Automation and Top Wealth Inequality

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Abstract

This paper studies the impact of automation on wealth concentration in the United States using a dynamic model with a task-based framework and collateral-constrained entrepreneurs. Automation is shown to increase wealth inequality by boosting income concentration and widening capital return dispersion. The calibrated model explains about one-third of the observed rise in the top 1% wealth share. Welfare analysis shows automation raised worker welfare by 5% and entrepreneur welfare by 8%, underscoring its role in expanding wealth inequality through increased capital and entrepreneurial returns.

JEL classification: E23, J23, J3, O33.

Keywords: automation, top wealth inequality, entrepreneurship, superstars.

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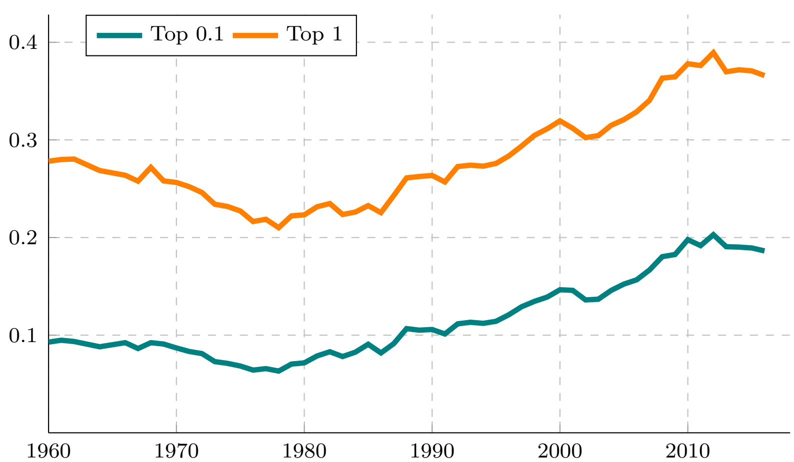
1 Introduction

Over the last 50 years, wealth concentration in the United States has increased substantially (as documented by Saez & Zucman (2016) and others). Figure 1 below shows the share of wealth held by the top 1% and the top 0.1% based on data from the World Inequality Database.[1] Since the 1960s, the wealth share of the top 1% has risen from 27% to 36.5%. Even more strikingly, the wealth share of the top 0.1% has doubled from 9% to 18%. This trend has sparked ongoing debates in both public and academic spheres about the causes of this rising wealth concentration.

n this paper, I analyze the impact of automation on wealth concentration, specifically examining two channels through which automation affects the wealth share of the top 1%. The first channel is a rise in income concentration due to higher returns to entrepreneurial productivity, and the second is an increase in the dispersion of the return to capital. In the model, increased automation accounts for one-fourth of the rise in the wealth share of the top 1% in the United States.

Figure 1: Top Wealth Shares



Note: The orange line plots the share of wealth that owned by top 1%. The green line plots the share of wealth that owned by top 0.1%.
Source: World Inequality Database.

[1] https://wid.world/wid-world/.

I use the term ”automation” broadly, encompassing robots and machines as well as computers and software. Over the last 50 years, automation technologies have expanded significantly. For instance, the mid-1970s—when the rise in top wealth shares began—coincided with the dawn of the information technology (IT) revolution, as computers and software started being used widely across various industries. Automation has both substituted some workers, suppressing wages, and generated higher returns for those owning capital or using automation technology effectively. Consequently, automation is a key factor influencing inequality.

In this paper, I make two contributions to the literature. First, I introduce the concept of automation technology into a macroeconomic model by incorporating a task-based production function and a convex labor cost (as in Koru (2019)) into an Aiyagari model featuring entrepreneurs and financial frictions, similar to Quadrini (2000) and Cagetti & De Nardi (2006). I model financial friction as a collateral constraint, where entrepreneurs can borrow only up to a fraction of their assets. I show that automation affects wealth concentration through two channels: it increases income concentration and widens the dispersion of capital returns. Second, I quantify the impact of automation on wealth inequality by calibrating the model and analyzing exogenous improvements in automation. I focus on entrepreneurs because business capital is a major component of the wealthiest individuals' assets. Nearly half of those in the top 1% of wealth and income distributions own a business, and they hold one-third of their wealth in those businesses (Kuhn & Ríos-Rull, 2016; Smith et al., 2019). I model the financial friction as the collateral constraint; in other words, entrepreneurs can only borrow up to a fraction of their assets for their businesses. Around one-third of entrepreneurs use their assets as collateral for business loans, and almost one-fifth are denied credit, as documented by Cagetti & De Nardi (2006). Therefore, I use collateral constraints to model the incomplete market for entrepreneurs.

I depart from the canonical Aiyagari model by modifying the production function in two ways. irst, to account for automation decisions, I incorporate a task-based framework as in Zeira (1998) and Acemoglu & Restrepo (2018). Entrepreneurs must complete a set of tasks to produce the final good. There are two types of tasks: automated and non-automated. Automated tasks can be performed using capital, while non-automated tasks require labor. Entrepreneurs choose which tasks to automate, which provides a measure of automation choice in the model. The automation level is defined as the share of tasks that can be automated and is treated as exogenous. I analyze how shifts in this share impact wealth concentration. Second, I introduce a convex labor cost, similar to Koru (2019), resulting in a production function with decreasing returns to scale. Unlike the literature that defines decreasing returns to scale at the aggregate level, this approach links the severity of diseconomies of scale in the entrepreneurial sector directly to automation technology. By reducing dependency on labor, automation mitigates the convexity of the cost function and, consequently, the severity of diseconomies of scale. Since decreasing returns to scale are often linked to the span of control of entrepreneurs (Lucas, 1978), and the span of control is generally proxied by the number of employees (Ouchi & Dowling, 1974), it is intuitive to link scalability to labor input. The convex labor cost effectively captures this.

An improvement in automation technology influences wealth concentration through two main mechanisms. The first is its impact on the top of the income distribution. Automation reduces the severity of diseconomies of scale, thereby increasing returns to entrepreneurial skill. As shown by Koru (2019) in a static model with a similar production function, if entrepreneurial productivity follows a Pareto distribution, then the income distribution's tail can be approximated with a Pareto tail, where the shape parameter is inversely related to automation level. Improved automation reduces labor dependency, allowing highly productive entrepreneurs to scale up their production relative to less productive entrepreneurs, which enhances the "superstar" effect identified by Rosen (1981), thereby increasing income concentration. Thus, as automation technology improves, the return to the "superstar" stage rises, amplifying wealth concentration.

The second impact of automation is through increased dispersion in the returns to capital. Automation raises the demand for capital, and if the collateral constraint was binding before this improvement, it will now tighten even further, pushing up returns to business capital. Consequently, the incentive to save increases, particularly for more productive entrepreneurs, whose demand for capital rises more than that of less productive ones. This results in greater dispersion in capital returns, which, in turn, amplifies wealth concentration.

One implication of the model is that automation increases capital intensity, average firm size, and the employment share of the largest firms. Using data on European private firms, I document that industries with faster growth in IT intensity saw larger increases in average firm size, average capital intensity, and employment concentration. The model can replicate this positive relationship between automation and firm size distribution.

To quantify the impact of automation on wealth inequality, I calibrate the model to represent the U.S. economy in 1968. I examine the effects of an unexpected improvement in automation technology and measure the resulting change in the wealth share of the top 1%. An implication of the task-based framework is that the capital share of income is a function of the automation level (Acemoglu & Restrepo, 2018; Martinez, 2021). In this model, the capital share of income directly corresponds to the automation level, so I use the capital share as a proxy for automation. The model matches the initial steady-state reasonably well. When the automation level is increased to its 2016 level, the wealth share of the top 1% rises by three percentage points in the new steady state, compared to a nine percentage points increase observed in the data. Therefore, the model can explain approximately one-third of the increase in the wealth share of the top 1%.

In the data, most of the increase in wealth concentration is due to the rise in the wealth share held by the top 0.1%. However, the model does not replicate this sharp increase; it can only account for 10% of the observed rise in the wealth share of the top 0.1%. The main reason for this is that the second channel is not effective for very wealthy entrepreneurs. Since the collateral constraint does not bind for them, there is no resulting dispersion in the return to capital. Therefore, the impact of automation for these individuals is solely due to the increase in returns to entrepreneurial skills, which limits the impact of improvement of automation technology on wealth concentration.

To understand who benefited from improvements in automation technology, I calculate the welfare gains across different wealth groups. Accounting for the entire transition path, I find that everyone gained from the technological advancement. Welfare for workers in the bottom quartile increased by 4%, while it rose by 10% for those in the top percentile. The gains for poorer workers primarily stem from overall productivity growth, which can be attributed to the reallocation of labor towards more productive firms. In contrast, wealthier workers benefit additionally from increased returns to capital and higher wealth levels. The welfare improvement for entrepreneurs is slightly greater than the gains experienced by workers.

