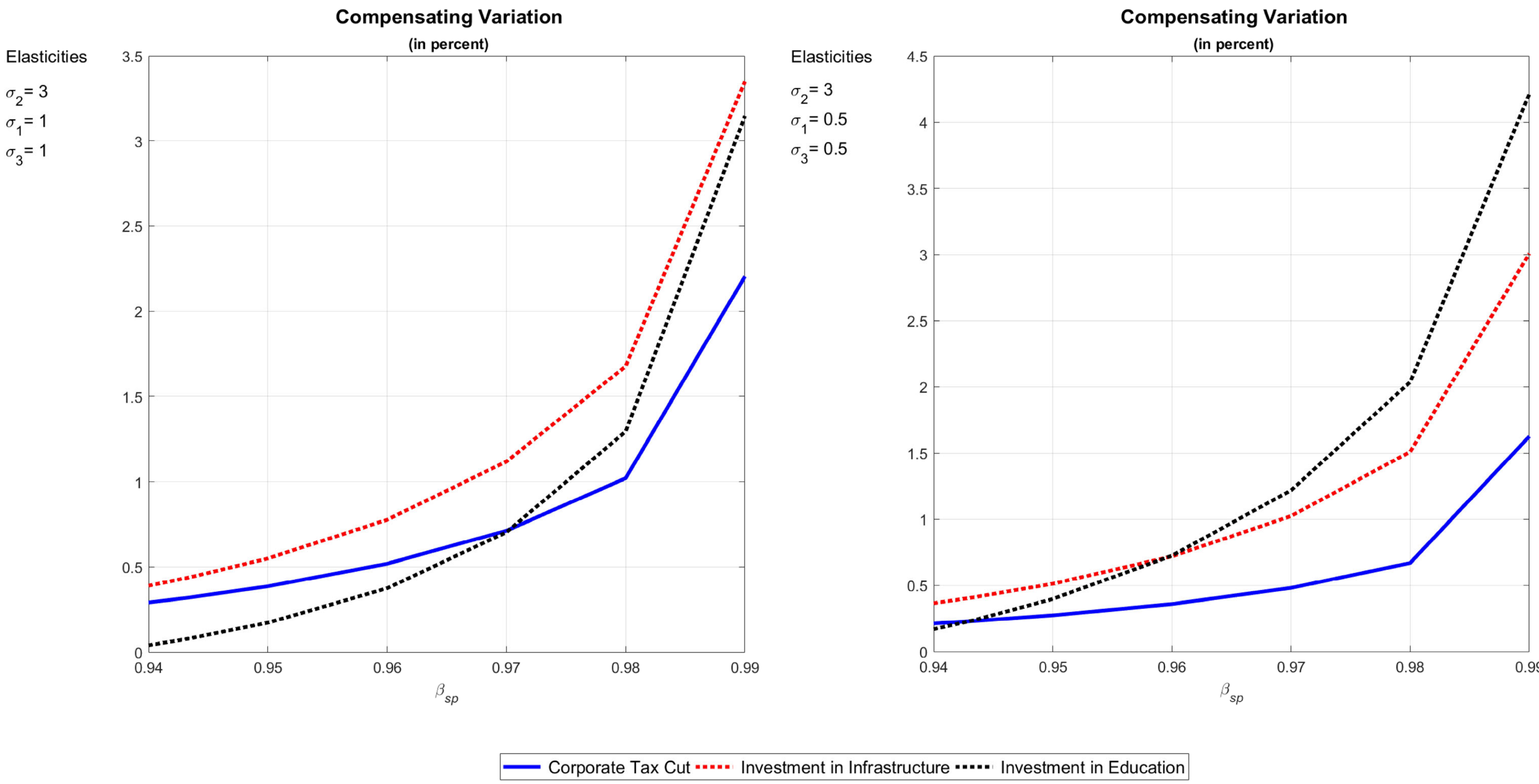

Figure 5. Welfare gains across policies:
The role of the elasticity of substitution between robots and low-skill labor (σ_2)

