WORKING PAPER

TOWARDS A POLITICAL ECONOMY OF AUTOMATION

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Abstract

This paper analyzes automation as the outcome of political choice. Firms substitute capital for labor through automation, which affects productivity and reduces the labor income share. The automation preferred by a household depends on the composition of its income, specifically its relative dependence on capital versus labor. The median voter theorem aggregates these preferences into a political choice of automation. When wealth is more concentrated than labor, a democratic one-person-one-vote regime implements less automation than the output-maximizing competitive equilibrium, while a plutocratic one-dollar-one-vote regime may induce excessive automation. Increasing wealth concentration intensifies under-automation in democracy and over-automation in plutocracy. We further show that, under plausible conditions, the competitive equilibrium entails excessive automation relative to the social welfare optimum. A calibration to U.S. data demonstrates that alternative political regimes can generate quantitatively large shifts in the labor share.

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1 Introduction

In his recent Nobel Prize lecture, Daron Acemoglu stated that "there is currently very little work on the political economy of technology choices" (Acemoglu, 2025, p. 1744). In this paper, we attempt to formalize the political process behind the adoption of automation technology.

Automation is commonly defined as the use of machines to replace labor in production. Recent economic literature has extensively investigated its effect on the functional income distribution. Both theoretical (Acemoglu and Restrepo, 2018a, 2018b; Irmen, 2021; Moll et al., 2022; Prettner and Strulik, 2020) and empirical (Acemoglu, Lelarge, and Restrepo, 2020; Autor and Salomons, 2018; Bergholt et al., 2022) analyses generally indicate that automation reduces the labor share. We take this negative relationship as a starting point to develop a political economy theory of automation where agents hold conflicting interests over the adoption of automation technology due to their heterogeneous reliance on labor and capital income. More specifically, we build on the task-based model of automation put forward by Acemoglu and Restrepo (2018b). In this framework, production depends on a series of tasks that can be executed by either capital or labor. Automation is conceptualized as the expansion of the set of tasks executed by capital instead of labor. This process may bring productivity gains, but it also lowers labor's income share by displacing labor from tasks. As a result, the effect of automation on household income depends on how much they rely on labor income versus capital income. In line with the recent literature on the inequality of income composition (Ranaldi, 2022; Ranaldi and Milanovic, 2022), we acknowledge that in most countries the individual labor and capital shares of income vary substantially across the income distribution. We model this type of inequality by assuming that households have heterogeneous relative capital-labor endowments, similarly to Alesina and Rodrik (1994). Heterogeneous preferences on automation levels then emerge, with more capital-reliant households preferring more automation.

If technology adoption is only driven by market forces, competitive firms choose the level of automation that minimizes costs without regard for what households prefer. In reality, however, various regulations constrain firms' technology decisions (Acemoglu and Johnson, 2023; Frey, 2019). Mokyr (1998) in particular argues that technology adoption is largely governed by non-market institutions:

> It might seem that in the vast majority of cases this decision is trivial: if the new technique increases efficiency and profits it will be adopted, otherwise it will not. But historically speaking, few economies have ever left these decisions entirely to the decentralized decision-making processes of competitive firms. There usually is, at some level, an non-market institution that has to approve, license, or provide some other imprimatur without which firms cannot change their production method. The market test by itself is not always enough. In the past, it almost never was. (Mokyr, 1998, p. 39)

A recent and notable example of such technology regulation is the European Union AI Act (European Parliament and Council of European Union, 2024), a legal framework regulating the development and deployment of artificial intelligence, which has been approved by the European Union's political bodies in 2024. If the institutional context governing technology adoption is the outcome of a political process, household preferences become relevant in the determination of the equilibrium level of automation technology chosen by firms. We investigate this relationship by applying the median voter theorem. Under this framework, the automation preferences of the relevant median household determine the political economy equilibrium level of automation. Below, we clarify how the identity of the pivotal median household depends on the political decision rule adopted in a given society.

Our main findings are as follows. We show that, when households' relative capital-labor endowments are heterogeneous, their optimal level of automation does not generally coincide with the one that maximizes aggregate output. Households whose relative capital-labor endowment exceeds (is lower than) the aggregate capital-labor ratio prefer a higher (lower) level of automation than the output-maximizing one delivered by the competitive market equilibrium. Alternatively, one can compare households' individual capital shares with the aggregate capital income share. In other words, capital-rich households are willing to accept efficiency losses in exchange for a sufficiently strong shift in the functional income distribution from labor towards capital. The heterogeneity in income source composition thus generates clashing interests regarding technology adoption between more capital-reliant and more labor-reliant households. The actual political decision rule adopted in a society determines the automation technology outcome.

In a democratic regime, when every household has a single vote on the desired level of automation, equilibrium automation is determined by the household with the median capital-labor endowment. When this median ratio is lower than the aggregate ratio, the political economy equilibrium results in under-automation compared to the output-maximizing market outcome. We identify two sufficient conditions on the distributions of capital (wealth) and labor endowments that generate a right-skewed distribution of their ratio, which in turn generates under-automation and a labor share exceeding that of the competitive benchmark. First, we assume that wealth endowments follow a Pareto distribution, consistent with the empirical evidence on wealth inequality (Atkinson et al., 2011; Gabaix, 2009; Vermeulen, 2018). Second, we posit that labor endowments are an increasing, concave function of wealth endowments. On the one hand, the positive relationship between capital and labor is in accordance with the recent evidence that an increasing percentage of people who are capital-income rich are also labor-income rich (see Atkinson and Lakner, 2021; Berman and Milanovic, 2024; Smith et al., 2019), a phenomenon termed homoploutia by Milanovic (2019). On the other hand, the assumption of concavity reflects a well-documented fact, namely that labor income is less concentrated than wealth (Alvaredo et al., 2018; Piketty, 2014). We also show that this functional relation is consistent with U.S. data on capital and labor endowments. Furthermore, we show that greater wealth concentration exacerbates under-automation and further raises the labor share by lowering the median household's capital-labor ratio. Our analysis thus demonstrates that allowing markets to determine automation levels leads to outcomes that exceed what the majority of the population would support. A formal welfare analysis confirms that the social optimum requires under-automation when high labor income households are more reliant on capital than poorer households. At the same time, our results also show that endowment inequality entails efficiency losses by preventing the adoption of the output-maximizing level of automation.

Next, we derive the outcome of an alternative regime in which political influence is allocated in proportion to wealth. Inspired by Benabou (2000), we assume that each household receives one vote per unit of wealth (e.g., per dollar owned). We refer to this political system as a plutocratic regime to reflect its wealth-based suffrage. Within this framework, automation advances as long as it benefits the owners of the majority of wealth. While we continue to apply the median voter theorem to find the equilibrium level of automation, the relevant "median voter" in this context is the household that owns the median dollar of wealth—i.e., the household at the 50th percentile of the wealth distribution. The politically chosen level of automation thus coincides with the desired level of automation of the median wealth-holder. When wealth is sufficiently concentrated, this household has a higher capital-labor endowment than the aggregate economy. As a result, the equilibrium level of automation exceeds the output-maximizing level and the labor share of income is lower than in the competitive case. Additionally, further increases in wealth concentration leads to a greater degree of over-automation and a further decrease in the labor share. Wealth-based suffrage systems, like the one described here, were prevalent during the 19th century but have since vanished from contemporary political systems. Nevertheless, wealth continues to exert indirect influence on political power, primarily through mechanisms such as campaign financing and lobbying. This phenomenon is well-documented in political science and economics literatures, which illustrate how policy outcomes often align more closely with the preferences of affluent individuals than with those of the general public (Bartels, 2016; Bonica et al., 2013; Elkjær and Klitgaard, 2024; Gilens and Page, 2014).

To conclude, we replace the theoretical endowment distributions with U.S. data, showing that the model's qualitative predictions continue to hold, and we calibrate the model to assess the quantitative differences between the two political economy equilibria. Household endowment heterogeneity is set to match the U.S. distribution of labor and capital income as reported in the Distributional National Account (Piketty et al., 2018).

First, we find that about 65% of the population has an individual capital share below the aggregate capital share, while almost 85% of U.S. wealth is owned by households with capital shares above the aggregate. Consistent with our theoretical analysis, this implies that most U.S. citizens prefer under-automation, whereas most U.S. wealth favors over-automation. Calibrating the model, we compute the preferred level of automation for each household as a function of its relative factor endowment. Using these preferences, we construct public support functions that specify, for any given degree of automation, the share of the population favoring further automation in both regimes. These functions then allow us to derive the equilibrium levels of automation and the associated labor share in each regime. Our results indicate that shifting from a democratic to a plutocratic automation choice reduces the labor share by roughly 13 percentage points. These findings suggest that conflicts of interest over automation adoption are substantial, and that political economy considerations could provide a possible explanation for the documented shift toward labor-saving production technologies. Finally, we also show that the democratic (plutocratic) regime leads to insufficient (excessive) automation relative to the socially optimal level, but the deviation is much smaller in the democratic regime.

The remainder of the paper is structured as follows. Section 2 discusses the related literature. Section 3 develops the model and derives the theoretical results. Section 4 calibrates the model and shows its quantitative implications. Section 5 concludes.

2 Literature and Discussion

This paper is related to multiple streams of literature. First, our results speak to the literature on political economy, redistribution and growth. Seminal works by Alesina and Rodrik (1994), Krusell et al. (1997), and Persson and Tabellini (1994) establish that higher inequality can lead to slower growth, as democracies opt for higher redistributive taxation that discourages investment. Notably, in Alesina and Rodrik (1994), the critical factor is the heterogeneous income composition over labor and capital across households—a feature we incorporate in our model. We extend this literature by shifting the focus of political choice from the level of taxation to the choice of technology. In our framework, the political outcome is the level of automation, which then determines aggregate output and the functional distribution of income rather than growth. Furthermore, we provide a plutocratic counterpart of the median voter theorem where households' influence is determined by their wealth. This framework, following Benabou (2000), allows the politically pivotal agent to have a relative factor endowment above the median, offering a more realistic depiction of political power in unequal societies.

Second, our analysis contributes to the recent literature on inefficient automation adoption. Several arguments for the occurrence of automation in excess of the output-maximizing level have been advanced. Acemoglu and Restrepo (2018b) show how labor market frictions can lead to wages being above their opportunity cost, hence leading to excessive automation. Recently, Acemoglu and Restrepo (2024) have provided evidence that this has been an important channel in the US. Additionally, Acemoglu, Manera, and Restrepo (2020) show that the tax bias against labor (and in favor of capital) could lead to excessive automation in the US. Most closely related to our work, Acemoglu (2025) illustrates how fixation on capital intensity by researchers and investors could drive excessive automation. Note that excessive automation may also provide a possible explanation for the modern Solow paradox (Brynjolfsson et al., 2019), where apparently rapid technology adoption (as we see with AI and robotics) fails to generate large positive growth effects. Regarding under-automation, Frey (2019) argues that workers have historically attempted to block labor-saving technologies because they are harmful to their livelihoods (e.g., Luddites in 1810s England). Relative to these studies, we progress by proposing a novel driver of inefficient automation, namely the political support for automation in the presence of income composition inequality. We also formally derive the conditions for under- and over-automation in a joint framework.

Next, our findings are relevant to the contributions on the inequality effects of automation. Many studies focus on automation's wage inequality effects (Acemoglu and Restrepo, 2022; Hémous and Olsen, 2022; Lankisch et al., 2019; Prettner and Strulik, 2020). Recently, Jacobs (2025) and Moll et al. (2022) have focused on automation's effect on the inequality between wealth owners and workers, which originates from the negative labor share effect of automation. We build on these latter works by showing how this type of inequality generates conflicting interests between households regarding the desired level of automation. In doing so, we reverse the literature's perspective: we study how distribution affects technology choice, rather than how technology affects distribution. In contrast to the macro heterogeneous-agent literature where wealth inequality is an endogenous object, capital endowments are given in our framework.

Finally, beginning with the seminal paper by Akerlof and Kranton (2000), the literature on the role of identity in economics and politics has shown that individuals often place significant weight on non-economic factors when making political choices (see Bonomi et al., 2021; Enke, 2020; Panunzi et al., 2024 as recent examples). Such factors can even lead voters to act against their own material self-interest—for example, by supporting tax cuts that disadvantage them (Mutz, 2018; Shayo, 2009). In contrast, identity motives play no role in our model since households form their preferences regarding automation solely based on income considerations. While non-economic elements could, in principle, alter the predicted relationship between factor endowments and desired automation levels, they may in fact reinforce our core results. If households endowed primarily with labor identify with a working-class status (Shayo, 2009), this would provide an additional, non-economic rationale for demanding lower levels of automation. Conversely, if capital-rich households identify as entrepreneurial innovators—as technology company owners and CEOs appear to do—their identity motives may reinforce their economic preference for higher automation. Consequently, the introduction of identity politics would likely strengthen the predicted outcomes: exacerbating the demand for under-automation in a democratic regime and for over-automation in a plutocratic one.