Related Literature:

This paper contributes to two main strands of literature.

First, it relates to the literature on the impact of automation on the labor market. Acemoglu & Restrepo (2020) provide evidence on the impact of industrial robots on employment. Autor & Dorn (2013) and Goos et al. (2014) explore job polarization caused by routine-biased technological change. Hémous & Olsen (2018), Koru (2019), Prettner & Strulik (2019), and Acemoglu & Restrepo (2022) consider the effects of automation on income inequality. Acemoglu & Restrepo (2018), Martinez (2021), and Eden & Gaggl (2018) analyze how improvements in automation technology impact the labor share of income. In contrast, this paper focuses on the impact of automation on wealth concentration.

The second strand of literature to which this paper contributes concerns the dynamics of top wealth distribution. Studies such as Piketty (2014), Saez & Zucman (2016), Kopczuk (2015), Kuhn & Ríos-Rull (2016), and Smith et al. (2020) document the increase in wealth concentration using the capitalization method, estate tax data, and survey data. Other works, including Hubmer et al. (2020), Kaymak & Poschke (2016), Cao & Luo (2017), and Aoki & Nirei (2017), study the channels that drive top wealth inequality.

Kaymak & Poschke (2016) analyze the effects of rising wage inequality and declining marginal tax rates. They argue that the increase in wage inequality is the primary driver of top wealth inequality, as the effects of tax changes are offset by changes in prices. Unlike their study, in which the change in wage inequality is directly fed into the model, the change in income concentration in this paper is a consequence of shifts in automation technology.

Hubmer et al. (2020), Cao & Luo (2017) and Aoki & Nirei (2017) show that changes in income tax schedules can explain a substantial portion of the observed increase in wealth concentration. Aoki & Nirei (2017) also provide a micro-foundation for heterogeneous returns to wealth and income inequality, showing how a reduction in taxes encourages entrepreneurs to invest in risky projects, thereby increasing income dispersion. In contrast, this paper attributes the increase in income dispersion and heterogeneous returns to wealth to changes in production technology driven by advances in automation. I focus specifically on the link between automation and wealth concentration, abstracting from other potential factors to isolate the effect of automation technology.

The paper most closely related to this study is Moll et al. (2022), which investigates the impact of automation on income and wealth inequality using a task-based framework within the perpetual youth model. In their model, the main mechanism is an increase in the return to capital. Due to a birth and death process, only a small fraction of households live long enough to accumulate wealth exponentially, leading to a concentration of wealth among long-lived households. As automation progresses, returns to capital rise, causing increased savings and higher wealth inequality at the top. In contrast, my mechanism hinges on higher returns to entrepreneurial skill. Since more than 40% of individuals at the top of the wealth distribution are entrepreneurs, and over two-thirds of their income comes from returns to human capital (either through labor or business) (Kuhn & Ríos-Rull, 2016), this channel is crucial. Moreover, a significant share of top wealth owners are self-made, accumulating their wealth over a short period. For instance, half of the individuals on the 2017 Forbes 400 list are self-made billionaires (Guvenen et al., 2019).

The production function used in this model builds on my companion paper Koru (2019). Using the same production function, I developed a theory linking automation to the Pareto parameter of the top income distribution. I demonstrated that in a static model where entrepreneurial skill productivity follows a Pareto distribution, the right tail of the income distribution can also be approximated by a Pareto distribution. The shape parameter of the top income distribution is determined by the shape parameter of the productivity distribution, the level of automation, and the convexity of labor costs. Moreover, it shows that the thickness of the right tail increases with the level of automation. In this paper, I focus on the impact of automation on top wealth inequality and quantify how changes in income concentration driven by automation affect wealth concentration.

This paper is structured as follows. Section 2 describes the model and discusses the impact of automation on wealth concentration. Section 3 provides details about calibration. Section 4 presents the results. Section 5 analyses welfare consequences and Section 6 concludes.

2 The Model

My model is based on the dynamic general equilibrium incomplete market model of Aiyagari (1994), augmented by entrepreneurial choice and financial frictions, as in Cagetti & De Nardi (2006) and Quadrini (2000). The main difference between the current model and the standard models found in the literature is the production function. There are two main differences in this production function. First, I use a task-based framework, as in Acemoglu & Restrepo (2018), that provides a notion of automation choice in the model. Second, I define the span-of-control as a function of the measure of labor, instead of total output, as in Koru (2019). This leads the severity of the diseconomies scale to be a function of automation.

2.1 Demographics and Preferences

There is a continuum of the infinitely lived individual of measure one. The utility of individuals from consumption is given by $u(c)$. Individuals discount the future at a rate of β. Individuals are subject to uninsurable labor productivity shock; however, there is no aggregate uncertainty. The labor market productivity of an individual evolves according to a Markov process. Let $p_s(s'|s)$ denote the probability density function of the next period's labor productivity s', conditional on this period's labor productivity s. Let $\mathcal{S}$ be the set of all possible levels of labor productivity.

In a given period, an individual can be either a worker or an entrepreneur. A worker supplies a unit of labor inelastically. In each period, a worker gets an entrepreneurial idea with probability p. The productivity of the idea z follows a Pareto distribution with the shape parameter μ and the scale parameter $\underline{z}$. Let $\phi(.)$ denote the pdf of the distribution of z and let $\mathcal{Z}$ denote the set of all possible values of z. If the individual implements the idea, he becomes an entrepreneur; otherwise, he remains a worker. The productivity of the idea remains constant throughout the entrepreneurship spell. At the beginning of the period, an entrepreneur decides whether to continue to operate his firm or become a worker. If he becomes a worker, he loses the idea and needs to find another one to become an entrepreneur again. With probability p_e, his business fails for some exogenous reason and he becomes a worker.

2.2 Technology

There are two production sectors: corporate and non-corporate. Firms in the non-corporate sector are owned by entrepreneurs. However, in reality, not all firms are closely held by entrepreneurs. Therefore, following Cagetti & De Nardi (2006) and Quadrini (2000), I also include a corporate sector. There is a unique homogeneous good in the economy; hence, both sectors produce the same good. Both sectors have a similar production function. The main difference is that firms in the non-corporate sector face a convex cost of labor, which leads to a production function that exhibits decreasing returns to scale.

2.2.1 Corporate Sector

I use a task-based framework similar to Zeira (1998) and Acemoglu & Restrepo (2018). To produce a final good, a measure of one of the tasks must be completed. There is no market for tasks; hence, each firm needs to complete all tasks inside the firm.

There are two types of tasks: automated and non-automated. If a task is automated, then capital and labor are perfect substitutes in production. On the other hand, if a task is not automated, then the only input in the production function is labor. I assume that the productivity of labor and capital is the same across all tasks. Let I be automation technology frontier such that any task below I is automated and any tasks above I are non-automated. Formally, the production function of task $i \in [0, 1]$ is given by:

$$y_i = \begin{cases} k_i + \ell_i & \text{if } i \leq I, \\ \ell_i & \text{if } i > I, \end{cases} \tag{1}$$

Tasks are complements and they are aggregated into output by a unit elastic aggregator (i.e., Cobb-Douglas):

$$\ln Y = \int_0^1 \ln(y_i) di, \tag{2}$$

where Y is the total output. The problem of a corporate firm is:

$$\max_{\ell_i, k_i} AY - w \int_0^1 \ell_i di - (r + \delta) \int_0^1 k_i di,$$

where A is the aggregate TFP and δ is the depreciation rate.

Observe that automation is a labor replacing technology. An improvement in automation, i.e., an increase in I, means that labor can be replaced in this new automated task. However, a task complements other tasks. Therefore, even though automation replaces labor within a task, it improves the productivity of other tasks by cost reduction.

Since capital and labor are perfect substitutes, only one of them is used to produce a task. Because the productivity of capital and labor is the same across all tasks, the cheaper input is used in automated tasks. In equilibrium, because there is a positive supply of capital, it is the case that the price of capital is less than the wage; hence, only capital is used in automated tasks, i.e., $\ell(i) = 0$ for $i \leq I$. Moreover, by the symmetry of tasks, the optimal choice of capital is the same for all automated tasks and the optimal choice of labor is the same for all non-automated tasks, i.e., $k(i) = k$ for all $i \leq I$ and $\ell(i) = \ell$ for all $i > I$. Hence, the optimal solution induces to a Cobb-Douglas production function for a firm with the capital share equal to I:

$$Y = k^I \ell^{1-I}. \tag{3}$$

2.2.2 Non-corporate Sector

Entrepreneurs have access to a decreasing returns to scale production function. The production of tasks and aggregation into the final good is similar to the corporate sector. However, there is an additional convex cost that depends on the measure of labor used in the production. The profit function of an entrepreneur with productivity z is given by:

$$zAY - w \int_0^1 \ell_i di - v \left(\int_0^1 \ell_i di \right) - (r + \delta) \int_0^1 k_i di,$$

where Y is given by (2) and $v(.)$ is the convex cost with properties $v' > 0$ and $v'' > 0$.