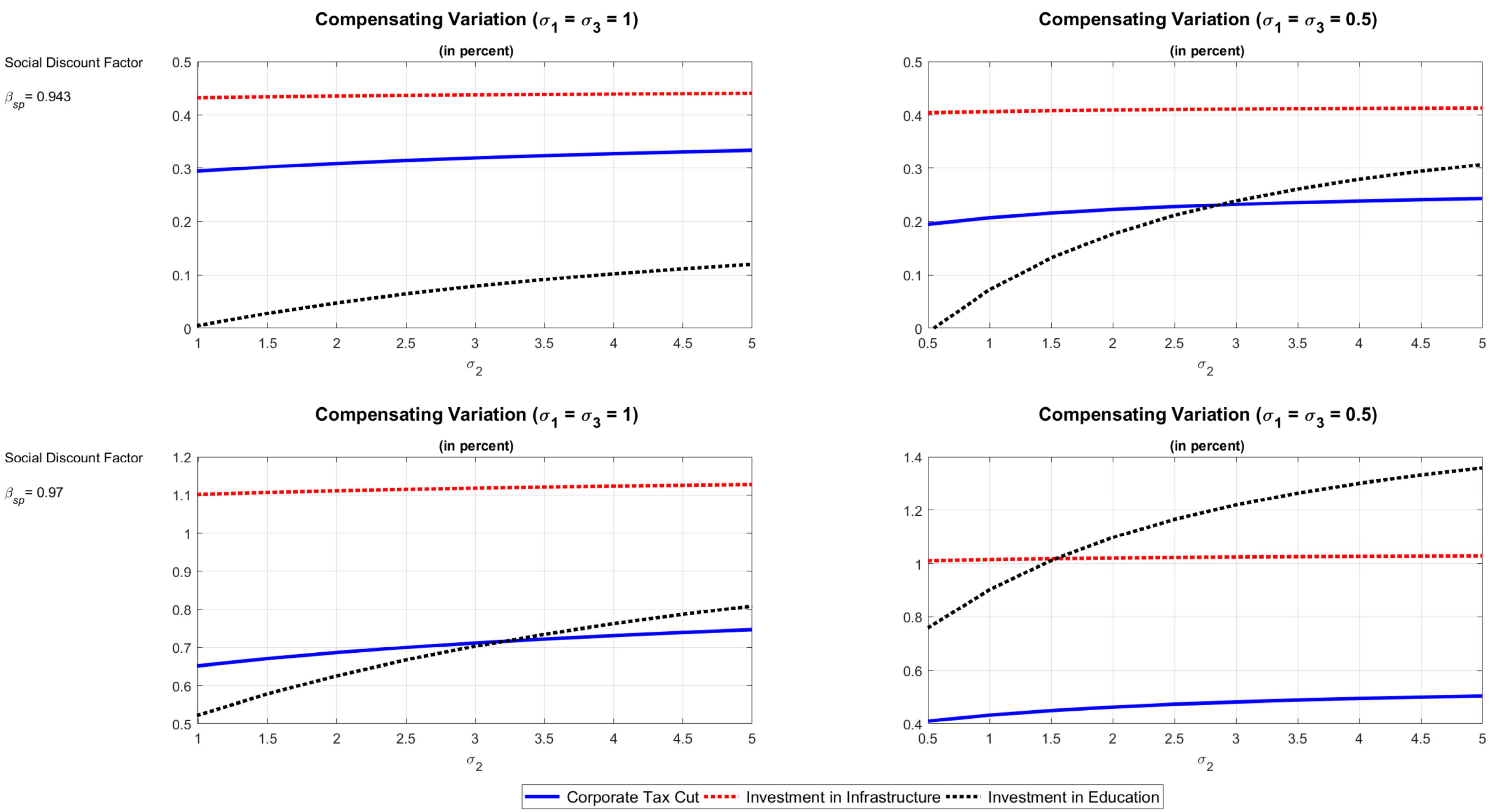

Figure 6. Welfare gains across policies: basecase with distribution (σ_2)