3 The model

3.1 Production technology and factor prices

Output Y is produced according to a Cobb-Douglas production function that aggregates an infinite range of tasks, $t(x)$, normalized to the interval $[0,1]$:

$$\ln(Y) = \int_0^1 \ln(t(x))\mathrm{d}x. \tag{1}$$

Each task can be executed either through capital (κ) or labor (λ), which substitute perfectly. If we denote capital productivity by ζ and labor productivity by χ, the production function for a task x is given by

$$t(x) = \zeta(x)\kappa(x) + \chi(x)\lambda(x),\ \forall x \in [0,1]. \tag{2}$$

The productivity of capital and labor in producing each task is given by the following two equations:

$$\zeta(x) = b^{1+\gamma}(1-x)^{\gamma},\quad \chi(x) = (1-b)^{1+\gamma}x^{\gamma}, \tag{3}$$

where $b \in (0,1)$ and $\gamma > 0$ respectively affect the level and the steepness of the relative productivity schedule $\frac{\zeta(x)}{\chi(x)} = \left(\frac{b}{1-b}\right)^{1+\gamma}\left(\frac{1-x}{x}\right)^{\gamma}$. The shape of the productivity schedule affects the eventual substitutability between capital and labor in the production of final output. The schedule is strictly decreasing over the range of tasks x so that labor has the competitive advantage in higher-indexed tasks. The set of automated tasks $[0,\alpha]$ is produced by capital, while the set of non-automated tasks $(\alpha,1]$ is produced by labor. Let N denote the total supply of labor and K the total supply of capital; and let us define $k \equiv \frac{K}{N}$ and $y \equiv \frac{Y}{N}$. In Appendix A1, we derive the intensive production function as:

$$y(\alpha) = e^{-\gamma}\left(\frac{b}{\alpha}\right)^{(1+\gamma)\alpha}\left(\frac{1-b}{1-\alpha}\right)^{(1+\gamma)(1-\alpha)} k^{\alpha}, \tag{4}$$

when $\alpha \in (0,1)$; and $y(0) = e^{-\gamma}(1-b)^{1+\gamma},\ y(1) = e^{-\gamma}b^{1+\gamma}k$.

In Appendix A2, we show that the derivative of output with respect to the level of automation is

$$\frac{\partial y}{\partial \alpha} = y \ln \left(k \left(\frac{b}{1-b} \frac{1-\alpha}{\alpha} \right)^{1+\gamma} \right), \tag{5}$$

which is defined over $\alpha \in (0, 1)$.

Let α_y solve $\frac{\partial y}{\partial \alpha}(\alpha_y) = 0$. Since y is strictly positive, this condition requires that $\ln \left(k \left(\frac{b}{1-b} \frac{1-\alpha_y}{\alpha_y} \right)^{1+\gamma} \right) = 0$. Hence, $\alpha_y = \frac{bk^{\frac{1}{1+\gamma}}}{1-b+bk^{\frac{1}{1+\gamma}}} \in (0, 1)$ is the unique stationary point of $y(\alpha)$. Since $\frac{\partial y}{\partial \alpha}(\alpha) > 0$ for $\alpha < \alpha_y$ and $\frac{\partial y}{\partial \alpha}(\alpha) < 0$ for $\alpha > \alpha_y$, it follows that α_y maximizes y in $\alpha \in (0, 1)$. In Appendix A2 we prove that $y(0)$ and $y(1)$ are local minima, so that α_y is also a global maximum in $[0, 1]$.

Under perfect competition, the return to capital r is given by the marginal product of capital: $r = e^{-\gamma}\alpha(\frac{b}{\alpha})^{(1+\gamma)\alpha}(\frac{1-b}{1-\alpha})^{(1+\gamma)(1-\alpha)}k^{\alpha-1} = \alpha\frac{y}{k}$ for $\alpha \in (0, 1)$. When $\alpha = 0$, no task is automated, capital is not used in production so that $r(0) = 0$. When $\alpha = 1$, the economy is fully automated so that capital income absorbs the whole output and $r(1) = y(1)/k = e^{-\gamma}b^{(1+\gamma)}/k$. Notice that the capital income share of the economy coincides with the share of automated tasks: $r(0)K/Y(0) = 0$; $rK/Y = \alpha\frac{y}{k}\frac{K}{Y} = \alpha$; and $r(1)K/Y(1) = 1$. The derivative of the return to capital with respect to the level of automation is

$$\frac{\partial r}{\partial \alpha} = \frac{y}{k} + \frac{\alpha}{k}\frac{\partial y}{\partial \alpha}. \tag{6}$$

It consists of two terms. The first term is the displacement effect, and it is always positive as automation expands the set of automated tasks. Diluting capital over more tasks raises its marginal product since tasks face diminishing returns. The second term is the indirect productivity effect of automation, whose sign is positive for low levels of α and negative for high levels of α.

We now show that there exists a unique level of automation α_r which maximizes r in $\alpha \in [0, 1]$. Using $r = \alpha\frac{y}{k}$, we can rewrite $\frac{\partial r}{\partial \alpha}$ as

$$\frac{\partial r}{\partial \alpha} = r \left(\frac{1}{\alpha} + \frac{1}{y}\frac{\partial y}{\partial \alpha} \right) = r \left(\frac{1}{\alpha} + \ln \left(k \left(\frac{b}{1-b} \frac{1-\alpha}{\alpha} \right)^{1+\gamma} \right) \right), \tag{7}$$

which is defined in $\alpha \in (0,1)$. It is a product of two factors: r and $\frac{1}{\alpha} + \ln[\cdot]$. Since the first factor r is strictly positive and the second factor $\frac{1}{\alpha} + \ln[\cdot]$ is a continuous, monotonically decreasing function in α that goes from $+\infty$ to $-\infty$, there exists a unique $\alpha_r : \frac{\partial r}{\partial \alpha}(\alpha_r) = 0$. Since $\frac{\partial r}{\partial \alpha}(\alpha) > 0$ for $\alpha < \alpha_r$ and $\frac{\partial r}{\partial \alpha}(\alpha) < 0$ for $\alpha > \alpha_r$, it follows that α_r maximizes y in $\alpha \in (0,1)$. Since $r(\alpha_r) > 0 = r(0)$, and $r(1)$ is a local minimum as we show in Appendix A2, then α_r is a global maximum.

Under perfect competition, the wage rate w is given by $w = y - rk = (1-\alpha)y$ and its derivative with respect to automation is

$$\frac{\partial w}{\partial \alpha} = -y + (1-\alpha)\frac{\partial y}{\partial \alpha}. \tag{8}$$

Again, the first term is the displacement effect, and it is always negative in this case as automation contracts the set of non-automated tasks. Squeezing labor into fewer tasks reduces its marginal product since tasks face diminishing returns. The second term is the productivity effect, whose sign is positive for low levels of α and negative for high levels of α.

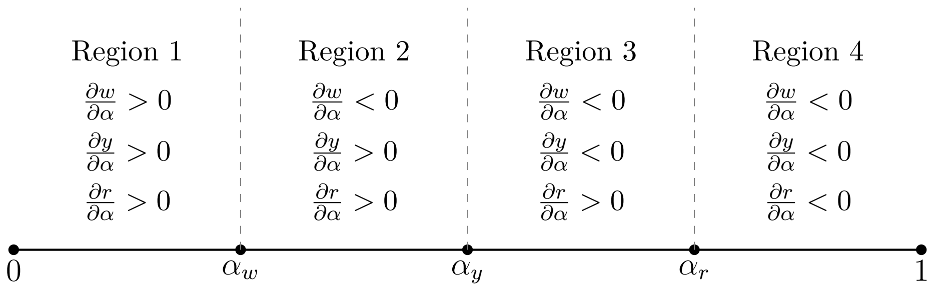
We now show that there exists a unique level of automation α_w which maximizes w in $\alpha \in [0,1]$. Using $w = (1-\alpha)y$, we can rewrite $\frac{\partial w}{\partial \alpha}$ as

$$\frac{\partial w}{\partial \alpha} = w\left(\frac{-1}{1-\alpha} + \frac{1}{y}\frac{\partial y}{\partial \alpha}\right) = w\left(\frac{-1}{1-\alpha} + \ln\left(k\left(\frac{b}{1-b}\frac{1-\alpha}{\alpha}\right)^{1+\gamma}\right)\right), \tag{9}$$

which is defined in $\alpha \in (0,1)$. It is a product of two factors: w and $\frac{-1}{1-\alpha} + \ln[\cdot]$. Since the first factor w is strictly positive and the second factor $\frac{-1}{1-\alpha} + \ln[\cdot]$ is a continuous, monotonically decreasing function in α that goes from $+\infty$ to $-\infty$, there exists a unique $\alpha_w \in (0,1) : \frac{\partial w}{\partial \alpha}(\alpha_w) = 0$. Since $\frac{\partial w}{\partial \alpha}(\alpha) > 0$ for $\alpha < \alpha_w$ and $\frac{\partial w}{\partial \alpha}(\alpha) < 0$ for $\alpha > \alpha_w$, it follows that α_w maximizes the wage rate w in $\alpha \in (0,1)$. Since $w(\alpha_w) > 0 = w(1)$, and $w(0)$ is a local minimum as we show in Appendix A2, then α_w is a global maximum.

We can prove that the wage-maximizing level of automation is lower than the output-maximizing level of automation, which, in turn, is lower than the level of automation that maximizes the return to capital: $\alpha_w < \alpha_y < \alpha_r$. From equations (5) and (9) notice that $\frac{\partial w}{\partial \alpha}(\alpha_y) = \frac{-w}{1-\alpha} < 0$. Since $\frac{\partial w}{\partial \alpha}(\alpha)$ has a global maximum in α_w, then $\frac{\partial w}{\partial \alpha}(\alpha) < 0$ requires $\alpha > \alpha_w$. Hence $\alpha_y > \alpha_w$. On the other hand, equations (5) and (7) show that $\frac{\partial r}{\partial \alpha}(\alpha_y) = \frac{r}{\alpha} > 0$. Since $\frac{\partial r}{\partial \alpha}(\alpha)$ has a global maximum in α_r, then $\frac{\partial r}{\partial \alpha}(\alpha) > 0$ requires $\alpha < \alpha_r$. Hence $\alpha_y < \alpha_r$. In summary, the automation domain can be divided in four regions depending on the sign of the effect of automation on factor prices and output. Figure 1 displays this in a diagram.

Figure 1: Effect of automation on wage, output and rate of return across automation domain



In the first region $0 \leq \alpha < \alpha_w$, automation increases wages, output and the rate of return ($\frac{\partial w}{\partial \alpha} > 0$, $\frac{\partial y}{\partial \alpha} > 0$, $\frac{\partial r}{\partial \alpha} > 0$). In the second region $\alpha_w < \alpha < \alpha_y$, automation is still productivity-enhancing ($\frac{\partial y}{\partial \alpha} > 0$), but labor loses out because the productivity effect is dominated by the negative displacement effect ($\frac{\partial w}{\partial \alpha} < 0$). In the third region $\alpha_y < \alpha < \alpha_r$, further automation is productivity-decreasing ($\frac{\partial y}{\partial \alpha} < 0$), but it still increases the rate of return because of the displacement from labor to capital ($\frac{\partial r}{\partial \alpha} > 0$). In the fourth region $\alpha_r < \alpha \leq 1$, the negative productivity effect dominates and automation hurts all factor prices. The possibility that too little or too much automation may hurt all types of agents in an economy is already established in the automation literature. Region 1 and Region 4 correspond to the two backward-bending arms of the utility-technology possibilities frontier proposed by Acemoglu (2025) (see for instance his Figure 10).

3.2 Households

We consider a static economy with a fixed number of households indexed by i with $i = 1, 2, ...T$. We borrow from the set-up of Alesina and Rodrik (1994) and assume that households have constant labor and wealth endowments, L_i and a_i, which they supply inelastically. We define the relative factor endowment as $\sigma_i \equiv \frac{a_i}{L_i}$. Individual endowments sum up to the aggregate labor supply ($\sum_i L_i = N$) and the aggregate capital stock ($\sum_i a_i = K$). As a result, a household's income level is given by $I_i = wL_i + ra_i$. All households share the same continuous and twice differentiable utility function, which is increasing in consumption c: $u_i(c_i) = u(c_i)$, with $u' > 0, u'' \leq 0$. Given the static environment and the positive marginal utility of consumption, households consume their whole income $c_i = I_i$.