Convex cost of labor

The main mechanism in this paper depends on the convex cost of labor. Observe that Y is constant returns to scale, and, therefore $zAY - v(.)$ is decreasing returns to scale. Here, the convex cost can be seen in a reduced form as the organization cost of labor or the hiring-firing cost of labor or search cost. For example, Koru (2019) shows that this convex cost can be micro-founded by Shapiro & Stiglitz's (1984) efficiency wage theory of the shirking model. In order to prevent labor from shirking, the entrepreneur needs to spend additional resources. Because capital does not have an incentive to shirk, it does not create any moral hazard problem; hence, this additional cost does not depend on capital. The general idea is that if entrepreneurs want to grow, they need to pay more. In this sense, a theory of a firm-size-wage premium can generate the desired result.

I assume that this convex cost of labor is only relevant in the non-corporate sector. In other words, the corporate sector can scale its production perfectly and can replicate the process that causes this cost in the non-corporate sector, whether it is vacancy posting in search friction or problem of monitoring workers or something else. This assumption leads to constant returns to scale production function in the corporate sector. Therefore, there is a representative firm in the corporate sector and I do not need to make assumptions about firm distribution, who owns these firms, and competition structure.

2.3 Financial Market

To raise capital for a business, an entrepreneur can borrow from the financial market. However, an entrepreneur needs to provide collateral in order to borrow. Hence, the amount of borrowing depends on the entrepreneur's asset. An entrepreneur can use up to λ fraction of his asset in his business; i.e.,

$$\int_0^1 k_i di \leq \lambda a, \tag{4}$$

where a is the level of asset owned by the entrepreneur and $\lambda > 1$. In another words, an entrepreneur can only rent up to $(\lambda - 1)$ fraction of his asset.

Workers cannot borrow from the financial market. Only entrepreneurs can borrow, but they can only use it in their business; they cannot consume it.

2.4 Problem of an individual

Let $V(a, s)$ denotes the lifetime value of a worker with labor productivity s and asset a and let $E(a, s, z)$ be the lifetime value of an entrepreneur with entrepreneurial productivity z.

2.4.1 Problem of a Worker

Consider a worker with labor productivity s and asset a. He earns ws as labor income and ra as capital income. With probability p, he gets an idea and decides whether to become an entrepreneur or not. With the remaining probability, he remains as a worker. The lifetime value of a worker is

$$\begin{aligned} V(a,s) = \max_{c,a'} \; u(c) + \beta \Bigg[p \sum_{s' \in \mathcal{S}} \int_{z \in \mathcal{Z}} \left[\max\{V(a',s'), E(a',s',z')\} \right] phi(z') dz' p_s(s'|s) \\ + (1-p) \sum_{s' \in \mathcal{S}} V(a',s') p_s(s'|s) \Bigg] \\ s.t. \quad c + a' \leq ws + (1+r)a, \; a \geq 0, \; c \geq 0. \end{aligned} \tag{5}$$

2.4.2 Problem of an Entrepreneur

Consider an entrepreneur with entrepreneurial productivity z, labor productivity s and asset a. He chooses which tasks to automate, how much capital and labor he needs for each task, and how much to save. First, consider the profit maximization problem. For a given asset level this problem is static. Because in an automated task labor and capital are perfect substitutes, only one of the inputs is used. Therefore, if an entrepreneur automates a task, he uses only capital in that task. An entrepreneur faces two constraints. The first constraint is the automation constraint: he can only automate only the tasks that are technologically amenable to automation. In other words, the choice of automation $I^\star$ must be lower than the exogenously given automation level I. The second constraint is the financial constraint defined in equation (4).

Formally, the problem of an entrepreneur is:

$$\pi(z,a) = \max_{\substack{I^\star, \{\ell_i\}_{i\in[I^\star,1]},\\ \{k_s\}_{s\in[0,I^\star)}}} zY - w\int_{I^\star}^{1} \ell_i di - v\left(\int_{I^\star}^{1} \ell_i di\right) - (r+\delta)\int_{0}^{I^\star} k_s ds \tag{6}$$

$$\begin{aligned} s.t.\;\; & 0 \le I^\star \le I, \\ & \int_0^{I^\star} k(s)ds \le \lambda a, \\ & \ell_i \ge 0,\;\; k_s \ge 0, \end{aligned}$$

and the production function of tasks (1) and the production function of final good (2).

Then, the lifetime value of an entrepreneur is

$$E(a,s,z) = \max_{c,a'}\; u(c) + \beta\left[(1-p_e)\mathbb{E}\left[\max\{V(a',s'), E(a',s',z)\}\right] + p_e\mathbb{E}[V(a',s')]\right] \tag{7}$$

$$\begin{aligned} s.t.\quad & c + a' \le \pi(a,z) + (1+r)a, \\ & a' \ge 0,\;\; c \ge 0. \end{aligned}$$

$u(c)$ is the utility from today's consumption. With probability p_e his business will fail and he will become a worker for an exogenous reason. With probability $1-p_e$ his business will continue, however, he can still close and become a worker if his labor productivity becomes high enough. His resources today are profit, $\pi(a,z)$, and return to the asset.

2.5 Definition of Equilibrium

Now I can define a competitive equilibrium:

Definition 1. *A stationary equilibrium consists of prices w and r; lifetime value function and policy function for a worker with asset level a and labor productivity a, $V(a,s), g_w(a,s)$; a lifetime value function and policy function for entrepreneur with asset level a, labor productivity s and en-*

trepreneurial productivity z, $E(a,s,z), g_e(a,s,z)$; and an automation decision, a labor and capital demand of entrepreneur $I^\star(a,z), \ell(a,z,i), k(a,z,i)$; a labor and capital demand of corporate firms, $\ell_c(i), k_c(i)$; an optimal choice of occupation, $g_o(a,s,z)$; and a stationary distribution of individuals over asset level, labor productivity and entrepreneurial productivity $\Gamma(a,s,z)$, where $z=0$ is for workers, such that:

- *Value functions and policy functions solve* (5) *and* (7)*,*
- $I^\star(a,z), \ell(a,z,i), k(a,z,i)$ *solve entrepreneur problem* (6)*,*
- *labor and capital demand of corporate firm are given by:*
  - $\ell_c(i) = \ell_c$ *for* $i > I$*, and* $k_c(i) = k$ *for* $i \leq I$*,*
  - $A(k_c/\ell_c)^I = w$*,*
  - $A(\ell_c/k_c)^{1-I} = r + \delta$*,*
- *optimal occupational choice:* $g_o(a,s,z) = 1$ *if* $E(a,s,z) > V(a,s)$*,*
- *distribution of individuals is stationary:*

$$\begin{aligned}
\Gamma(a',s',z) = &\int\int_{\mathbb{B}_e} (1-p_e) g_o(a',s',z) p_s(s,s')\Gamma(a,s,z)db + \\
&\int\int_{\mathbb{B}_w} p g_o(a',s',z) phi(z) p_s(s,s')\Gamma(a,s,0)dads, \\
\Gamma(a',s',0) = &\int\int_{\mathbb{B}_e} [p_e p_s(s,s')\Gamma(a,s,z) + (1-p_e)(1-g_o(a',s',z)\Gamma(a,s,z)]dads + \\
&\int\int_{\mathbb{B}_w} (1-p) p_s(s,s')\Gamma(a,s,0)dads + \\
&\int_z^\infty\int\int_{\mathbb{B}_w} p p_s(s,s') phi(z')(1-g_o(a',s',z'))\Gamma(a,s,0)dadsdz',
\end{aligned}$$

where $\mathbb{B}_w = \{(a,s)|g_w(a,s) = a'\}$*, and* $\mathbb{B}_e = \{(a,s,z)|g_e(a,s,z) = a'\}$*,*

- *labor market clears:*

$$\int \int_{I^\star(a,z)}^{1} \ell(a,z,i) d\Gamma(a,s,z) di + (1-I)\ell_c = \int s d\Gamma(a,s,0),$$

- *capital market clears:*

$$\int \int_{0}^{I^\star(a,z)} k(a,z,i) d\Gamma(a,s,z) di + I k_c = \int a d\Gamma(a,s,z).$$

2.6 Impact of An Improvement in Automation

The main mechanism in this paper is the impact of automation on returns to entrepreneurial skills. Improvements in automation technology influence the entrepreneur's problem through two channels: by relaxing the automation constraint and by tightening the collateral constraint. In this section, I discuss how these two factors affect wealth concentration.