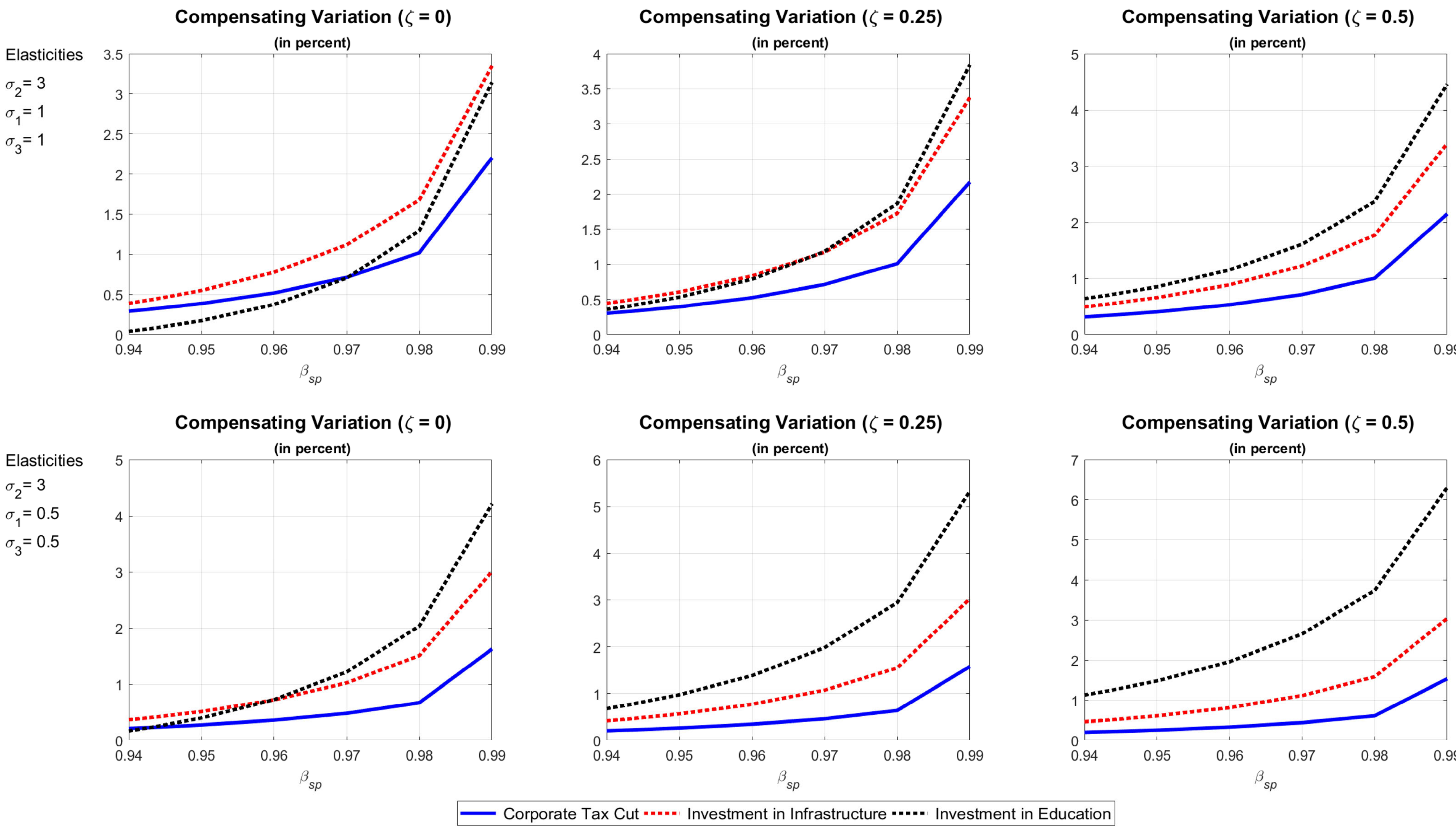

Figure 7. Welfare gains across policies: robots with distribution–Cobb-Douglas (σ_2)

(σ_1 = σ_3 =1)