3.3 Automation under perfect competition

Under perfectly competitive conditions, firms choose the level of automation that minimizes costs. Since the relative capital-labor productivity schedule $\frac{\zeta(x)}{\chi(x)}$ is strictly diminishing over the range of tasks, a cost-minimizing firm would automate all tasks with index $x \leq \alpha_{\text{pc}}$, where α_{pc} denotes the task for which capital and labor are equally cost-effective $\frac{\zeta(\alpha_{\text{pc}})}{\chi(\alpha_{\text{pc}})} = \frac{r}{w}$. The cost-minimizing level of automation corresponds to the output-maximizing one: $\alpha_{\text{pc}} = \alpha_y$. This follows from replacing r and w by their respective expressions under perfect competition, that is $\alpha\frac{y}{k}$ and $(1-\alpha)y$. The condition for cost-minimization becomes $(\frac{b}{1-b})^{1+\gamma}(\frac{1-\alpha_{\text{pc}}}{\alpha_{\text{pc}}})^{\gamma} = \frac{\alpha_{\text{pc}}}{1-\alpha_{\text{pc}}}\frac{1}{k}$. Hence, $\alpha_{\text{pc}} = \frac{bk^{\frac{1}{1+\gamma}}}{1-b+bk^{\frac{1}{1+\gamma}}} = \alpha_y$: perfect competition produces the output-maximizing level of automation. Nakamura and Nakamura (2008) showed that the productivity schedules of capital and labor in equation (3) lead to a CES production function. Indeed, when re-inserting our expression α_{pc} into the production function of equation (4), we find that the competitive automation adoption equilibrium results in a CES production function $y = e^{-\gamma}\left(1 - b + bk^{\frac{1}{1+\gamma}}\right)^{1+\gamma}$ with the elasticity of substitution being $1 + \frac{1}{\gamma} > 1$.

3.4 The political choice of automation

We proceed by exploring a political rule for selecting the economy's level of automation. Once the politically chosen level of automation is given, firms behave competitively so that factor prices coincide with marginal products.

Since $c_i = I_i$, households favor automation if it increases their income. Deriving household income with respect to automation, yields

$$\frac{\partial I_i}{\partial \alpha} = L_i \frac{\partial w}{\partial \alpha} + a_i \frac{\partial r}{\partial \alpha} = L_i \left((1-\alpha) \frac{\partial y}{\partial \alpha} - y \right) + a_i \left(\frac{y}{k} + \frac{\alpha}{k} \frac{\partial y}{\partial \alpha} \right) \tag{10}$$

$$= \frac{\partial y}{\partial \alpha} \left(L_i (1-\alpha) + a_i \frac{\alpha}{k} \right) + y \left(\frac{a_i}{k} - L_i \right) = L_i \left(\left(1 + \alpha \frac{\sigma_i - k}{k} \right) \frac{\partial y}{\partial \alpha} + \left(\frac{\sigma_i - k}{k} \right) y \right).$$

For a household whose capital-labor endowment is equal to the macro average ($\sigma_i = k$), it holds that $\frac{\partial I}{\partial \alpha} = L_i \frac{\partial y}{\partial \alpha}$. As a result, this household prefers the output-maximizing level of automation α_y. In other words, this household only cares about the productivity effect of automation, since a representative household's optimization problem reduces to maximizing output. Without heterogeneity in the capital-labor endowment σ_i, households' interests are aligned, and there is no scope for a political conflict over technology adoption. The representative-agent model is an obvious example. However, σ_i is also identical across households even when there is arbitrarily large inequality in wealth and labor endowments, provided that a_i and L_i are linearly related. What matters is not inequality in labor income or wealth *per se*, but inequality of income composition.

We now derive a household's optimal level of automation α_i^*. Since $r(0) = w(1) = 0$, and $w(1)$ and $r(1)$ are local minima for wage and capital income, we know that $\alpha_i^* \in (0,1)$. Then, α_i^* must be a stationary point for I_i:

$$\frac{\partial I_i}{\partial \alpha}(\alpha_i^*) = 0 \Leftrightarrow \frac{\partial y}{\partial \alpha}(\alpha_i^*) = -\frac{y(\alpha_i^*)\frac{\sigma_i - k}{k}}{1 + \alpha_i^* \frac{\sigma_i - k}{k}}. \tag{11}$$

Equation (11) solves for α_i^* as an implicit function of the relative factor endowment σ_i. We can now state

Lemma 1. *The difference between the household's optimal automation level and the output-maxiziming automation level has the same sign as the difference between the household's relative factor endowment and the macro capital-labor ratio:*
$\mathrm{sign}(\alpha_i^* - \alpha_y) = \mathrm{sign}(\sigma_i - k)$.

Proof. Equation (11) implies that $(\sigma_i - k) \gtreqqless 0 \Leftrightarrow \frac{\partial y}{\partial \alpha}(\alpha_i^*) \lesseqqgtr 0$, since $1 + \alpha_i^* \frac{\sigma_i - k}{k} = 1 - \alpha_i^* + \alpha_i^* \frac{\sigma_i}{k} > 0$. Lemma (1) then follows since we showed in the previous sub-section that $\frac{\partial y}{\partial \alpha}(\alpha) \lesseqqgtr 0 \Leftrightarrow (\alpha - \alpha_y) \gtreqqless 0$. $\square$

Lemma 1 shows that a household desires a level of automation that is greater (lower) than the output-maximizing level if they are relatively more (less) dependent on capital than the representative agent who has a relative factor endowment equal to the macro capital-labor ratio. Equivalently, a household prefers over-automation if their personal labor share is lower than the aggregate labor share. This holds since $\sigma_i > k \Leftrightarrow \frac{a_i}{L_i} > \frac{K}{N} \Leftrightarrow \frac{ra_i}{wL_i} > \frac{rK}{wN} \Leftrightarrow \frac{ra_i+wL_i}{wL_i} > \frac{rK+wN}{wN} \Leftrightarrow \frac{wL_i}{ra_i+wL_i} < \frac{wN}{rK+wN}$. This will be used when comparing the model with the data in Section 4.1.

To convert household preferences into statements regarding the political outcome, we will apply the median voter theorem. The application of this theorem is valid, because three conditions hold (Meltzer and Richard, 1983; Roberts, 1977; Romer, 1975): (1) voting must concern a single topic, (2) household preferences must be single-peaked, and (3) household preferences on the topic must be monotonic. The first condition holds as in our case households only choose the level of automation. We now show that the second and third conditions are also satisfied: there is only one solution α_i^* to the household's optimization of income I_i, and the household's optimal α_i^* is strictly increasing in their relative factor endowment σ_i.

We start from equation (11) and replace $\frac{\partial y}{\partial \alpha}(\alpha_i^*)$ by its expression in equation (5). Then we divide both sides by $y(\alpha_i^*)$ to find

$$\ln\left(k\left(\frac{b}{1-b}\frac{1-\alpha_i^*}{\alpha_i^*}\right)^{1+\gamma}\right) = -\frac{\frac{\sigma_i - k}{k}}{1+\alpha_i^*\frac{\sigma_i-k}{k}}. \tag{12}$$

Preferences are single-peaked if there is only one α_i^* that solves this equality. To show this, it suffices to note that the left-hand side is continuous and strictly decreasing in α_i^* and goes from $+\infty$ to $-\infty$ in $\alpha_i^* \in (0,1)$, and the right-hand side is continuous and non-decreasing in $\alpha_i^* \in (0,1)$. We prove this in Appendix B1.

To show that households' optimal level of automation α_i^* is strictly increasing in their relative factor endowment σ_i, we use the implicit function theorem in equation (12) and find that $\frac{\partial \alpha_i^*}{\partial \sigma_i} > 0 \ \forall \alpha_i^* \in (0,1)$. We show this in Appendix B2.

We conclude that the three conditions hold and the median voter theorem can be applied. If we let M be the median household and we denote the level of automation that occurs under a democratic technology choice by α_{demo}, it follows that $\alpha_{\text{demo}} = \alpha^*_M$. In other words, the democratic outcome corresponds to the automation level preferred by the household with the median relative factor endowment σ_M.

We can now state

Proposition 1. *The difference between the democratically chosen level of automation and the output-maximizing level of automation has the same sign as the difference between the median household's relative factor endowment and the macro capital-labor ratio:* $\text{sign}(\alpha_{\text{demo}} - \alpha_y) = \text{sign}(\sigma_M - k)$.

Proof. This follows from applying the median voter theorem to Lemma 1. □

Proposition 1 shows that a democratic choice on automation can lead to under- or over-automation. Since wealth inequality is typically higher than labor income inequality, the empirically relevant case is that of $\sigma_M < k$ (as argued for example in Alesina and Rodrik, 1994), which leads to under-automation. In the next section, we provide a formal theoretical analysis regarding the relationship between $\sigma_M - k$ and the distributions of wealth and labor income.

3.4.1 Theoretical distributions for wealth and labor

In line with the established literature on wealth inequality (Atkinson et al., 2011; Gabaix, 2009; Vermeulen, 2018), we let wealth endowments follow a Pareto distribution. Accordingly, the counter-cumulative distribution function is given by

$$P(a_i > a) = \left(\frac{a}{a_0}\right)^{-\eta}. \tag{13}$$

The constant $\eta > 0$ is the tail parameter: the lower η is, the more strongly wealth is concentrated at the top of the distribution. $a_0 > 0$ is a scale parameter.

In light of the recent evidence that an increasing percentage of people who are capital-income rich are also labor-income rich (see Atkinson and Lakner, 2021; Berman and Milanovic, 2024; Smith et al., 2019), a phenomenon termed homoploutia by Milanovic (2019), we assume a positive relation between labor and capital endowments. Specifically, we posit that the household's labor endowment is an increasing power function of its wealth endowment: $L_i = \xi(a_i)^\theta,\ \xi > 0,\ 0 < \theta < 1$. In Appendix C1, we prove that labor endowments follow a Pareto distribution with tail parameter $\frac{\eta}{\theta}$. Assuming concavity $(0 < \theta < 1)$ thus ensures that the tail parameter of labor income exceeds that of wealth, implying that labor income is less concentrated at the top than wealth, consistent with established empirical findings (Alvaredo et al., 2018; Piketty, 2014). In Appendix D, we use recent U.S. individual-level data from the Distributional National Accounts (Piketty et al., 2018) to provide evidence for this positive and concave dependence of L_i on a_i. Notice also that if $\theta = 1$, then $\sigma_i = \frac{1}{\xi} = \sigma$, and there is no income composition inequality and hence no heterogeneous preferences on the automation level. Returning to Appendix C1, we find that the relative factor endowments σ_i also follow a Pareto distribution with tail parameter $\frac{\eta}{1-\theta}$. This implies that σ_i are more concentrated at the top when wealth endowments a_i are more unequal and labor endowments L_i are more evenly distributed.

In Appendix C1, we find that factor market clearing is only possible if $\eta > 1$. With this restriction, factor market equilibria yield solutions to a_0 and ξ, which can be used in $P(\sigma_i > \sigma_M) = 0.5$ to find

$$\sigma_M = \left(\frac{\eta - 1}{\eta - \theta}\right) 2^{\frac{1-\theta}{\eta}} k. \tag{14}$$

We can now state

Proposition 2. *Under democratic technology choice, the equilibrium level of automation is lower than the output-maximizing level of automation:* $\alpha_{\text{demo}} < \alpha_y$.

Proof. Rearranging equation (14) and taking its natural logarithm yields: $\ln(\frac{\sigma_M}{k}) = \ln(\frac{\eta-1}{\eta-\theta}) + \frac{1-\theta}{\eta}\ln(2)$. Since we know that $\ln(x) \leq x - 1$, it follows that $\ln(\frac{\sigma_M}{k}) = \ln(\frac{\eta-1}{\eta-\theta}) + \frac{1-\theta}{\eta}\ln(2) \leq \frac{\eta-1}{\eta-\theta} - 1 + \frac{1-\theta}{\eta}\ln(2) = \frac{1-\theta}{\eta}(\ln(2) - \frac{\eta}{\eta-\theta})$. Since $0 < \theta < 1$ and $\eta > 1$, then $\frac{1-\theta}{\eta}(\ln(2) - \frac{\eta}{\eta-\theta}) < 0$. As a result, $\ln(\frac{\sigma_M}{k}) < 0$ and $\sigma_M < k$. Proposition 1 then implies that $\alpha_{\text{demo}} < \alpha_y$. □

Since $\sigma_M < k$, the individual labor income share of the median voter is higher than the labor income share for the aggregate economy. For this reason, she stops benefiting from automation before it reaches its competitive output-maximizing level. We are in Region 2 of Figure 1. Inequality in the distribution of relative factor endowments thus produces efficiency losses.