To understand how advancements in automation technology impact wealth concentration, it is crucial to understand why the model generates a thick wealth tail. The basic setup in Aiyagari (1994) fails to produce a thick tail because the precautionary savings motive among wealthy individuals is insufficient—they have enough assets to effectively self-insure (for further discussion, see De Nardi & Fella (2017)). The literature suggests several mechanisms for generating a thick wealth distribution (Benhabib & Bisin, 2018). In this model, there are two primary channels: an endogenous, high, and persistent "superstar" income state, and a heterogeneous return to capital.

First, in the model, with a small probability, workers can draw a highly productive idea that has a high return and become a "superstar". However, in each period they face business failure risk, with probability p_e they become a worker. This creates an income risk for entrepreneurs. They earn multiples of wage income today, but tomorrow their business can fail and, consequently, suffer a drastic decrease in income. This risk provides a strong precautionary saving motive for entrepreneurs—they save more to smooth consumption in case of business failure. Castañeda et al. (2003) show that such significant income risk among high-income earners can generate a realistic income and wealth distribution.

Proposition 1. *Fix prices w and r. Let $\tilde{\pi}(z; I)$ be the profit function when automation technology is given by I and without the collateral constraint, i.e., when entrepreneurs operate their businesses at the efficient level. Then, $\tilde{\pi}'(z; I') > \tilde{\pi}'(z; I)$ for $I' > I$, where $\tilde{\pi}'$ is the derivative with respect to z.*

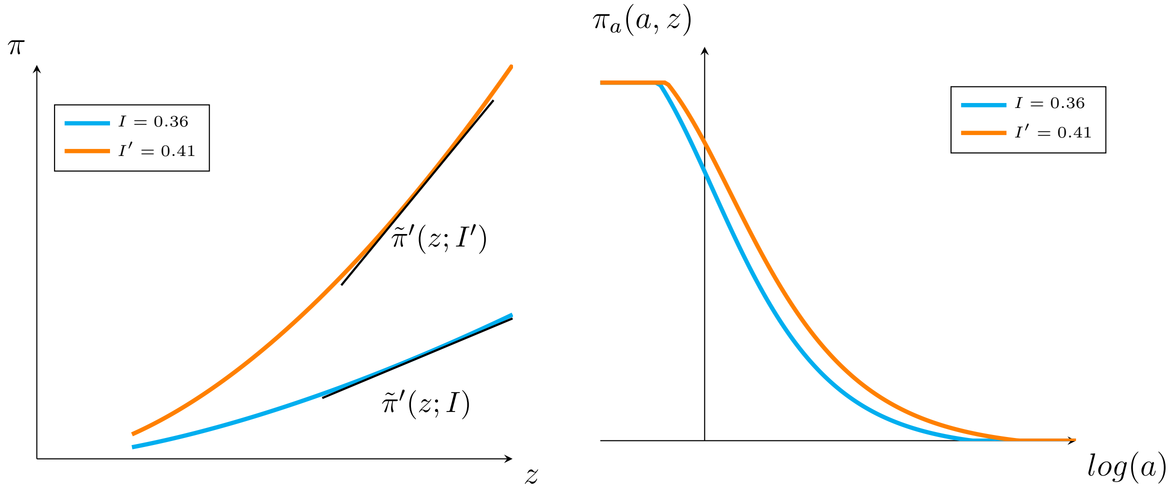
The proposition states that an improvement in automation increases the profits of highly productive entrepreneurs more than those of less productive entrepreneurs. The intuition for this result is explained in Koru (2019): an advancement in automation relaxes the technology constraint in (6). Since this constraint is more costly for highly productive entrepreneurs, they benefit more from its relaxation compared to less productive entrepreneurs. As a result, the gap between highly and less productive entrepreneurs widens, implying that the income of top entrepreneurs increases substantially relative to lower-skilled entrepreneurs. In other words, by relaxing the automation constraint, highly productive entrepreneurs can scale up their production significantly more than less productive entrepreneurs. This leads to higher returns during the "superstar" stage. Moreover, the widening gap between entrepreneurial income and wages suggests an increased risk of business failure. Consequently, highly productive entrepreneurs save more, which contributes to an increase in wealth concentration.

To illustrate the impact more clearly, assume that the convex cost of labor takes the form $v(L) = cL^{\alpha}$, and consider an entrepreneur with sufficient assets such that the collateral constraint does not bind. In this case, we have a closed-form solution, and the profit function is given by:

$$\pi(a, z) = c(\alpha - 1)L^{\star\alpha} = c^{-\frac{1}{\alpha-1}}(\alpha - 1)\left[\left(\frac{z}{(r+\delta)^I}\right)^{\frac{1}{1-I}} - w\right]^{\frac{\alpha}{\alpha-1}}\left(\frac{1}{\alpha}\right)^{\frac{\alpha}{\alpha-1}}. \tag{8}$$

Note that the profit function is convex in z, and this convexity increases with I. In essence, the "superstar" effect—wherein a small increase in entrepreneurial ability leads to a substantial

Figure 2



(a) Profit function $\tilde{\pi}(z)$ (b) Marginal return to business capital.

rise in returns (Rosen, 1981)—becomes more pronounced as automation improves. Thus, the income distribution spreads out, which enhances income concentration and, eventually, wealth concentration.

Koru (2019) shows that when z is distributed according to a Pareto distribution with shape parameter μ, the right tail of the income distribution can also be approximated by a Pareto distribution, with shape parameter $\mu(1 - I)(\alpha - 1)/\alpha$. However, this result does not apply here due to the collateral constraint, which makes entry into entrepreneurship dependent on individual asset levels. Consequently, the equilibrium distribution of active entrepreneurs' productivity differs from the distribution of z. Nevertheless, the underlying idea remains similar: the thickness of the income distribution is influenced by the productivity distribution, the automation level, and the convexity of the labor cost function.

The second channel affecting the tail of the wealth distribution is the heterogeneous return to capital, which is a significant driver of thick wealth tails (Hubmer et al., 2020; Benhabib et al., 2019). Due to the collateral constraint, returns to capital are not equalized across entrepreneurs. Since entrepreneurs cannot reach the efficient production level, the marginal productivity of capital is higher than the risk-free interest rate. Consequently, the return to capital is higher for entrepreneurs compared to workers, leading to greater capital income for entrepreneurs. Moreover, because the tightness of the collateral constraint increases with productivity, there is also dispersion in the returns to capital among entrepreneurs. A higher return to capital thus creates a stronger incentive to save.

An improvement in automation technology raises the return on business capital for entrepreneurs whose collateral constraints bind, as it increases the marginal product of capital. For an entrepreneur, a higher asset level has two advantages: it increases capital income through the risk-free rate and relaxes the collateral constraint, thereby increasing profit. Clausen & Strub (2012) prove that the envelope theorem holds in dynamic models with occupational choice. Therefore, the marginal return to higher capital today can be calculated using the envelope theorem and the first-order condition for consumption:

$$E_a(a, s, z) = [\pi_a(a, z) + (1 + r)]u'(c),$$

where subscripts denote partial derivatives with respect to the indicated argument. The first term on the right-hand side represents the shadow cost of the collateral constraint in the entrepreneur's problem in (6), which is positive for constrained entrepreneurs. I now show that $\pi_a(a, z)$ increases with automation technology.

Proposition 2. *Fix prices w and r. Let $\pi(a, z; I)$ denote the profit function when automation technology is I. Then, the derivative of profit function with respect to a is increasing with I, i.e., $\pi_a(a, z; I') \geq \pi_a(a, z; I)$ when $I' > I$. When the automation constraint binds, this condition holds with strict inequality.*

This implies that the return to savings increases for entrepreneurs whose collateral constrain binds with improvement in automation technology. This is intuitive because when the automation constraint binds, an increase in I leads to a higher marginal product of capital. However, because of the collateral constraint, the entrepreneur cannot rent more capital. Hence, the entrepreneur's incentive to save increases. Formally, the shadow cost of the collateral constraint increases with an increase of I. As the savings of entrepreneurs increases, the wealth concentration increases.