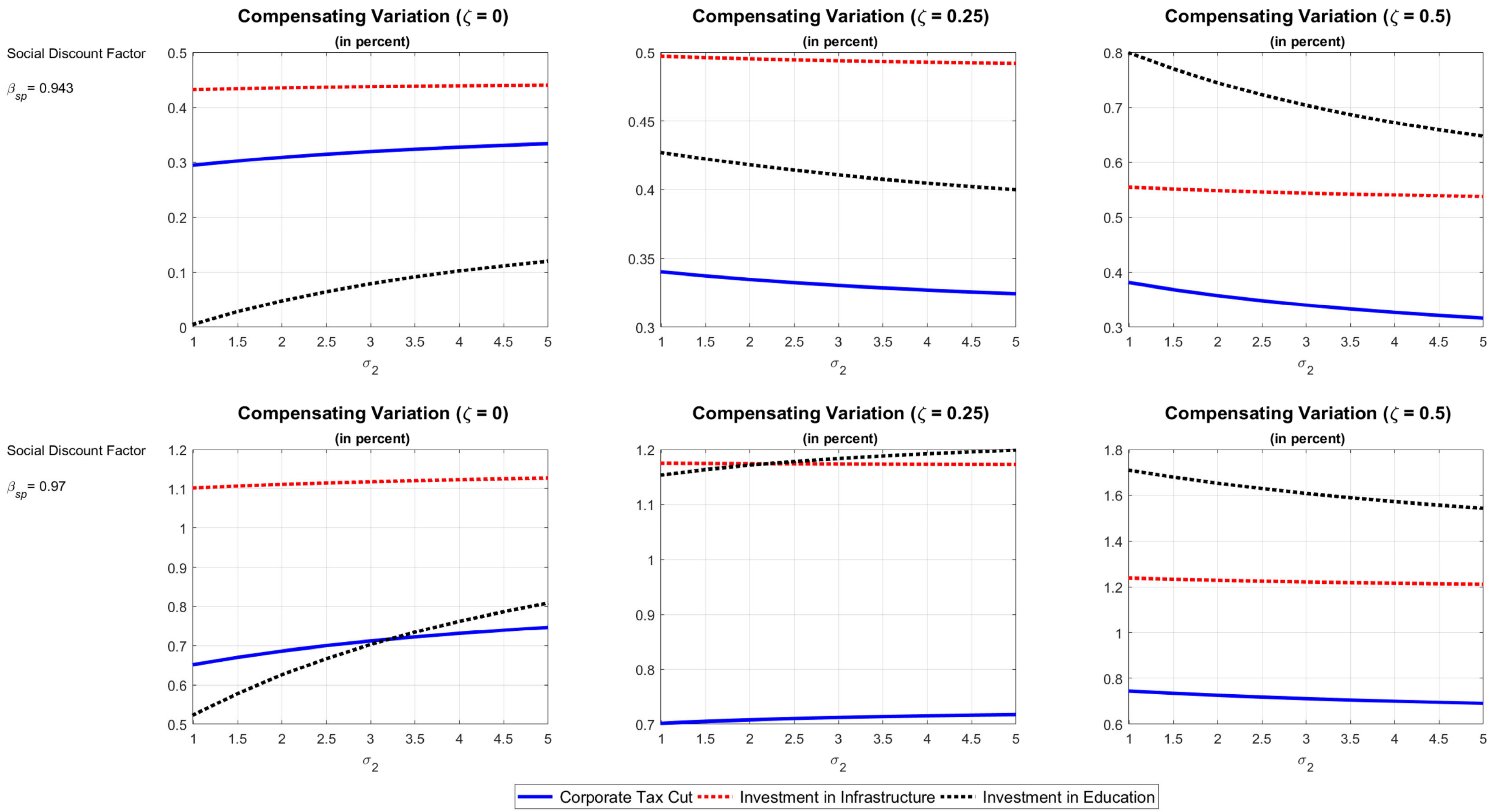

Figure 8. Welfare gains across policies: robots with distribution CES (σ_2)

(σ_1 = σ_3 = 0.5)