Alesina and Rodrik (1994) interpret the distance of the median household's relative capital-labor endowment σ_M from the macro average capital-labor ratio k as an indicator of "inequality". In our framework, the explicit modeling of the distributions of wealth and labor endowments allows us to be more precise on the link between endowment inequalities and economic outcomes based on political decision rules. This leads us to

Proposition 3. *Under democratic technology choice, a higher concentration of wealth (labor income) leads to lower (higher) equilibrium levels of automation and output:* $\frac{\partial \alpha_{\text{demo}}}{\partial \eta} > 0, \frac{\partial y_{\text{demo}}}{\partial \eta} > 0$ *and* $\frac{\partial \alpha_{\text{demo}}}{\partial \theta} > 0, \frac{\partial y_{\text{demo}}}{\partial \theta} > 0.$

Proof. In Appendix C2, we show that $\frac{\partial \sigma_M}{\partial \eta} > 0$ and $\frac{\partial \sigma_M}{\partial \theta} > 0$ for $0 < \theta < 1$ and $\eta > 1$. We know that $\frac{\partial \alpha_M}{\partial \sigma_M} > 0$ and $\alpha_M = \alpha_{\text{demo}}$, then $\frac{\partial \alpha_{\text{demo}}}{\partial \eta} > 0$ and $\frac{\partial \alpha_{\text{demo}}}{\partial \theta} > 0$. Since $\alpha_{\text{demo}} < \alpha_y$ under Proposition 2 and $\frac{\partial y}{\partial \alpha} > 0 \ \forall \alpha < \alpha_y$, it follows that $\frac{\partial y_{\text{demo}}}{\partial \eta} > 0$ and $\frac{\partial y_{\text{demo}}}{\partial \theta} > 0$. □

In other words, if wealth becomes more concentrated at the top compared to labor income, the bulk of households have less to win from the higher return to wealth. As a result, the democratic equilibrium level of automation decreases and the output loss due to under-automation increases.

3.4.2 Automation under plutocratic technology choice

We now consider the case where a plutocratic process decides the level of automation. By plutocracy, we mean that a household's political influence depends on its wealth. Similarly to Benabou (2000), we consider a "one-dollar-one-vote" regime, where households are weighted by their wealth endowment a_i in the political decision rule. When applying the median voter theorem, we now no longer consider the median household's relative endowment σ_M, but the endowment of the household who holds the median dollar of wealth, which we denote by $\sigma_{\tilde{M}}$. If we maintain the Pareto distributions for the wealth and labor endowments as in the previous section, we can find

$$\sigma_{\tilde{M}} = \frac{\eta - 1}{\eta - \theta} 2^{\frac{1-\theta}{\eta-1}} k, \tag{15}$$

as shown in Appendix C3.

If we denote the level of automation that occurs under a plutocratic technology choice by α_{pluto}, the median voter theorem implies that $\alpha_{\text{pluto}} = \alpha^*_{\tilde{M}}$. We can now state

Proposition 4. *Under a plutocratic technology choice, the equilibrium level of automation is greater than the output-maximizing level of automation if wealth is sufficiently fat-tailed and labor income is sufficiently light-tailed:*
$\theta + \eta < 2 \Leftrightarrow \alpha_{\text{pluto}} > \alpha_y$.

Proof. In Appendix C3, we show that $\sigma_{\tilde{M}} > k$ if $\eta + \theta < 2$. Proposition 4 then follows from Lemma 1 and the median voter theorem. □

In other words, a "one-dollar-one-vote" regime results in over-automation if the distribution of wealth is sufficiently fat-tailed relative to the distribution of labor income. This is intuitive. The more uniform the distribution of wealth, the closer the plutocratic and democratic outcomes will be. Empirically realistic values for the tail parameters of both distributions suggest that over-automation may indeed occur under the plutocratic regime. Gaillard et al. (2023) find values of 1.35 and 2.3 for the tail parameters of wealth and labor income, respectively. In our model, that implies $\eta = 1.35$ and $\frac{\eta}{\theta} = 2.3$. Under this calibration, $\eta + \theta \approx 1.94 < 2$. In line with this, our own empirical analysis in section 4.1 suggests that $\sigma_{\tilde{M}} > k$ so that, under a plutocratic rule, there would be over-automation.

While Proposition 4 established the condition for over-automation, we now turn to the relation between changes in the labor income and wealth distribution and the degree of over-automation. This results in

Proposition 5. *Under a plutocratic technology choice with over-automation, a higher concentration of wealth (labor income) leads to a higher (lower) equilibrium level of* *automation and lower (higher) output:*

$\eta + \theta < 2 \Rightarrow \frac{\partial \alpha_{\text{pluto}}}{\partial \eta} < 0, \frac{\partial y_{\text{pluto}}}{\partial \eta} > 0$ *and* $\frac{\partial \alpha_{\text{pluto}}}{\partial \theta} < 0, \frac{\partial y_{\text{pluto}}}{\partial \theta} > 0.$

Proof. In Appendix C4, we show that $\frac{\partial \sigma_{\tilde{M}}}{\partial \eta} < 0$ and $\frac{\partial \sigma_{\tilde{M}}}{\partial \theta} < 0$ when $\eta + \theta < 2$. We know that $\frac{\partial \alpha_{\tilde{M}}}{\partial \sigma_{\tilde{M}}} > 0$ and $\alpha_{\tilde{M}} = \alpha_{\text{pluto}}$, then $\frac{\partial \alpha_{\text{pluto}}}{\partial \eta} < 0$ and $\frac{\partial \alpha_{\text{pluto}}}{\partial \theta} < 0$. Since $\alpha_{\text{pluto}} > \alpha_y$ when $\eta + \theta < 2$ (Prop. 4) and $\frac{\partial y}{\partial \alpha} < 0 \; \forall \alpha > \alpha_y$, it follows that $\frac{\partial y_{\text{pluto}}}{\partial \eta} > 0$ and $\frac{\partial y_{\text{pluto}}}{\partial \theta} > 0$. □

Starting from a situation of over-automation, if the wealth distribution becomes more fat-tailed or the labor income distribution more light-tailed, over-automation in the plutocratic regime increases, thus resulting in higher efficiency losses.

3.5 Automation choice of the social planner

The social welfare function of a utilitarian planner is given by

$$W = \sum_i u(c_i) = \sum_i u(I_i). \tag{16}$$

The planner will choose the level of automation that maximizes W. If $u'' = 0$, then u is linear and the maximization problem simplifies to maximizing $\sum_i I_i = y$ so that the planner will opt for $\alpha = \alpha_y$. If $u'' < 0$, we have that

$$\max_\alpha W = \max_\alpha \sum_i u(wL_i + ra_i) = \max_\alpha \sum_i u((1-\alpha)yL_i + \alpha \frac{y}{k} a_i) = \max_\alpha \sum_i u\left(yL_i\left((1-\alpha) + \alpha\frac{\sigma_i}{k}\right)\right). \tag{17}$$

Assuming $u(c) = \ln(c)$ yields

$$\max_\alpha W = \max_\alpha \sum_i \ln(yL_i\left((1-\alpha) + \alpha\frac{\sigma_i}{k}\right)) = \max_\alpha \left(T\ln(y) + \sum_i \ln(L_i) + \sum_i \ln\left((1-\alpha) + \alpha\frac{\sigma_i}{k}\right)\right). \tag{18}$$

If we define the social planner's optimal level of automation as α_{SW}, social welfare maximization requires the first-order condition $\frac{\partial W}{\partial \alpha}(\alpha_{\text{SW}}) = 0$, or

$$\frac{\partial W}{\partial \alpha}(\alpha_{\text{SW}}) = \frac{T}{y}\frac{\partial y}{\partial \alpha}(\alpha_{\text{SW}}) + \sum_i \frac{-1 + \frac{\sigma_i}{k}}{(1-\alpha_{\text{SW}}) + \alpha_{\text{SW}}\frac{\sigma_i}{k}} = \frac{T}{y}\frac{\partial y}{\partial \alpha}(\alpha_{\text{SW}}) + \sum_i \frac{\frac{\sigma_i - k}{k}}{1 + \alpha_{\text{SW}}\frac{\sigma_i - k}{k}} = 0. \tag{19}$$

Rearranging gives

$$\frac{1}{y}\frac{\partial y}{\partial \alpha}(\alpha_{\text{SW}}) = -\frac{1}{T}\sum_i \frac{\frac{\sigma_i - k}{k}}{1+\alpha_{\text{SW}}\frac{\sigma_i - k}{k}}. \tag{20}$$

We can now state

Proposition 6. *If the covariance between labor endowments and relative capital-labor endowments is positive, the level of automation that maximizes social welfare is lower than the output-maximizing level of automation:*
$\text{cov}(L_i, \sigma_i) > 0 \Rightarrow \alpha_{\text{SW}} < \alpha_y$.

Proof. First, notice that $\sum_i \sigma_i = \sum_i \frac{a_i}{L_i}$, and $\frac{\sum_i a_i}{\sum_i L_i} = \frac{K}{N} = k$. It follows that $\frac{\sum_i a_i}{\sum_i L_i} = \frac{\sum_i \frac{a_i}{L_i} L_i}{\sum_i L_i} = \sum_i \frac{L_i}{N}\frac{a_i}{L_i} \equiv \sum_i w_i \frac{a_i}{L_i} = \sum_i w_i \sigma_i = k$, where $w_i = \frac{L_i}{N}$ are weights that sum up to 1. The difference between the uniformly weighted and non-uniformly weighted sum of σ_i depends on the covariance between the elements of the sum and the weights. In particular, $\frac{1}{T}\sum_i \sigma_i < \sum_i w_i \sigma_i$ if $\text{cov}(w_i, \sigma_i) > 0$ which implies $\text{cov}(L_i, \sigma_i) > 0$. Then, if the relative capital-labor endowments are positively associated with the labor endowments, it follows that $\frac{1}{T}\sum_i \sigma_i < \sum_i w_i \sigma_i = k$, which implies that $\frac{1}{T}\sum_i \sigma_i - k < 0$.

We now turn to investigate $\sum_i \frac{\frac{\sigma_i - k}{k}}{1+\alpha\frac{\sigma_i - k}{k}}$. Let us define $\omega_i \equiv \frac{1}{1+\alpha\frac{\sigma_i - k}{k}}$ and notice that ω_i is a decreasing function of σ_i. It follows that $\sum_i \frac{\frac{\sigma_i - k}{k}}{1+\alpha\frac{\sigma_i - k}{k}} = \sum_i \omega_i \frac{\sigma_i - k}{k} < \sum_i \omega_i \sum_i \frac{\sigma_i - k}{k}$ since $\text{cov}(\omega_i, \frac{\sigma_i - k}{k}) < 0$. Because $\frac{1}{T}\sum_i \sigma_i - k < 0$, it follows that $\frac{1}{T}\sum_i \sigma_i - \frac{1}{T}\sum_i k < 0 \Leftrightarrow \sum_i \frac{\sigma_i - k}{k} < 0$. Since $\sum_i \omega_i > 0$, then $\sum_i \frac{\frac{\sigma_i - k}{k}}{1+\alpha\frac{\sigma_i - k}{k}} < \sum_i \omega_i \sum_i \frac{\sigma_i - k}{k} < 0$.

It follows that $\text{cov}(L_i, \sigma_i) > 0$ is a sufficient condition to state that $(-\frac{1}{T}\sum_i \frac{\frac{\sigma_i - k}{k}}{1+\alpha\frac{\sigma_i - k}{k}}) > 0$. As a result, $\frac{1}{y}\frac{\partial y}{\partial \alpha}(\alpha_{\text{SW}}) > 0$ which implies $\frac{\partial y}{\partial \alpha}(\alpha_{\text{SW}}) > 0$. Hence, $\alpha_{\text{SW}} < \alpha_y$. □

In other words, if low labor income households are less reliant on capital, social welfare maximization requires under-automation compared to the output-maximizing level of automation. Note that this condition is satisfied when wealth follows a Pareto distribution and labor endowments are a power law of wealth endowments as in sub-section 3.4.1. It then holds that $\sigma_i = \frac{a_i}{L_i} = \frac{(L_i/\xi)^{\frac{1}{\theta}}}{L_i} = \xi^{\frac{-1}{\theta}} L_i^{\frac{1-\theta}{\theta}}$, so that $\text{cov}(\sigma_i, L_i) > 0$.

4 Quantitative implications of the model

4.1 Under-automation and over-automation in the data

In Propositions 2 and 4, we showed that democracy can lead to under-automation and plutocracy to over-automation when assuming theoretical Pareto distributions on a_i and L_i. We now consider actual U.S. data from the Distributional National Accounts (Piketty et al., 2018) on personal capital shares and show that these predictions continue to hold.