However, notice that in Figure 2b, both ends of the graph remain constant, indicating that an increase in I does not impact those regions. The reason for this is straightforward: for high levels of a, the collateral constraint does not bind, so this channel disappears for wealthy entrepreneurs. For low levels of a, the automation constraint does not bind either. Entrepreneurs with low asset levels do not utilize all available automation technology due to insufficient capital to allocate across various tasks, opting instead to use labor. As their assets increase, they start automating new tasks, but the overall effect on the marginal product of capital remains constant. Hence, entrepreneurs with low asset levels are unaffected by improvements in I. The impact of this channel, therefore, depends on the distribution of these regions. If z is concentrated at a low productivity level, efficient production can be easily achieved, and a rise in I may not significantly influence savings.

It is important to note that these are partial equilibrium results with fixed prices. In a general equilibrium setting, prices will adjust, and the overall effect may differ. Nevertheless, in (8), the convexity of the profit function is independent of prices, meaning that prices affect only the level, not the relative outcomes. Thus, even when prices adjust, highly productive entrepreneurs still benefit more from advances in automation technology.

2.7 Testing Model Predictions

In this section, I use the data to test the model's prediction.

A central assertion of this paper is that automation enables entrepreneurs to scale up production, implying that average firm size should increase with higher levels of automation. As shown in Equation (8), profit is a power function of employment. Thus, as the convexity of the profit function increases, the optimal labor choice becomes more convex as a function of productivity. This suggests that the employment share of highly productive entrepreneurs grows, and, consequently, average firm size in the entrepreneurial sector increases.

To test the hypothesis that higher automation leads to larger firms, I regress changes in

Table 1

	Dependent variable:	
	Δlog(Ave. FS)	Δlog(Top Emp Share)
	(1)	(2)
Δlog(IT Intensity)	0.581***	0.276*
	(0.147)	(0.151)
Nobs	182	182

*p<0.1; **p<0.05; ***p<0.01

Note: Robust standard errors are clustered at the industry level. Employment size data is sourced from Amadeus, and industry-level IT intensity is derived from the EU KLEMS database.

firm size on changes in automation. Since this result pertains to the entrepreneurial sector, I focus solely on the employment distribution within private firms. I use data from the Amadeus database, which provides information on private firms across European countries. For each industry-country pair, I calculate two metrics: average firm size and the employment share of the top 1% of firms. For the automation measure, I use IT intensity, which is defined as the ratio of total IT capital to total capital, constructed using data from EU KLEMS. I examine changes from 2006 to 2016 due to limited observations in earlier Amadeus data.

Table 1 presents the results. Each metric of firm size change is positively correlated with IT intensity, suggesting that industries with higher IT growth also exhibit higher firm size growth. A 1% increase in IT intensity growth correlates with a 0.6% increase in average firm size growth and a 0.3% rise in the employment share of the top 1% of firms. Further, Bessen (2017) and Brynjolfsson et al. (2008) indicate that higher IT intensity leads to greater market concentration, especially in terms of sales, and Stiebale et al. (2020) show that robot-driven productivity and sales gains benefit larger firms more than smaller ones. Together, this evidence supports the model's prediction that automation facilitates firm growth for entrepreneurs.

The model also predicts that labor productivity should increase with employment size

Table 2

	log(Productivity)	
	All Sample	Top 10%
log(Employment)	0.0725^{***}	0.018^{**}
	(0.005)	(0.006)
log(Assets)	-0.26^{***}	-0.26^{***}
	(0.005)	(0.005)

Note: Standard errors are clustered at the country-industry pair level. Data is sourced from Amadeus. Each cell is a different regression, controlling for industry and country fixed effects. In the first column, there is no restriction on the data. In the second column, data is restricted to the top 10% in employment distribution of the country-industry pair.

while capital productivity should decrease with capital size, due to the convex cost of labor. Large firms face higher marginal labor costs, leading to higher labor productivity, while capital productivity remains unaffected by convex costs. This can be derived from the entrepreneurs' first-order conditions:

$$\frac{zY}{L} = \frac{w + v'(L)}{1 - I}, \quad \frac{zY}{K} = \frac{r + \delta + \lambda\eta(z, a)}{I},$$

where $\eta(z, a)$ is the Lagrange multiplier of the collateral constraint.Due to the convexity of v, labor productivity increases with employment size. While the effect on capital productivity is less clear, it remains constant for large firms as λ approaches zero. This model thus predicts a positive relationship between employment size and labor productivity, with constant capital productivity.

To test this prediction, I use firm-level data from the Amadeus database for the year 2016 and use sales over input as a measure of factor productivity. For capital, I consider total assets. TableTo test this, I use firm-level data from Amadeus for 2016, with sales over input as a measure of productivity and total assets representing capital. Table 2 shows the regression results.

Each cell represents a separate regression. Both columns control for country and industry fixed effects. The first column shows results from an unrestricted sample, confirming a positive relationship between labor productivity and employment size, while the relationship for capital is negative. This pattern holds in the second column, where the sample is limited to the top 10%

of firms by employment within each country-industry pair. Thus, the data supports the model's assumption of convex labor costs and refutes the presence of convex capital costs.

Note that these regressions do not claim causality; they simply demonstrate that the model's predictions align with observed data patterns.

3 Quantitative Analysis

I calibrate the model to the US economy in 1968. I choose 1968 because this is the first year for which I can calculate the entrepreneurship rate in PSID.[2] Moreover, the top wealth share and labor share were stable in the 1960s, and they only started to change in the 1970s. In this regard, I believe 1968 is a good starting point. A period in the model is a year.

The aim of this paper is to analyze the impact of an improvement in automation technology on top wealth inequality. After calibrating the model to 1968, I change the automation level I to the 2016 value, leaving all other parameters at the same calibrated values. Then, I calculate the change in the top wealth shares between the two steady states.

The main parameter in this analysis is the automation level, I. Recall that the optimal solution of the corporate sector induces a Cobb-Douglas looking production function, equation (3), with capital share I. So, I set the automation level to the capital share of income. It is important to notice that I only use the capital share in the corporate sector. First, this allows me to exogenously pin down I because the capital share in the non-corporate sector is endogenous. Hence, I cannot set it exogenously for 2016. Second, the Penn World Table splits self-employed income using the share of the non-self-employed sector's capital share. The capital share of income was 0.36 in 1968, and it was 0.41 in 2016, which is the latest year for which I have wealth inequality data.

[2]Business ownership question was not included before 1969.

3.1 Parametrization

This section describes the quantitative specification of the model.

Preferences: I consider the CRRA utility function, $c^{1-\sigma}/(1-\sigma)$ and the risk aversion parameter, σ, is set to 1.5 exogenously. I calibrate the discount factor β to match the capital-to-GDP ratio of 3, $K/Y = 3$.

Technology: I normalized the total factor productivity A to 1. As I noted above, automation technology is set to the capital share of income. The depreciation rate, δ, is set to 5%.

I assume that the convex cost of labor is given by $v(L) = cL^{\alpha}$. Since this cost function is novel, there is no standard way to calibrate these parameters. Coefficient c determines the level of the cost function and, therefore, the level of profit. This is clear from equation (8). Because in this model, the top of the income distribution is populated by entrepreneurs, it will directly affect the share of the top 1%. Thus, I calibrate c to match the wealth share of the top 1%.

The convexity of the cost function, α, affects the size of entrepreneurs' businesses. I use County Business Pattern (CBP) data for 1970 to calculate the employment distribution. Ideally, I would target the tail of the employment distribution of private firms. However, CBP 1970 does not differentiate firm types. Therefore, instead of targeting concentration, I assume that the tail parameter is the same for corporate and non-corporate firms and targets the relative employment shares of top percentiles. Specifically, I target the employment share of firms with more than 500 employees to the employment share of firms with more than 250 employees. In the model, instead of using fixed employee cutoffs, I determine the thresholds by comparing the percentiles of the firm size distribution. This allows the model to align more closely with the relative positions of firms within the distribution, making it more comparable to the empirical data.

Labor Productivity Process: I assume that the log of labor productivity, $\log(s)$, evolves with an AR(1) process:

$$log(s') = \rho log(s) + \epsilon, \epsilon \sim N(0, \sigma_s^2).$$

I set the autocorrelation $\rho = 0.9$ and the standard deviation of innovation to 0.2 following Guvenen et al. (2019). I use the Tauchen & Hussey (1991) method to discretize the labor productivity process.

Distribution of Ideas: There are four parameters for the process of ideas: the probability of getting an idea, p; the probability of exogenous exit, p_e; and the scale and the shape parameter of the Pareto distribution of z, $\underline{z}$ and μ. I set the exogenous exit probability to 26.5%, which is the share of entrepreneurs in PSID that leave entrepreneurship status next year.