Figure 2: Percentile plot of personal capital shares, U.S. in 2019 (DINA data)

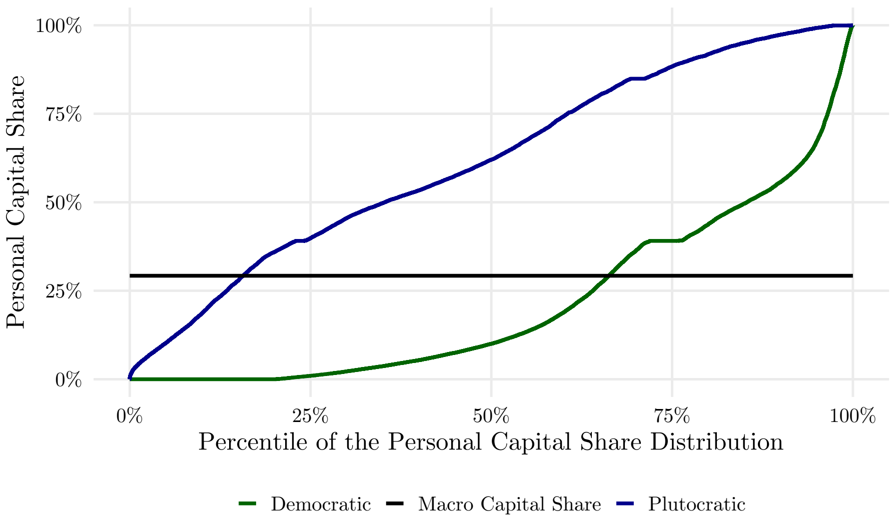


Figure 2 shows the distribution of capital income shares across U.S. individuals. In Appendix D, we explain how these shares are constructed. On the horizontal axis, individuals are ordered by increasing pre-tax capital income share and grouped in percentiles. In the democratic case, each individual has the same weight. If we look at the intersection between the democratic (green) line and the macro line, we find that about 65% of the population has a capital share below the aggregate capital share of 29%. In the plutocratic case, individuals are weighted by their net total wealth. The majority of wealth is in the hands of individuals whose capital share is greater than the aggregate capital share. In fact, the intersection between the plutocratic (blue) line and the macro line shows that this is the case for almost 85% of U.S. wealth. Following Lemma 1, households with a personal capital share smaller (greater) than the aggregate capital share prefer a level of automation below (above) what is output-maximizing. As a result, most U.S. citizens would strive for under-automation, while most U.S. wealth prefers over-automation. This is the data-driven counterpart of Propositions 2 and 4: democracy leads to under-automation and plutocracy to over-automation.

4.2 Effect size in a calibrated model

In the previous section, we showed that there is scope for under-automation or over-automation if technology choice is political. We now establish how quantitatively important the automation effects of a political regime shift are.

Table 1: Calibration of Parameters

Parameter	**Value**	**Target Moment**	**Source**
Level of relative task productivity schedule b	0.346	Cost-effective gross labor share $1-\alpha_y$ of 58.7%	BLS, nonfinancial sector 2019
Slope of relative task productivity schedule γ	2.86	Macro elasticity of substitution between capital and labor of 1.35	Hubmer (2023) and Karabarbounis and Neiman (2014)
Output at α_y	1	Normalized	/
Capital-labor ratio k	3	Capital-output ratio of 3	Standard value
Depreciation rate δ	5.7%	Net capital share of 29.2%	DINA 2019 (Piketty et al., 2018)
Wealth endowments a_i	vector	U.S. wealth inequality in 2019	DINA 2019 (Piketty et al., 2018)
Labor endowments L_i	vector	U.S. labor income inequality in 2019	DINA 2019 (Piketty et al., 2018)

To do this, we first calibrate the model. Table 1 summarizes the calibration of the model's parameters. The steepness of the capital-labor productivity schedule γ is set to match the long-run elasticity of substitution between capital and labor equal to $1+\frac{1}{\gamma}$, as indicated in Section 3.3. We set this elasticity of substitution to 1.35 (Acemoglu, Manera, and Restrepo, 2020; Hubmer, 2023; Karabarbounis and Neiman, 2014), and thus find that $\gamma = \frac{1}{0.35} = 2.86$. Assuming that the 2019 U.S. situation is characterized by the cost-efficient competitive market outcome, the productivity parameter b is calibrated so that the output-maximizing labor share coincides with the observed labor share $1-\alpha_y = 0.587$ (from the BLS series for 2019 for the nonfinancial corporate sector) for the given capital-output ratio $\frac{k}{y} = 3$. We introduce capital depreciation to account for the wedge between the gross capital share (which coincides with the share of automated tasks) and the net capital share. Appendix E shows how the introduction of depreciation affects the social planner's solution to the model, and derives how the technology parameter b is calibrated.

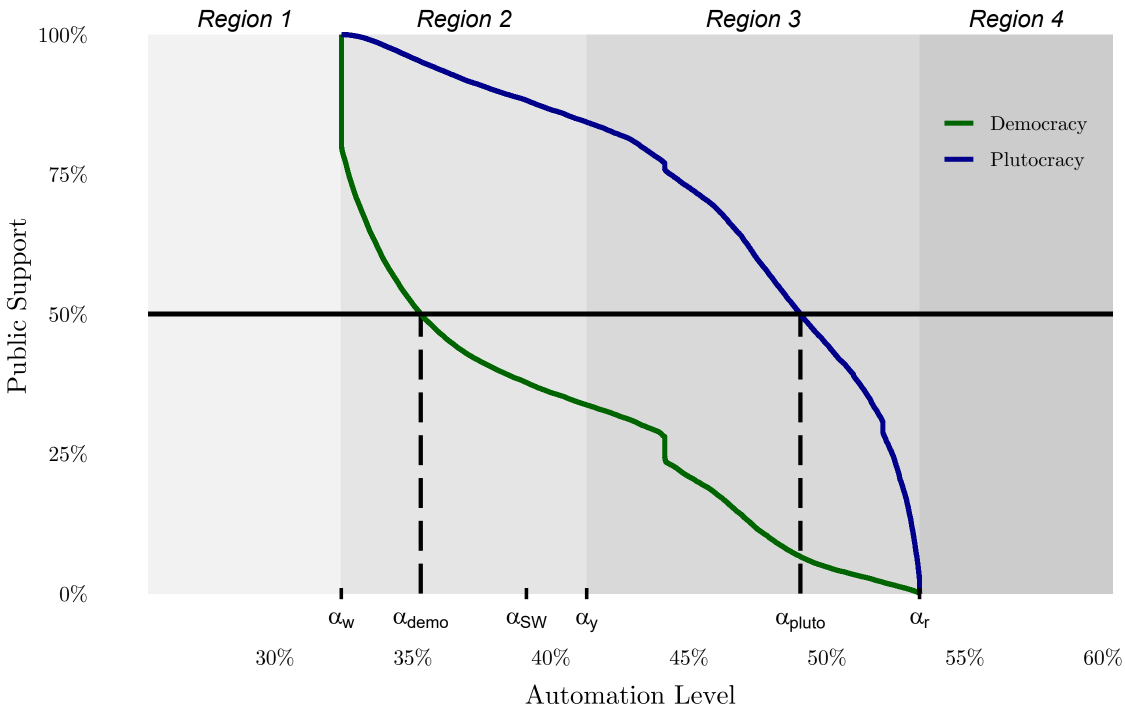
Given our calibration, we can compute the preferred level of automation α_i^* for each household as a function of their relative factor endowment from equation (12). We obtain data on individuals' pre-tax capital income and labor income for 2019 in the U.S. from the Distributional National Accounts data (Piketty et al., 2018), and we use them to construct the distributions of L_i, a_i, and σ_i. Details on the construction of these endowments and the resulting distributions are given in Appendix D.

Figure 3 indicates the level of public support for more automation for each automation value α under the democratic (green curve) and plutocratic (blue curve) regimes. The level of public support is the counter-cumulative density function of α_i^*, that is $P(\alpha_i^* > \alpha)$. In other words, for each value of α, the share of households that prefer a higher level of automation $\alpha_i^* > \alpha$ is shown. The democratic and plutocratic cases differ in their weighting of households. Just like in our theoretical analysis, we distinguish four regions of automation (based on the signs of $\frac{\partial w}{\partial \alpha}$, $\frac{\partial y}{\partial \alpha}$ and $\frac{\partial r}{\partial \alpha}$) and indicate them with different shades. Setting equations (9), (5) and (7) equal to zero, we find a wage-maximizing level of automation $\alpha_w = 32.4\%$, an output-maximizing level of automation $\alpha_y = 41.3\%$ and return-to-capital-maximizing level of automation $\alpha_r = 53.4\%$. For levels of automation below α_w, there is unanimous support for more automation. On the other hand, for levels of automation greater than α_r, no one desires additional automation. The socially optimal level of automation can be computed from the first-order condition for social welfare maximization in equation (20). This results in an automation level of 39.1%.

When using the real U.S. data on capital and labor income from the Distributional National Accounts (Piketty et al., 2018) to calibrate wealth and labor endowments, we find that the political regime has a substantial impact on a society's automation choice. A democratic regime would select an automation level of 35.3% ($\alpha_{\text{demo}} = 0.353$), whereas a plutocratic regime would select a level of 49.0% ($\alpha_{\text{pluto}} = 0.490$). These values correspond to the points at which public support for automation reaches 50% on the respective democratic and plutocratic curves in Figure 3. Accordingly, the difference in the labor share between regimes amounts to 13.8 percentage points ($\alpha_{\text{pluto}} - \alpha_{\text{demo}} = 0.138$).[1] The

[1]Under a more conservative long-run macro elasticity of 1.2, we still find a large 9.1 pp decline in the labor share when a democratic regime turns plutocratic.

Figure 3: Public support for further automation by level of automation α



automation choice also affects the distribution of personal income by changing capital returns relative to the wage rate. For instance, shifting from the democratic to the plutocratic automation level raises the income share of the top 1% by 4.3 percentage points, from 18.3% to 22.6%.

5 Conclusion

In this paper, we developed a theoretical framework that introduces political economy considerations in the determination of automation. We found that when households are heterogeneous in their capital and labor endowments, their optimal level of automation depends on their relative capital-labor endowments. Households which are less (more) reliant on capital income than the macro average, prefer a level of automation that is smaller (greater) than the competitive output-maximizing level. Applying the median voter theorem, we find that what matters under a political technology choice is the relation between the relative capital-labor endowment of the relevant median household and the macro capital-labor ratio.

Under realistic theoretical distributions of wealth and labor endowments, we have shown that in a democratic (plutocratic) regime the relevant median household's capital-labor endowment is lower (higher) than the aggregate capital-labor ratio. Accordingly, democratic (plutocratic) technology choice leads to under-automation (over-automation) relative to the competitive output-maximizing benchmark. Furthermore, greater wealth concentration exacerbates under-automation and over-automation outcomes under the two alternative regimes. From a normative perspective, social welfare maximization requires under-automation when high labor income households are more reliant on capital than poorer households. Finally, we showed that replacing the theoretical endowment distributions with U.S. data preserves the model's key qualitative predictions, while the calibration indicates that a move from democratic to plutocratic automation reduces the labor share by about 13 percentage points.

Appendices

Appendix A

Appendix A1

We start by showing that the amount of capital (or labor) that is assigned to a task does not vary over the set of automated (non-automated) tasks.

Given that $\ln(Y) = \int_0^1 \ln(t(x))\mathrm{d}x$, then $Y = \prod_0^1 t(x)^{\mathrm{d}x}$, and the price of a certain task x in terms of the final good is

$$p_x = \frac{\partial Y}{\partial t(x)} = \frac{Y}{t(x)}\mathrm{d}x.$$

Two sets of tasks can be defined. $\mathfrak{K}$ denotes the subset of tasks which are executed by capital (automated), and $\mathfrak{L}$ denotes the subset of tasks executed by labor (non-automated). That is

$$\mathfrak{K} = \{x : \lambda(x) = 0\} \quad \text{with} \quad t(x) = \zeta(x)\kappa(x) \ \forall x \in \mathfrak{K}$$

$$\mathfrak{L} = \{x : \kappa(x) = 0\} \quad \text{with} \quad t(x) = \chi(x)\lambda(x) \ \forall x \in \mathfrak{L}.$$

A cost-minimizing firm will allocate capital to the execution of an automated task $x \in \mathfrak{K}$ up to the point that its marginal product (priced in terms of final output) is equal to the cost of capital r:

$$\forall x \in \mathfrak{K} : \frac{\partial Y}{\partial \kappa(x)} = p_x \frac{\partial t(x)}{\partial \kappa(x)} = \frac{Y\mathrm{d}x}{t(x)}\zeta(x) = \frac{Y}{\kappa(x)}\mathrm{d}x = r.$$

Likewise, a cost-minimizing firm will allocate labor to the execution of a non-automated task $x \in \mathfrak{L}$ up to the point that its marginal product (priced in terms of final output) is equal to the cost of labor w:

$$\forall x \in \mathfrak{L} : \frac{\partial Y}{\partial \lambda(x)} = p_x \frac{\partial t(x)}{\partial \lambda(x)} = \frac{Y\mathrm{d}x}{t(x)}\chi(x) = \frac{Y}{\lambda(x)}\mathrm{d}x = w.$$

This shows that the amount of capital (or labor) that is assigned to a task does not vary over the set of automated (non-automated) tasks so that $\kappa(x) = \kappa \; \forall x \in \mathfrak{K}$, and $\lambda(x) = \lambda \; \forall x \in \mathfrak{L}$.

We now move to the derivation of the production function in intensive form.

Given the task-based production function (eqs. (1) and (2)), the productivity schedule (eq. (3)), and the sets of automated and non-automated tasks α: $\mathfrak{K} = [0, \alpha]$ and $\mathfrak{L} = (\alpha, 1]$, it follows that

$$
\begin{gathered}
\ln(Y(\alpha)) = \int_0^1 \ln(t(x))\mathrm{d}x = \int_0^\alpha \ln(\zeta(x)\kappa)\mathrm{d}x + \int_\alpha^1 \ln(\chi(x)\lambda)\mathrm{d}x = \\
\int_0^\alpha \ln(b^{1+\gamma}(1-x)^\gamma \kappa)\mathrm{d}x + \int_\alpha^1 \ln((1-b)^{1+\gamma} x^\gamma \lambda)\mathrm{d}x = \\
\int_0^\alpha \left((1+\gamma)\ln(b) + \gamma \ln(1-x) + \ln(\kappa)\right)\mathrm{d}x + \int_\alpha^1 \left((1+\gamma)\ln(1-b) + \gamma\ln(x) + \ln(\lambda)\right)\mathrm{d}x = \\
\alpha(1+\gamma)\ln(b) + \alpha\ln(\kappa) + (1-\alpha)(1+\gamma)\ln(1-b) + (1-\alpha)\ln(\lambda) + \\
\gamma\left(\int_0^\alpha \ln(1-x)\mathrm{d}x + \int_\alpha^1 \ln(x)\mathrm{d}x\right) \\
= \alpha(1+\gamma)\ln(b) + \alpha\ln(\kappa) + (1-\alpha)(1+\gamma)\ln(1-b) + (1-\alpha)\ln(\lambda) + \\
\gamma\left(-(1-\alpha)\ln(1-\alpha) - 1 - \alpha\ln(\alpha)\right) = \\
\alpha\left((1+\gamma)\ln(b) + \ln(\kappa) - \gamma\ln(\alpha)\right) + (1-\alpha)\left((1+\gamma)\ln(1-b) + \ln(\lambda) - \gamma\ln(1-\alpha)\right) - \gamma.
\end{gathered}
$$

Taking exponentials on both sides gives

$$
Y(\alpha) = \left(b^{1+\gamma}\kappa\alpha^{-\gamma}\right)^\alpha \left((1-b)^{1+\gamma}\lambda(1-\alpha)^{-\gamma}\right)^{1-\alpha} e^{-\gamma}.
$$

We now use the condition for factor market clearing. Total supply of capital (labor) has to be equal to the sum of all capital (labor) demand by firms: $K = \int_0^\alpha \kappa \mathrm{d}x = \alpha\kappa$ and $N = \int_\alpha^1 \lambda \mathrm{d}x = (1-\alpha)\lambda$. Hence,

$$
Y(\alpha) = e^{-\gamma} \left(\left(\frac{b}{\alpha}\right)^{1+\gamma} K\right)^\alpha \left(\left(\frac{1-b}{1-\alpha}\right)^{1+\gamma} N\right)^{1-\alpha},
$$

which in intensive form yields

$$
y(\alpha) = e^{-\gamma} \left(\left(\frac{b}{\alpha}\right)^{1+\gamma} k\right)^\alpha \left(\left(\frac{1-b}{1-\alpha}\right)^{1+\gamma}\right)^{1-\alpha}.
$$

We now focus on the endpoints of the task interval. When $\alpha = 0$ we have

$$\begin{aligned}
\ln(Y(0)) &= \int_0^1 \ln(t(x))\,\mathrm{d}x = \int_0^1 \ln(\chi(x)\lambda)\,\mathrm{d}x \\
&= \int_0^1 \ln\Big((1-b)^{1+\gamma} x^{\gamma} \lambda\Big)\,\mathrm{d}x \\
&= \int_0^1 \Big((1+\gamma)\ln(1-b) + \gamma \ln(x) + \ln(\lambda)\Big)\,\mathrm{d}x \\
&= (1+\gamma)\ln(1-b) + \ln(\lambda) + \gamma \int_0^1 \ln(x)\,\mathrm{d}x \\
&= (1+\gamma)\ln(1-b) + \ln(\lambda) - \gamma.
\end{aligned}$$

Taking exponentials on both sides and using $\int_0^1 \lambda\,\mathrm{d}x = \lambda = N$, we obtain $Y(0) = e^{-\gamma}(1-b)^{1+\gamma}N$, and $y(0) = e^{-\gamma}(1-b)^{1+\gamma}$.

When $\alpha = 1$ we have

$$\begin{aligned}
\ln(Y(1)) &= \int_0^1 \ln(t(x))\,\mathrm{d}x = \int_0^1 \ln(\zeta(x)\kappa)\,\mathrm{d}x \\
&= \int_0^1 \ln\Big(b^{1+\gamma}(1-x)^{\gamma}\kappa\Big)\,\mathrm{d}x \\
&= \int_0^1 \Big((1+\gamma)\ln b + \gamma \ln(1-x) + \ln(\kappa)\Big)\,\mathrm{d}x \\
&= (1+\gamma)\ln b + \ln(\kappa) + \gamma \int_0^1 \ln(1-x)\,\mathrm{d}x \\
&= (1+\gamma)\ln b + \ln(\kappa) - \gamma.
\end{aligned}$$

Taking exponentials on both sides and using $\int_0^1 \kappa\,\mathrm{d}x = \kappa = K$, we find $Y(1) = e^{-\gamma}b^{1+\gamma}K$, and $y(1) = e^{-\gamma}b^{1+\gamma}k$.

Appendix A2

To calculate $\frac{\partial y}{\partial \alpha}$, we start by taking the natural logarithm of equation (4). This gives

$$\ln(y) = -\gamma + \alpha(1+\gamma)\ln(\frac{b}{\alpha}) + (1-\alpha)(1+\gamma)\ln(\frac{1-b}{1-\alpha}) + \alpha \ln(k).$$

Deriving the last equation yields

$$\frac{\partial \ln(y)}{\partial \alpha} = (1+\gamma)\left(\ln(\frac{b}{\alpha}) - \ln(\frac{1-b}{1-\alpha})\right) + \ln(k) = \ln\left(\left(\frac{b}{1-b}\frac{1-\alpha}{\alpha}\right)^{1+\gamma} k\right).$$

Since $\frac{\partial \ln(y)}{\partial \alpha} = \frac{1}{y}\frac{\partial y}{\partial \alpha}$, equation (5) follows.

Let us now prove that α_y is a global maximum. We know that α_y is a maximum in $(0,1)$. We only need to show that $\alpha = 0$ and $\alpha = 1$ are local minima. Start by calculating

$$\lim_{\alpha\to 0^+} y(\alpha) = e^{-\gamma}\left(\left(\frac{b}{\alpha}\right)^{1+\gamma} k\right)^{\alpha}\left(\left(\frac{1-b}{1-\alpha}\right)^{1+\gamma}\right)^{1-\alpha} = e^{-\gamma}(1-b)^{1+\gamma} = y(0)$$

, and

$$\lim_{\alpha\to 1^-} y(\alpha) = e^{-\gamma}\left(\left(\frac{b}{\alpha}\right)^{1+\gamma} k\right)^{\alpha}\left(\left(\frac{1-b}{1-\alpha}\right)^{1+\gamma}\right)^{1-\alpha} = e^{-\gamma}b^{1+\gamma}k = y(1).$$

Hence, $y(\alpha)$ is a continuous function over $\alpha \in [0,1]$. From equation (5) we can also calculate $\lim_{\alpha\to 0^+}\frac{\partial y}{\partial \alpha}(\alpha) = +\infty, \qquad \lim_{\alpha\to 1^-}\frac{\partial y}{\partial \alpha}(\alpha) = -\infty.$

Then there exists $\delta > 0$ such that $\frac{\partial y}{\partial \alpha}(\alpha) > 0$ for all $\alpha \in (0,\delta)$. Hence y is strictly increasing on $(0,\delta)$. Since 0 is the left endpoint of the domain and y is continuous at 0, we get $y(\alpha) > y(0)$ for all $\alpha \in (0,\delta)$, so that $\alpha = 0$ is a local minimum. Additionally, there also exists $\epsilon > 0$ such that $\frac{\partial y}{\partial \alpha}(\alpha) < 0$ for all $\alpha \in (1-\epsilon, 1)$. Hence y is strictly decreasing on $(1-\epsilon,1)$. Since 1 is the right endpoint of the domain and y is continuous at 1, we get $y(\alpha) > y(1)$ for all $\alpha \in (1-\epsilon,1)$, so that $\alpha = 1$ is a local minimum. This proves that α_y is the unique global maximum.

To prove that α_r is a global maximum it is sufficient to show that $r(1)$ is a local minimum. Start by calculating $\lim_{\alpha\to 1^-} r(\alpha) = e^{-\gamma}\alpha\left(\left(\frac{b}{\alpha}\right)^{1+\gamma} k\right)^{\alpha}\left(\left(\frac{1-b}{1-\alpha}\right)^{1+\gamma}\right)^{1-\alpha}/k = e^{-\gamma}b^{1+\gamma} = r(1)$, which shows that $r(\alpha)$ is continuous in 1. Next calculate $\lim_{\alpha\to 1^-}\frac{\partial r}{\partial \alpha}(\alpha) = -\infty$. Then there exists $\delta > 0$ such that $\frac{\partial r}{\partial \alpha}(\alpha) < 0$ for all $\alpha \in (1-\delta, 1)$. Hence r is strictly decreasing on $(1-\delta,1)$. Since 1 is the right endpoint of the domain and r is continuous at 1, we get $r(\alpha) > r(1)$ for all $\alpha \in (1-\delta,1)$, so that $\alpha = 1$ is a local minimum.

To prove that α_w is a global maximum it is sufficient to show that $w(0)$ is a local minimum. Start by calculating $\lim_{\alpha \to 0^+} w(\alpha) = (1-\alpha)e^{-\gamma} \left(\left(\frac{b}{\alpha}\right)^{1+\gamma} k \right)^{\alpha} \left(\left(\frac{1-b}{1-\alpha}\right)^{1+\gamma} \right)^{1-\alpha} = e^{-\gamma}(1-b)^{1+\gamma} = w(0)$, which shows that $w(\alpha)$ is continuous in 0. Next calculate $\lim_{\alpha \to 0^+} \frac{\partial w}{\partial \alpha}(\alpha) = +\infty$. Then there exists $\delta > 0$ such that $\frac{\partial w}{\partial \alpha}(\alpha) > 0$ for all $\alpha \in (0, \delta)$. Hence w is strictly increasing on $(0, \delta)$. Since 0 is the left endpoint of the domain and w is continuous at 0, we get $w(\alpha) > w(0)$ for all $\alpha \in (0, \delta)$, so that $\alpha = 0$ is a local minimum.

Appendix B

Appendix B1

We now define the left-hand side of equation (12) as $L(\alpha_i^*) = \ln\left(k\left(\frac{b}{1-b}\frac{1-\alpha_i^*}{\alpha_i^*}\right)^{1+\gamma}\right)$ and the right-hand side as $r(\alpha_i^*) = -\frac{\frac{\sigma_i - k}{k}}{1+\alpha_i^*\frac{\sigma_i-k}{k}}$. Deriving these expressions, it follows that

$$\frac{\partial L(\alpha_i^*)}{\partial \alpha_i^*} = -\frac{1+\gamma}{\alpha_i^*(1-\alpha_i^*)},$$

$$\frac{\partial r(\alpha_i^*)}{\partial \alpha_i^*} = \left(\frac{\frac{\sigma_i-k}{k}}{1+\alpha_i^*\frac{\sigma_i-k}{k}}\right)^2.$$

It follows that $\frac{\partial L(\alpha_i^*)}{\partial \alpha_i^*} < 0$ and $\frac{\partial r(\alpha_i^*)}{\partial \alpha_i^*} \geq 0 \ \forall \alpha_i^* \in (0,1)$. Both $L(\alpha_i^*)$ and $r(\alpha_i^*)$ are continuous $\forall \alpha_i^* \in (0,1)$. Moreover, $\lim_{\alpha_i^* \to 0^+} L(\alpha_i^*) = +\infty$ and $\lim_{\alpha_i^* \to 1^-} L(\alpha_i^*) = -\infty$. From this, it follows that the α_i^* which solves equation (12) is unique so that preferences are single-peaked.