The probability of getting an idea and the scale parameter cannot be identified jointly. To see this consider the problem of a worker (5). Because $W(a, s, z)$ is increasing in z, let $z^\star(a, s)$ be the marginal productivity of the entrepreneur who is indifferent between becoming an entrepreneur and a worker. Let z' be the minimum of such $z^\star$. Assume $z' > \underline{z}$. Since $z^\star \geq z'$, I can write the problem as

$$V(a, s) = \max_{a'} u(ws + (1 + r)a - a') \\ + \beta \left[(1 - p)V(a, y) + pP_z(z')V(a, s) + \int_{z'}^{\infty} \max\{V(a, s), W(a, s, z)\} p_z(z) dz \right].$$

Now consider $p' = p(1 - P_z(z'))$. Observe that:

$$p_z(z|z > z') = g(z)/(1 - P_z(z')) = \frac{\mu \underline{z}^\mu}{z^{\mu+1}} \cdot \frac{z'^\mu}{\underline{z}^\mu} = \frac{\mu z'^\mu}{z^{\mu+1}}.$$

This implies that $z|z > z' \sim Pareto(\mu, z')$, so set $\underline{z}' = z'$. Then, the problem of a worker with new parameters is:

$$V(a,s) = \max_{a'} u(ws + (1+r)a - a') + \beta \Bigg[(1 - p(1 - P_z(z')))V(a,s) + p(1 - P_z(z)) \int_{z'}^{\infty} \max\{V(a,s), W(a,s,z)\} p_z(z)/(1 - P_z(z)) dz\Bigg].$$

This is the same problem as before. Hence, there is no change in the solution. Thus, for any $z < z'$, I can find $(\tilde{p}, \tilde{z})$ such that the solution is the same with $(p, \underset{\sim}{z})$. For computational reasons, I fixed the probability of getting an idea to 1 and calibrated $\underset{\sim}{z}$ to match the entrepreneurship date. I calculate this moment using the PSID. I define entrepreneurs as self-employed workers who own a business.

The shape parameter determines the thickness of entrepreneurial productivity. It directly impacts the tail of the income distribution, which affects the tail of the wealth distribution. To this end, I calibrate the shape of the Pareto distribution to match the ratio of the top 0.1% share to the top 1% share.[3] Because I set the coefficient of convex cost of labor, c to match the share of the top 1%, instead of the relative share, I match directly the wealth share of the top 0.1%. The main idea is that c determines the level, and μ determines the thickness of the top distribution.

Collateral Constraint: The last parameter of the model is the collateral constraint of entrepreneurs, λ. Clearly, this parameter affects how much entrepreneurs can borrow, given their asset level. Therefore, I calibrate this parameter to match the debt-to-asset ratio of the non-corporate business sector, which is obtained from the Flow of Funds.[4].

Table 3 summarizes the parametrization.

[3]It is known, first, that top wealth distribution can be approximated by a Pareto distribution and, second, that the relative shares at the top are a function of the shape parameter. In other words, matching the relative share is similar to matching the Pareto tail.

[4]FRED series TLBSNNB over TABSNNB

Table 3: Exogenously Calibrated

I	capital share	0.36	Penn World Table
δ	depreciation rate	0.05	Standard
ρ_y	labor productivity persistency	0.9	Guvenen et al. (2019)
σ_y	labor productivity variance	0.2	Guvenen et al. (2019)
σ_u	risk aversion	1.5	Standard
p_e	entrepreneur exit	0.265	PSID
p	probability of getting an idea	1	Normalization
A	TFP	1	Normalization

Table 4: Calibration Result

Parameter		Value	Target	Data	Model
Discount Factor	β	0.9	K/Y	3	2.9
Col. Cons	λ	1.2	Debt-to-Asset (%)	18.8	18.6
Convexity of Cost	α	1.5	Relative Emp. Share (%)	62.5	59.1
Minimum productivity	$\underset{\sim}{z}$	1.1	Ent Rate (%)	8	8.1
Coef. of cost	c	1	Top 1 Share (%)	27.2	26.4
Pareto shape	μ	8.6	Top 0.1 Share (%)	9.2	9.3

3.2 Model Fit

To sum up, I choose the minimum productivity, $\underset{\sim}{z}$, the discount factor β, the collateral constraint λ, the coefficient of convex labor cost c, the convexity of convex labor cost α, and the shape parameter of Pareto distribution μ to match the entrepreneurial rate, the capital-to-income ratio, the debt-to-asset ratio, the ratio of non-financial non-corporate business assets to the total non-financial business asset, the wealth share of top 1% and the wealth share of top 0.1%. As can be seen from table 4, the model matches the targeted moments well.

The model also fits the overall distribution of wealth remarkably well. Figure 3a shows the Lorenz curve for the wealth distribution above the 50th percentile both from the data and the model. The horizontal axis is the percentiles of the wealth distribution, and the vertical axis is the cumulative shares of wealth. The inner plot zooms into the top 1 percentile. The model fits the

Table 5: Non-targeted Moments

	Income		Wealth	
	Data	Model	Data	Model
Gini	0.46	0.35	0.83	0.80
Bottom 50%	20.4%	27.7%	1.2%	2.3%
Top 10%	36.3%	31.2%	69.5%	66.7%
Top 1%	13.4%	11.4%		
Top 0.1%	5.1%	4.1%		
Top 0.01%	2%	1.3%	3%	2.7%

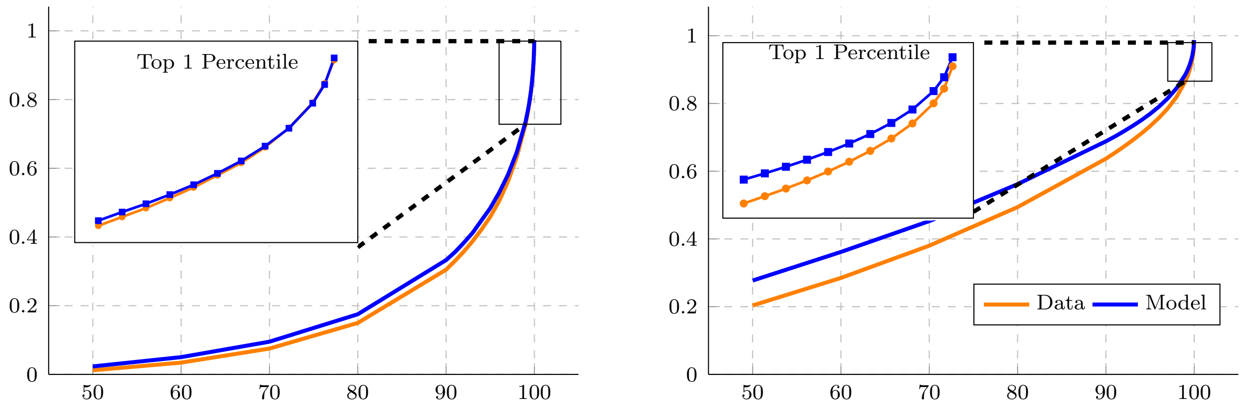
data very well: the two curves are almost on top of each other. Table 5 shows numerical values for some of the points in this graph to give a sense of the difference. Recall that I am only matching two points on the top percentile, but the model also matches the lower percentiles. As a measure of overall inequality, the model generates slightly lower Gini coefficient, which is 0.83 in the data and 0.8 in the model.

Even though the income distribution is not targeted, the model provides a good fit for top income inequality. Figure 3b plots the Lorenz curve for income distribution. The blue line lies above the orange line, which means that for any percentile, the cumulative share below that percentile is higher in the model than in the data. In other words, the model generates lower income inequality than the data. The Gini coefficient for income is 0.35 in the model and 0.46 in the data. However, the gap between these two lines is decreasing at the top of the distribution. Therefore, the model matches the top percentiles better than the low percentiles. This is also clear in the upper panel of table 5, which shows top shares for selected percentiles.

4 Quantitative Impact of an Increase in Automation

This paper aims to understand the impact of automation on wealth concentration. To do so, I increase the automation parameter, I, to the 2016 value, leaving all other parameters constant.

Figure 3: Lorenz Curve



(a) Wealth (b) Income

To this end, following Acemoglu & Restrepo (2022); Moll et al. (2022), I use the change in the labor share of income as an indicator of advancements in automation technology. Between 1968 and 2016, the labor share of income declined by five percentage points. To reflect this shift, I increase I from 0.36 to 0.41.

4.1 Impact on the Wealth Distribution

Table 6 summarizes the results. The first column shows the changes in wealth concentration observed in the data, while the second column reflects these changes in the model's equilibrium. All values, except for the Gini coefficient, are expressed in percentage points. The third column represents the proportion of the observed change that the model can explain, calculated as the ratio of the second column to the first.