Appendix B2

We re-write equation (12) as

$$\ln\left(k\left(\frac{b}{1-b}\frac{1-\alpha_i^*}{\alpha_i^*}\right)^{1+\gamma}\right) + \frac{\frac{\sigma_i-k}{k}}{1+\alpha_i^*\frac{\sigma_i-k}{k}} \equiv H(\alpha_i^*, \sigma_i) = 0. \tag{21}$$

We apply the implicit function theorem to $H(\alpha_i^*, \sigma_i) = 0$. This gives

$$\frac{\partial H(\alpha_i^*, \sigma_i)}{\partial \alpha_i^*} = \frac{k\left(\frac{b}{1-b}\right)^{1+\gamma}(1+\gamma)\left(\frac{1-\alpha_i^*}{\alpha_i^*}\right)^{\gamma}\frac{-1}{(\alpha_i^*)^2}}{k\left(\frac{b}{1-b}\frac{1-\alpha_i^*}{\alpha_i^*}\right)^{1+\gamma}} - \left(\frac{\frac{\sigma_i-k}{k}}{1+\alpha_i^*\frac{\sigma_i-k}{k}}\right)^2 =$$

$$-\left(\frac{1+\gamma}{\alpha_i^*(1-\alpha_i^*)} + \left(\frac{\frac{\sigma_i-k}{k}}{1+\alpha_i^*\frac{\sigma_i-k}{k}}\right)^2\right) < 0, \text{ and}$$

$$\frac{\partial H(\alpha_i^*, \sigma_i)}{\partial \sigma_i} = \frac{\frac{1}{k}\left(1+\alpha_i^*\frac{\sigma_i-k}{k}\right) - \frac{\alpha_i^*}{k}\frac{\sigma_i-k}{k}}{(1+\alpha_i^*\frac{\sigma_i-k}{k})^2} = \frac{1}{k(1+\alpha_i^*\frac{\sigma_i-k}{k})^2} > 0.$$

It follows that $\frac{\mathrm{d}\alpha_i^*}{\mathrm{d}\sigma_i} = -\frac{\frac{\partial H(\alpha_i^*,\sigma_i)}{\partial \sigma_i}}{\frac{\partial H(\alpha_i^*,\sigma_i)}{\partial \alpha_i^*}} > 0.$

Appendix C

Appendix C1

We first prove that labor endowments follow a Pareto distribution with a tail parameter $\frac{\eta}{\theta}$. Following the main text, we have that $L_i = \xi(a_i)^\theta$ and $P(a_i > a) = \left(\frac{a}{a_0}\right)^{-\eta}$. Then,

$$P(L_i > L) = P(\xi(a_i)^\theta > L) = P\left(a_i > \left(\frac{L}{\xi}\right)^{\frac{1}{\theta}}\right) = \left(\frac{L}{\xi(a_0)^\theta}\right)^{-\frac{\eta}{\theta}}.$$

Next, we prove that the relative factor endowments are Pareto distributed with tail parameter $\frac{\eta}{1-\theta}$. Since $\sigma_i = \frac{a_i}{L_i} = \frac{a_i}{\xi(a_i)^\theta} = \frac{1}{\xi}(a_i)^{1-\theta}$, we find

$$P(\sigma_i > \sigma) = P\left(\frac{(a_i)^{1-\theta}}{\xi} > \sigma\right) = P(a_i > (\xi\sigma)^{\frac{1}{1-\theta}}) = \left(\frac{\sigma}{(a_0)^{1-\theta}/\xi}\right)^{-\frac{\eta}{1-\theta}}.$$

We now impose that individual factor endowments sum up to macro aggregates to find solutions to a_0 and ξ. We first proceed to calculate the density function of wealth $f(a)$ by taking the derivative of the cumulative distribution function

$$P(a_i < a) = 1 - \left(\frac{a}{a_0}\right)^{-\eta}. \tag{22}$$

This yields

$$f(a) = \eta\frac{a_0^\eta}{a^{\eta+1}}.$$

Hence,

$$K = \int_{a_0}^{+\infty} af(a)\mathrm{d}a = \int_{a_0}^{+\infty} \eta\frac{(a_0)^\eta}{a^\eta}\mathrm{d}a = \eta(a_0)^\eta \int_{a_0}^{+\infty} a^{-\eta}\mathrm{d}a.$$

This integral has a finite solution only if $\eta > 1$. That is a typical condition, since a variable that follows a Pareto distribution only has finite moments of the order smaller than its tail parameter η. We thus require $\eta > 1$ to obtain a finite first moment for the distribution of a_i, which equals the aggregate capital stock K. We then find

$$a_0 = \frac{\eta - 1}{\eta}K.$$

Similarly, we can find the density function for labor endowments as

$$g(L) = \frac{\eta}{\theta} \frac{(\xi(a_0)^\theta)^{\frac{\eta}{\theta}}}{L^{\frac{\eta}{\theta}-1}},$$

which we can plug into $N = \int_\xi^{+\infty} Lg(L)\mathrm{d}L$. The problem is analogous to what we did before. Under the condition that $\frac{\eta}{\theta} > 1$ such that the mean of L is finite, we find that $N = \frac{\frac{\eta}{\theta}}{\frac{\eta}{\theta}-1}\xi(a_0)^\theta = \frac{\eta}{\eta-\theta}\xi(a_0)^\theta$, so that $\xi = \frac{\eta-\theta}{\eta(a_0)^\theta}N$.

Hence,

$$P(\sigma_i > \sigma) = \left(\frac{\sigma_i}{\xi^{-1}(a_0)^{1-\theta}}\right)^{\frac{-\eta}{1-\theta}} = \left(\frac{\sigma_i}{a_0 \frac{\eta}{\eta-\theta}\frac{1}{L}}\right)^{\frac{-\eta}{1-\theta}} = \left(\frac{1}{\sigma_i}\frac{\eta-1}{\eta-\theta}k\right)^{\frac{\eta}{1-\theta}}.$$

The median σ_M can then be calculated by solving

$$P(\sigma_i > \sigma_M) = 0.5,$$

which yields

$$\frac{\sigma_M}{k} = \left(\frac{\eta-1}{\eta-\theta}\right)2^{\frac{1-\theta}{\eta}}.$$

Appendix C2

We start from equation (14). Deriving σ_M with respect to η yields

$$\frac{\partial\sigma_M}{\partial\eta} = \frac{1-\theta}{\eta-\theta}2^{\frac{1-\theta}{\eta}}\frac{\ln(2)}{\eta-\theta}\left(\frac{1}{\ln(2)} - \frac{(\eta-1)(\eta-\theta)}{\eta^2}\right)k > 0,$$

because $0 < \theta < 1$, $\eta > 1$, $\frac{1}{\ln(2)} > 1$, and $\frac{(\eta-1)(\eta-\theta)}{\eta^2} < 1$.

Deriving σ_M with respect to θ yields

$$\frac{\partial\sigma_M}{\partial\theta} = \frac{\eta-1}{\eta-\theta}2^{\frac{1-\theta}{\eta}}\frac{\ln(2)}{\eta-\theta}\left(\frac{1}{\ln(2)} - \frac{\eta-\theta}{\eta}\right)k > 0,$$

because $0 < \theta < 1$, $\eta > 1$, and $\frac{1}{\ln(2)} > 1$.

Appendix C3

Given the counter-cumulative distribution function of the relative factor endowments found in Appendix C1, the associated cumulative distribution function is

$$P(\sigma_i < \sigma) = 1 - \left(\frac{1}{\sigma_i} \frac{\eta - 1}{\eta - \theta} k \right)^{\frac{\eta}{1-\theta}}.$$

We find the density function $h(\sigma)$ as its derivative

$$h(\sigma) = \frac{\partial P(\sigma_i < \sigma)}{\partial \sigma} = \frac{\eta}{1-\theta} \left(\frac{\eta - 1}{\eta - \theta} k \right)^{\frac{\eta}{1-\theta}} \left(\frac{1}{\sigma} \right)^{\frac{\eta}{1-\theta}+1}.$$

Shifting from a "one-person-one-vote" set-up to a "one-dollar-one-vote" set-up requires reweighting the density function $h(\sigma)$ by multiplying it by $\frac{a}{K}$. In other words, we weight households by their share of total wealth when considering who is the "median" voter. The resulting plutocratic density function is given by $\tilde{h}(\sigma)$. That yields

$$\tilde{h}(\sigma) = h(\sigma) \frac{a}{K} = \frac{\eta}{1-\theta} \frac{\left(\frac{\eta-1}{\eta-\theta} k \right)^{\frac{\eta}{1-\theta}}}{\sigma^{\frac{\eta}{1-\theta}+1}} \frac{a}{K} = \frac{\eta}{1-\theta} \frac{\left(\frac{\eta-1}{\eta-\theta} k \right)^{\frac{\eta}{1-\theta}}}{\sigma^{\frac{\eta}{1-\theta}+1}} \frac{1}{K} \left(\frac{L}{K^\theta} \frac{\eta - \theta}{\eta} \left(\frac{\eta}{\eta - 1} \right)^\theta \sigma \right)^{\frac{1}{1-\theta}}.$$

To find the median dollar of wealth, we set $\int_{\sigma_{\tilde{M}}}^{+\infty} \tilde{h}(\sigma) \mathrm{d}\sigma = 0.5$ and solve for $\sigma_{\tilde{M}}$. That is

$$\int_{\sigma_{\tilde{M}}}^{+\infty} \tilde{h}(\sigma) \mathrm{d}\sigma = \frac{\eta}{1-\theta} \frac{\left(\frac{\eta-1}{\eta-\theta} k \right)^{\frac{\eta}{1-\theta}}}{K} \left(\frac{L}{K^\theta} \frac{\eta - \theta}{\eta} \left(\frac{\eta}{\eta - 1} \right)^\theta \right)^{\frac{1}{1-\theta}} \int_{\sigma_{\tilde{M}}}^{+\infty} \sigma^{\frac{1-\eta}{1-\theta}-1} \mathrm{d}\sigma = 0.5.$$

This integral only has a finite solution if $\frac{1-\eta}{1-\theta} < 0$, which is true for $\eta > 1$ and $0 < \theta < 1$. This gives

$$\begin{aligned}
-\frac{\eta}{1-\theta} \frac{\left(\frac{\eta-1}{\eta-\theta} k \right)^{\frac{\eta}{1-\theta}}}{K} \left(\frac{L}{K^\theta} \frac{\eta - \theta}{\eta} \left(\frac{\eta}{\eta - 1} \right)^\theta \right)^{\frac{1}{1-\theta}} \frac{1-\theta}{1-\eta} (\sigma_{\tilde{M}})^{\frac{1-\eta}{1-\theta}} &= 0.5 \\
\Leftrightarrow \left(\frac{\eta - 1}{\eta - \theta} \right)^{\frac{\eta-1}{1-\theta}} \left(\frac{\sigma_{\tilde{M}}}{k} \right)^{\frac{1-\eta}{1-\theta}} &= 0.5 \\
\Leftrightarrow \frac{\sigma_{\tilde{M}}}{k} &= \frac{\eta - 1}{\eta - \theta} 2^{\frac{1-\theta}{\eta-1}}.
\end{aligned}$$

We now show that $\frac{\sigma_{\tilde{M}}}{k} > 1$ when $\theta + \eta < 2$. We have

$$\frac{\sigma_{\tilde{M}}}{k} > 1 \Leftrightarrow \frac{\eta - 1}{\eta - \theta} 2^{\frac{1-\theta}{\eta-1}} > 1 \Leftrightarrow \ln\left(\frac{\eta - 1}{\eta - \theta}\right) + \frac{1-\theta}{\eta - 1}\ln(2) > 0.$$

We now define $z = \frac{1-\theta}{\eta-1}$. Since $\eta > 1$ and $\theta \in (0, 1)$, then $z > 0$. It holds that $\eta + \theta < 2 \Leftrightarrow z > 1$. Given the definition of z and $1/(z+1) = \frac{\eta-1}{\eta-\theta}$, we find

$$\ln\left(\frac{\eta - 1}{\eta - \theta}\right) + \frac{1-\theta}{\eta - 1}\ln(2) > 0 \Leftrightarrow -\ln(z+1) + \ln(2)z > 0.$$

We now define $\phi(z) = -\ln(z+1) + \ln(2)z$, with $\phi(0) = 0$ and $\phi(1) = 0$. Its derivative is

$$\phi'(z) = \frac{-1}{z+1} + \ln(2),$$

so that that $\phi'(z) = 0$ for $z = \frac{1-\ln(2)}{\ln(2)} < 1$, with $\phi'(z) < 0$ when $z < \frac{1-\ln(2)}{\ln(2)}$ and $\phi'(z) > 0$ when $z > \frac{1-\ln(2)}{\ln(2)}$. Hence, $z \gtreqless 1 \Leftrightarrow \phi(z) \gtreqless 0$. It follows that $\frac{\sigma_{\tilde{M}}}{k} \gtreqless 1 \Leftrightarrow \theta + \eta \lesseqgtr 2$.

Appendix C4

We start from equation (15). Deriving $\sigma_{\tilde{M}}$ with respect to η yields

$$\frac{\partial \sigma_{\tilde{M}}}{\partial \eta} = 2^{\frac{1-\theta}{\eta-1}} \frac{1-\theta}{\eta-\theta}\left(\frac{1}{\eta-\theta} - \frac{\ln(2)}{(\eta-1)^2}\right)k.$$

For $\eta > 1$ and $0 < \theta < 1$, we have that $\frac{\partial \sigma_{\tilde{M}}}{\partial \eta} < 0 \Leftrightarrow \frac{(\eta-1)^2}{\eta-\theta} < \ln(2)$. Since $\eta + \theta < 2 \Leftrightarrow \eta < 2 - \theta$, we can write $\eta = 2 - \theta - \epsilon$, where $0 < \epsilon < 1 - \theta$ because $\eta > 1$ and $\theta < 1$. We can plug this expression for η into $\frac{(\eta-1)^2}{\eta-\theta}$ to find $\frac{(\eta-1)^2}{\eta-\theta} = (\eta - 1)\frac{1-\theta-\epsilon}{2(1-\theta)-\epsilon} < \ln(2)$. This holds because: $\frac{1-\theta-\epsilon}{2(1-\theta)-\epsilon} < 1/2$; $\eta - 1 < 1$; and $\ln(2) > 1/2$. We conclude that $\eta + \theta < 2 \Rightarrow \frac{\partial \sigma_{\tilde{M}}}{\partial \eta} < 0$. Greater wealth inequality (a fall in η) thus generates a greater "plutocratic median" $\sigma_{\tilde{M}}$.

Deriving $\sigma_{\tilde{M}}$ with respect to θ yields

$$\frac{\partial \sigma_{\tilde{M}}}{\partial \theta} = 2^{\frac{1-\theta}{\eta-1}} \frac{\eta-1}{(\eta-\theta)^2}\left(1 - \frac{(\eta-\theta)\ln(2)}{\eta-1}\right)k,$$

which implies $\frac{\partial \sigma_{\tilde{M}}}{\partial \theta} < 0 \Leftrightarrow \frac{\eta-1}{\eta-\theta} < \ln(2)$. Above, we have already shown that $\frac{\eta-1}{\eta-\theta} < 1/2 < \ln(2)$. We then conclude that $\eta + \theta < 2 \Rightarrow \frac{\partial \sigma_{\tilde{M}}}{\partial \theta} < 0$. Greater labor income inequality for given wealth inequality (a rise in θ) thus generates a lower "plutocratic median" $\sigma_{\tilde{M}}$.

Appendix D

We obtain data from the Distributional National Accounts (Piketty et al., 2018) on individuals' personal pre-tax capital income and labor income for 2019 in the US. The data reflect market incomes, but corrected for pensions and social security mechanisms such as disability benefits and unemployment benefits (for details see Piketty et al. (2018)). We drop households with non-positive labor income, which leaves around 97% of the population. Since, wealth endowments are non-negative in the model, negative capital income values are set to zero.

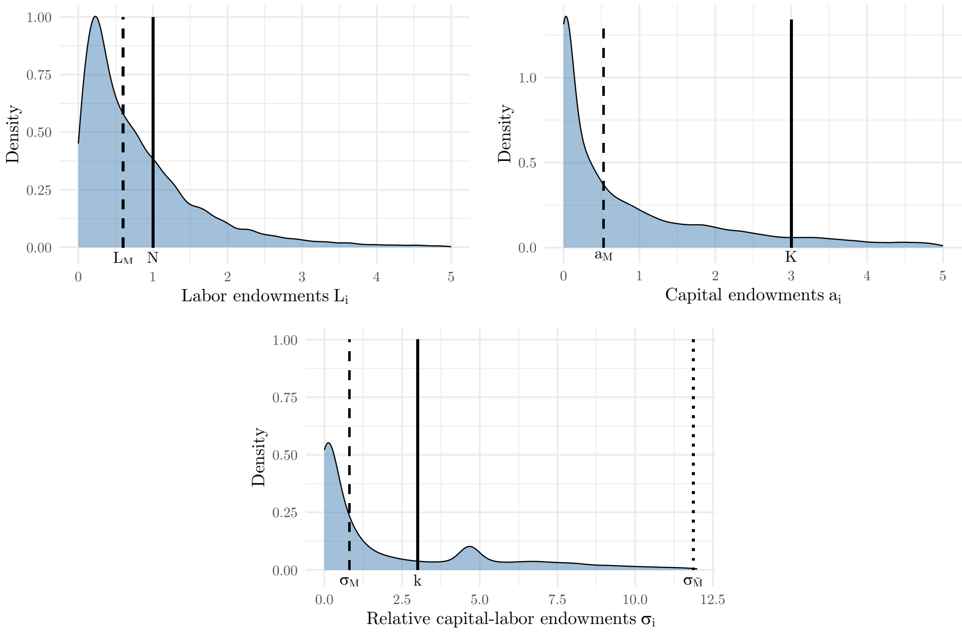
For the construction of Figure 2, we calculate personal capital shares as $\frac{\text{capital income}_i}{\text{capital income}_i + \text{labor income}_i}$, order individuals by increasing capital share and construct a percentile plot. Capital income is net of depreciation in this measure.

For the calibration of the model in Section 4.2, we construct individual factor endowments a_i and L_i from this data. Since factor prices r and w are constant in the model, $a_i \propto (\text{capital income})_i$ and $L_i \propto (\text{labor income})_i$. We find values for a_i and L_i by normalizing $\sum_i L_i = 1$ so that $k = \frac{K}{L} = K = \sum_i a_i$. Since in the calibration $\frac{k}{y} = 3$ and we normalize $y = 1$, it follows that $k = K = 3$. The individual relative factor endowments follow: $\sigma_i = \frac{a_i}{L_i}$.

Figure 4 shows the density plots of the obtained labor L_i, capital a_i and relative capital-labor endowments σ_i. In accordance with the Pareto distributions assumed in section 3.4.1, labor and wealth endowments are right-skewed such that the endowments of the median household are smaller than the aggregate endowments ($L_M < N = 1$ and $a_M < K = 3$). The relative capital-labor endowments σ_i are right-skewed as well. Its population-based median is smaller than the aggregate capital-labor ratio ($\sigma_M < k = 3$), while its wealth-based median is larger ($\sigma_{\tilde{M}} > k = 3$).

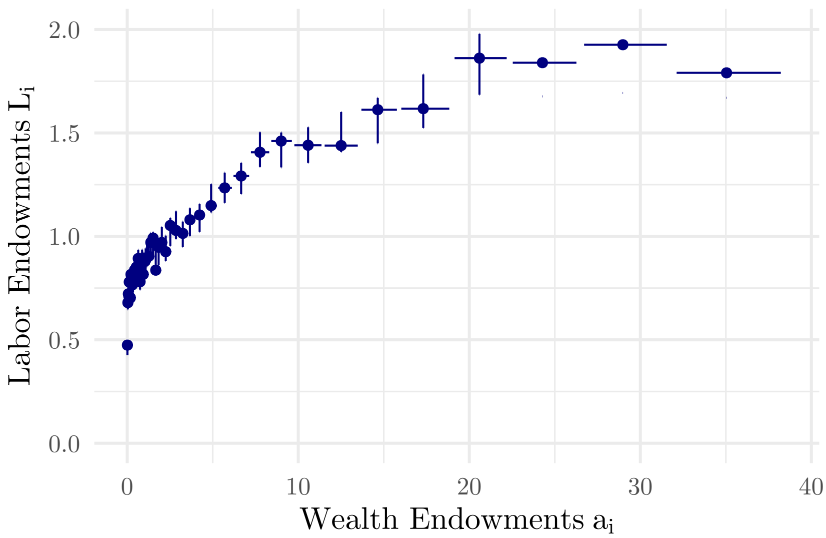
Moreover, we find evidence for a positive and concave dependence of labor endowments on capital endowments which supports our theoretical restriction in section 3.4.1 that $L_i = \xi(a_i)^\theta$ with $\xi > 0$ and $0 < \theta < 1$. Figure 5 shows a binned scatterplot of L_i against a_i, when restricting the sample to strictly positive endowments and trimming the outer

Figure 4: Density plots for labor, capital and relative capital-labor endowments
U.S. in 2019 (DINA data)



1% for both endowments. In line with a visual inspection of the graph, regressing L_i on a_i in logs results in $\theta = 0.157$ and $\xi = 0.566$.

Figure 5: Relationship between labor and capital endowments
U.S. in 2019 (DINA data)



Appendix E

Introducing capital depreciation at rate δ, net household income equals $\tilde{I}_i = wL_i + \tilde{r}a_i$ with $\tilde{r} = r - \delta$. Depreciation does not affect the competitive equilibrium for automation since cost-effective automation still occurs for $\frac{\zeta(\alpha_{\text{pc}})}{\chi(\alpha_{\text{pc}})} = \frac{r}{w}$. Each household's preferred automation level is the same as before, since $\frac{\partial \tilde{r}}{\partial \alpha} = \frac{\partial r}{\partial \alpha}$ so that the household income maximization in equation (10) is unchanged.

Social welfare maximization is affected by the introduction of depreciation, however. Households now consume their net income so that the social welfare function is given by

$$W = \sum_i u(c_i) = \sum_i u(\tilde{I}_i).$$

The planner is faced with the maximization of social welfare. We have that

$$\max_\alpha W = \max_\alpha \sum_i u(wL_i + \tilde{r}a_i) = \max_\alpha \sum_i u((1-\alpha)yL_i + \left(\frac{\alpha y}{k} - \delta\right) a_i).$$

As before, assuming that $u(c) = \ln(c)$, yields

$$\max_\alpha W = \max_\alpha \sum_i \ln((1-\alpha)yL_i + \left(\frac{\alpha y}{k} - \delta\right) a_i) = \max_\alpha \left(\sum_i \ln(L_i) + \sum_i \ln((1-\alpha)y + \left(\frac{\alpha y}{k} - \delta\right) \sigma_i)\right).$$

Social welfare maximization then requires the first order condition $\frac{\partial W}{\partial \alpha}(\alpha_{\text{SW}}) = 0$, or

$$\frac{\partial W}{\partial \alpha}(\alpha_{\text{SW}}) = \sum_i \frac{-y + (1-\alpha_{\text{SW}})\frac{\partial y}{\partial \alpha}(\alpha_{\text{SW}}) + \frac{y}{k}\sigma_i + \frac{\alpha_{\text{SW}}}{k}\sigma_i \frac{\partial y}{\partial \alpha}(\alpha_{\text{SW}})}{(1-\alpha_{\text{SW}})y + \left(\frac{\alpha_{\text{SW}} y}{k} - \delta\right)\sigma_i)} =$$
$$y \sum_i \frac{\frac{\sigma_i - k}{k} + \frac{1}{y}(1 - \alpha + \frac{\alpha}{k}\sigma_i)\frac{\partial y}{\partial \alpha}(\alpha_{\text{SW}})}{(1-\alpha_{\text{SW}})y + \left(\frac{\alpha_{\text{SW}} y}{k} - \delta\right)\sigma_i} = 0,$$

which is the condition we use to solve for the social welfare optimum α_{SW} in the calibrated model.

Defining the net capital share of income as $\alpha_n = \frac{\tilde{r}k}{y - \delta k} = \frac{(r-\delta)k}{y-\delta k}$, one finds that $\delta = \frac{\alpha - \alpha_n}{1 - \alpha_n}\frac{y}{k}$. Using data on the net and gross capital shares from the DINA and BLS respectively, we use this expression to calibrate δ.

To facilitate the calibration, we introduce a Hicks-neutral productivity factor A into the production function (4) such that

$$y(\alpha) = Ae^{-\gamma} \left(\frac{b}{\alpha}\right)^{(1+\gamma)\alpha} \left(\frac{1-b}{1-\alpha}\right)^{(1+\gamma)(1-\alpha)} k^{\alpha}.$$

We now derive the conditions for calibrating the technology parameters A and b. Since the calibration assumes that we start at the output-maximizing level of automation α_y, we impose that $\frac{\partial y}{\partial \alpha} = 0$. From equation (5), this yields a condition on k. That is

$$k = \left(\frac{1-b}{b}\frac{\alpha}{1-\alpha}\right)^{1+\gamma}.$$

Inserting this result in the production function above yields

$$y = A\left(\frac{1-b}{1-\alpha}\right)^{1+\gamma}.$$

Dividing both sides by k results in

$$\frac{y}{k} = A\left(\frac{b}{\alpha}\right)^{1+\gamma} \Leftrightarrow b = \alpha A^{\frac{-1}{1+\gamma}} \left(\frac{k}{y}\right)^{\frac{-1}{1+\gamma}}.$$

We normalize $y = 1$ such that $A = \left(\frac{1-\alpha}{1-b}\right)^{1+\gamma}$. We then find

$$b = \frac{1}{1 + \frac{1-\alpha}{\alpha}\left(\frac{k}{y}\right)^{\frac{1}{1+\gamma}}}.$$

For the calibrated values for α, $\frac{k}{y}$ and γ of the main text, we find that $b \approx 0.346$.

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