In the data, the wealth share held by the top 1% rose by 9.4 percentage points. The model accounts for an increase of about 3.1 percentage points, suggesting it can explain roughly one-third of the observed rise in the top 1% wealth share. This observed increase is entirely due to the heightened wealth concentration at the top 0.1%, whereas the model generates only a 1-percentage-point increase, capturing 11% of the observed change. This discrepancy arises because the heterogeneous return channel is less relevant for the wealthiest individuals, where the collateral

Table 6: Results - Wealth Distribution

	Δ Data	Δ Model	Model Explains
Bottom 50	−0.8 p.p.	−1.5 p.p.	175%
Top 10	1.8 p.p.	10.2 p.p.	557%
Top 1	9.4 p.p.	3.1 p.p.	33%
Top 0.1	9.4 p.p.	1 p.p.	11%
Top 0.01	6.5 p.p.	0.6 p.p.	9%
Gini	0.01	0.06	600%

constraint is not binding. Consequently, automation does not boost returns on business capital for these individuals, offering no additional incentive for increased saving.

Instead, the model's dynamics at the top are largely driven by rising income concentration. The heterogeneous return channel plays a more significant role for entrepreneurs with tighter collateral constraints, where wealth is lower. This channel's influence diminishes with increasing wealth, becoming most pronounced for the lower wealth tiers. This is evident in the model's prediction for the wealth share of the top 10%, which increases by about 10 percentage points—more than five times the observed 1.8 percentage point increase in the data.

4.2 Impact on the Income Distribution

Table 7 displays the changes in income distribution. The model accounts for half of the increase in the income share of the top 1% and one-fourth of the rise in the top 0.1%. It performs relatively well in capturing the increase in top income inequality, which is expected, as automation directly influences the income distribution. Consequently, the model explains a more substantial portion of income concentration, even at the highest levels of the income distribution.

Table 7: Results - Income Distribution

	Δ Data	Δ Model	Model Explains
Bottom 50	−7.9 p.p.	−2.8 p.p.	35%
Top 10	10.4 p.p.	6.4 p.p.	61%
Top 1	6.2 p.p.	2.9 p.p.	47%
Top 0.1	3.7 p.p.	1 p.p.	26%
Top 0.01	1.9 p.p.	0.4 p.p.	23%
Gini	0.14	0.05	36%

4.3 Discussion of the Results

To gauge the significance of this magnitude, I compare it with the findings of Kaymak & Poschke (2016), who analyze how shifts in the earnings distribution and fiscal policy impact wealth concentration. They find that between 1980 and 2010, changes in the earnings distribution alone can explain 60% of the increase in the wealth share held by the top 1%. By contrast, the current model explains 33% of this increase. However, it is crucial to note that Kaymak & Poschke (2016) directly incorporate the observed changes in the earnings distribution into their model. In the current model, by contrast, income concentration arises endogenously.

Since income concentration drives wealth concentration, the model's ability to match observed wealth concentration depends on how well it replicates income concentration. Given that the model does not fully capture the observed rise in income concentration, it faces challenges in aligning with the observed wealth concentration.

To explore the connection between top income inequality and top wealth inequality, consider the ratio of the change in the top wealth share to the change in the top income share. In the data, this ratio is 1.5, while in the model it is 1.06. This suggests that, given the observed increase in income concentration, the model accounts for two-thirds of the rise in top wealth inequality.

Table 8: Results - Wealth Distribution - IT Share

	Δ Data	Δ Model	Model Explains
Bottom 50	−0.8 p.p.	−1 p.p.	121%
Top 10	1.8 p.p.	5.8 p.p.	316%
Top 1	9.4 p.p.	1.4 p.p.	15%
Top 0.1	9.4 p.p.	0.5 p.p.	6%
Top 0.01	6.5 p.p.	0.3 p.p.	5%
Gini	0.01	0.04	400%

4.4 Alternative Measure of Automation

use the change in the labor share of income to approximate the increase in automation technology. However, the decline in labor share is not solely due to automation; other factors like increased market power, market concentration, and housing sector rents may also play significant roles (De Loecker et al., 2020; Autor et al., 2020; Rognlie, 2016). To isolate the effect of automation, I examine the income share attributable to IT capital as an indicator of increased automation technology. Although this measure doesn't account for robotics or machinery, it represents a component of automation technology, thus providing a lower-bound estimate for advancements in automation. Eden & Gaggl (2018) estimate that the IT share increased by 3 percentage points; in comparison, my primary estimate assumes a 5-percentage-point increase. Here, I examine the impact of a 3-percentage-point increase in IT share by raising I to 0.39.

An important point is that since capital in the model includes automation along with other assets, my initial calibration remains unaffected. Only changes in the capital share are assumed to be related to automation technology, so no re-calibration is needed.

Table 8 and Table 9 present the changes in wealth and income concentration. Compared to the benchmark results, the automation impact decreases by 50% to 60%, consistent with a 60% reduction in automation level changes. Clearly, as changes in automation decline, the model generates less impact on wealth concentration. Under these conditions, the model now accounts for 15% of the increase in the top 1% wealth share.

Table 9: Results - Income Distribution - IT Share

	Δ Data	Δ Model	Model Explains
Bottom 50	−7.9 p.p.	−1.6 p.p.	21%
Top 10	10.4 p.p.	3.6 p.p.	34%
Top 1	6.2 p.p.	1.5 p.p.	25%
Top 0.1	3.7 p.p.	0.5 p.p.	15%
Top 0.01	1.9 p.p.	0.3 p.p.	14%
Gini	0.14	0.03	21%

4.5 Alternative Estimates of Wealth Shares

There are several methods to estimate top wealth shares (Kopczuk, 2015). The data I use relies on the capitalization method (Saez & Zucman, 2016), which leverages capital tax return data. By analyzing tax payments, it infers wealth levels, though this inference depends on assumptions about returns to wealth. Fagereng et al. (2020) and Bach et al. (2020) demonstrate that returns to wealth vary across wealth groups, with significant variation in Norway and Sweden. Due to the positive correlation between wealth and returns, a simple capitalization approach tends to overestimate top wealth shares. To address this, Smith et al. (2020) adjust the capitalization method to account for return heterogeneity. They find that the top 1% share increases to only 30%, compared to the 37% reported by the World Inequality Database (WID).

Since the 1968 wealth share estimate in Smith et al. (2020) aligns closely with WID data, the current model calibration remains a good fit. By incorporating return heterogeneity, the model explains nearly the entire observed increase in wealth concentration, suggesting that the results in Table 6 provide a conservative estimate of automation's impact on top wealth concentration.

In other words, the WID figure can be viewed as an upper bound for wealth concentration, while Smith et al. (2020) serves as a lower bound. Given these bounds, the model accounts for between one-third and the entirety of the increase in wealth concentration. Thus, my findings likely represent a lower-bound estimate for automation's role in rising top wealth shares, allowing a direct comparison with the Smith et al. (2020) estimates.

5 Welfare Analysis

In the previous section, I discussed the increase in wealth concentration driven by automation. In this section, I analyze the welfare implications of automation. To calculate the welfare gains, I calculate the required percentage increase in consumption in each period and state that would make individuals indifferent between a world with improved automation and one without. Formally, the welfare gain in consumption equivalent terms, denoted by ν, is defined as follows:

$$\mathbb{E}\left[\sum_{t=0}^{\infty} \beta^t u((1+\nu(a,s,0))c_t(a',s'))|a,s\right] = V_0(a,s),$$
$$\mathbb{E}\left[\sum_{t=0}^{\infty} \beta^t u((1+\nu(a,s,z))c_t(a',s',z))|a,s,z\right] = E_0(a,s,z),$$

where $V_t(a,s)$ and $E_t(a,s,z)$ represent the lifetime value of a worker in state (a,s) and an entrepreneur in state (a,s,z), respectively, after t periods from the start of improvements in automation. Note that I am not comparing two steady states. Instead, I compare the lifetime value at the initial steady state with the value during the transition period when automation technology is changing, while taking into account the evolution of prices and value functions. Assuming the utility function is CRRA, ν simplifies to:

$$\nu(a,s,0) = \left(\frac{V_0(a,s)}{V_{na}(a,s)}\right)^{1/(1-\sigma)} - 1,$$
$$\nu(a,s,z) = \left(\frac{E_0(a,s,z)}{E_{na}(a,s,z)}\right)^{1/(1-\sigma)} - 1,$$

where V_{na} is the value function at the initial steady state.

To compute the value functions along the transition path, I assume that automation technology improves gradually over 45 years. Specifically, I let I increase from 0.36 to 0.41 at a constant rate over 45 years, and then remain fixed at 0.41 thereafter. Additionally, I assume that individuals have perfect foresight regarding the increase in I and its impact on prices.

Figure 4: Welfare Gains by Occupation and Asset Level

Note: Welfare gain computed in consumption equivalent terms, $\bar{\nu}$ in equation (9). The horizontal axis is the partition on asset, where $Px - Py$ denotes the asset level between the xth and yth percentile in overall distribution in the initial steady state (not conditional on occupation).

The impact of automation depends on the wealth of individuals. Therefore, I consider the welfare gains for individuals with different asset levels. For a partition of the asset distribution and skill distribution, $T \in \mathcal{A} \times \mathcal{S} \times \{\mathcal{Z} \cup 0\}$, I calculate the average welfare gain $\bar{\nu}$ as the weighted average of welfare gains for individuals within that partition:

$$\bar{\nu} = \int_T \Gamma(t)\nu(t)dt/\Gamma(T). \tag{9}$$

Figure 4 illustrates the welfare gains by occupation and asset level. The horizontal axis represents the asset partition, where $Px - Py$ denotes the asset level between the xth and yth percentiles of the overall distribution in the initial steady state (regardless of occupation). The figure shows that everyone gains from automation.[5] The average welfare gain for workers is approximately 5%, while the average gain for entrepreneurs is around 8%. It is evident that gains increase with asset levels, meaning that wealthier households benefit the most from automation. It is also intuitive that entrepreneurs gain more than workers, as automation directly enhances

[5]There are no entrepreneurs in the lowest quartile, so the gain is zero.

returns to entrepreneurial skills. Even the poorest workers gain, primarily due to the shift of employment towards more productive entrepreneurs. Since top-skilled entrepreneurs can scale up their production, the share of employment in top firms increases, leading to significant productivity gains in the economy, which ultimately benefits poor workers as well.

Some of the differences between the gains of average workers and average entrepreneurs can be attributed to the fact that entrepreneurs, on average, own more assets than workers. Within each asset partition, entrepreneurs gain more than workers. This is expected: automation directly affects the return to entrepreneurial skills, whereas its impact on workers is indirect. However, the gap between entrepreneurs and workers narrows with increasing wealth. At the very top of the wealth distribution, this gap becomes negligible, primarily because for individuals at the top, business income is small relative to capital income, making occupational differences less significant.

There are two important underlying assumptions for this result. First, there are no frictions (for example, search friction) that inhibit labor reallocation across firms, so workers can immediately move to highly productive firms. Second, the model does not differentiate between job types or occupations for workers. In reality, automation does not affect all occupations equally. If there were different job types, and if workers could not switch between these jobs, then automation would impact individuals differently. For example, workers in occupations more susceptible to automation would gain less or might even lose out. However, with frictionless labor reallocation, everyone in the economy experiences gains from automation, albeit with benefits concentrated among wealthy entrepreneurs.

6 Conclusion

Over the past 50 years, the United States has seen a substantial rise in wealth concentration. This paper examines the impact of automation technology on this shift in wealth distribution. Automation influences wealth accumulation in two primary ways. First, it heightens income concentration by enabling entrepreneurs to scale up production. Second, it increases heterogeneity in the returns to capital.

The model is calibrated to the US economy as of 1968, and then the automation technology parameter is adjusted to reflect its 2016 level while other factors remain constant. The results indicate that advancements in automation technology account for one-third of the increase in the wealth share held by the top 1%. Considering the transition path, worker welfare—measured in consumption equivalence terms—rose by 5%, while entrepreneur welfare increased by 8%. While all individuals benefited from the labor force shift to more productive firms, wealthier individuals gained more than those with lower incomes.

A limitation of this quantitative exercise is the lack of a direct measure for the convex cost of labor. Various factors could make labor costs convex, yet the underlying concept is that firms aiming for expansion must allocate additional resources. This firm-size wage premium can create a convex labor cost, and it is known to be declining—for instance, the wage gap between large and small firms has been narrowing (Bloom et al., 2018; Cobb & Lin, 2017). This trend could be seen as a reduction in the convexity of labor costs, which ultimately leads to higher returns on capital and entrepreneurial talent. Accounting for changes in firm-size wage premiums may offer insight into how shifts in the convex cost of labor impact wealth concentration.

In the current model, the top income brackets are primarily entrepreneurs. However, data indicates that for about half of individuals in the top 1%, wages are the main source of income (Smith et al., 2019). Automation may have driven wage growth for these individuals as well, possibly increasing CEO compensation and thereby contributing to wealth inequality. A more complex model of labor productivity would be needed to capture the role of high-earning wage earners within the top tiers of income and wealth distribution.

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A Proofs

Proposition 1. *Fix prices w and r. Let $\tilde{\pi}(z;I)$ be the profit function when automation technology is given by I and without the collateral constraint, i.e., when entrepreneurs operate their businesses at the efficient level. Then, $\tilde{\pi}'(z;I') > \tilde{\pi}'(z;I)$ for $I' > I$, where $\tilde{\pi}'$ is the derivative with respect to z.*

Proof. *Consider the problem of an entrepreneur in* (6) *without collateral constraint (assume a is high enough. By envelope theorem, the impact of increase in the automation technology on profit is the shadow cost of automation technology constraint. Let η be the Lagrange multiplier with that constraint, then:*

$$\tilde{\pi}_I(z;I) = \eta(z).$$

First order condition with respect to $I^\star$ is:

$$zY(ln(k(I)) - ln(\ell(I))) + w\ell(I) + v'(L)\ell(I) - (r+\delta)k(I) = \eta(z).$$

Since in optimal solution marginal rate of technical substitution is equal to relative marginal costs, this condition simplifies to:

$$zY(ln(k(I)) - ln(\ell(I))) = \eta(z).$$

Right hand side is the shadow cost of automation. Left hand side is the change in production when automation increases. Observe than left hand side is increasing with z. This is becase both zY and k/ℓ is increasing with z. In the optimal solution, $k/\ell = (w + v'(L))/(r+\delta)$. Since L is increasing with z, k/ℓ is also increasing. Hence, shadow cost of automation is increasing with z. This implies that $\tilde{\pi}_I(z;I)$ is increasing with z. By Young's theorem, second derivative is symmetric, hence $\tilde{\pi}_z(z;I)$ is increasing with I.

■

Proposition 2. *Fix prices w and r. Let $\pi(a, z; I)$ denote the profit function when automation technology is I. Then, the derivative of profit function with respect to a is increasing with I, i.e., $\pi_a(a, z; I') \geq \pi_a(a, z; I)$ when $I' > I$. When the automation constraint binds, this condition holds with strict inequality.*

Proof. *Consider the problem of an entrepreneur in* (6). *By envelope theorem, impact of increase in a is:*

$$\pi_a(a, z) = \lambda\gamma(I),$$

where $\gamma(I)$ is the Lagrange multiplier associated with the collateral constraint when automation technology is I. It is clear that when collateral constraint does not bind, $\gamma(I) = 0$. So we want to show that $\gamma(I)$ is increasing with I when collateral constraint binds. The first order condition with respect to $k(i)$ is

$$\frac{zY}{k_i} = r + \delta + \lambda\gamma(I),$$

Optimal solution yields to $Y = k^I \ell^{1-I}$, hence $Y/k = (\ell/k)^{1-I}$. Suppose than Y/k is decreasing with I, then $(1 - I)log(\ell/k)$ is decreasing in I. Derivative with respect to I:

$$-log(\ell/k) + (1 - I)\frac{d(\ell/k)}{dI} < 0.$$

Assume that automation constraint binds. Then $\ell < k$, which implies that $log(\ell/k) < 0$. Hence, ℓ/k is decreasing with I. We know that k is decreasing, because we are allocating the same level of capital to larger range of task. This implies that ℓ must be decreasing, hence total labor $L = (1-I)\ell$ is decreasing. Now consider the first order condition with respect to ℓ

$$\frac{zY}{\ell} = z\left(\frac{k}{\ell}\right)^I = w + v'(L).$$

Right hand side is decreasing because L is decreasing. However, left hand side is increasing *because* $(k/\ell)^I$ *is increasing. This leads to contradiction. This implies that marginal productivity of capital must be increasing with* I*, therefore the shadow cost of collateral constraint is increasing when automation technology and collateral constraint are binding.*

Now assume that automation constraint does not bind. Then $\ell = k$*, which implies that* $zY/k = z$*. Hence, marginal product of capital is constant. This implies that* $\gamma(I)$ *is constant and does not change with* I *when optimal automation level is interior.*

■