The occupational singularity: Cognitive technologies as new drivers of inequality

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ABSTRACT

We present a theory of rising inequality due to the emergence of an occupational singularity caused by cognitive technological disruptions. The main innovation of our theory is that, following Vernon Vinge, we assume that cybernetic technologies have physical and cognitive characteristics. We illustrate the theory with a simple Solow-inspired growth model with economic sectors and labor skills that are segmented as legacy or cybernetics, and in which occupational meaning is optimized as humans allocate time between labor and nonlabor occupations. The combination of these model assumptions produce a phase transition, that is, an occupational singularity, which explains emergent socio-economic patterns of the last few decades such as: rising income and wealth inequality, increasing cyber-entrepreneurs power and share of income, decreasing labor share of income, declining number of hours at work, instability of the skill premium, the productivity paradox, and a theoretical validation of Piketty's fundamental inequality when applied to the cybernetics sector.

Keywords: technological disruptions; cybernetics; occupational singularity; physical technological innovations; cognitive technological innovations; labor and nonlabor occupations

JEL Codes: O33, O41, I31, E25, P16, L63

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"Any labor which competes with slave labor must accept the economic consequences of slave labor."

Norbert Wiener in "*Cybernetics: Or Control and Communication in the Animal and Machine,*" 1948.

1. Introduction

Theories of technological disruption have evolved and changed with time, as social scientists struggled to understand the phenomenon and, at the same time, had to adapt to frequently changing observable patterns concerning its socio-economic effects. These difficulties are expected, since technological progress is probably better understood under a complexity theory perspective, involving properties such as emergence, nonlinearity, path dependence, multiple equilibria, nonergodicity, and phase transitions (Durlauf 1998; Brock and Durlauf 1999; Durlauf 2005, 2012).

Having this in mind, we present in this article a theory of cognitive technological disruption of labor and nonlabor occupations that generates a phase transition, in other words, that unveils an occupational singularity. The theory is based on a legacy sector and a cybernetics sector that differently combine skill-replacing technologies, skill-enhancing technologies, and production factors. Furthermore, inspired by Vinge's classification (Vinge 1993, 2008), we attribute to disruptive skill-replacing technological innovations two cybernetic characteristics: physical and cognitive. We also propose that it is important to broaden the study of the effects of skill-replacing technologies beyond a productivist labor approach by considering their effects on lifetime predominant nonlabor occupations.

The article is organized as follows: in the **Technologies and Cybernetics** section, we present the new concepts used in our theory. In the **Occupational Singularity Model** section, we present the model that supports our theory. In the **Interpretation and Evidence** section, we discuss the theory features, predictions, and the evidence in its favor. Finally, we summarize the original contributions of the article and possible future research in the **Conclusions** section.

2. Technologies and Cybernetics

Among the latest contributions to the understanding of technological change, one that we believe to have been somewhat overlooked is the game-changing role of cognitive cybernetics in technological innovations and technological disruptions. The existing economics literature is unquestionably aware of the developments in robotics, machine learning and artificial intelligence, as discussed in recent articles such as exemplified by Brynjolfsson, Rock, and Syverson (2018) and Korinek 2023. We think however that cybernetics science is still underutilized as a transdisciplinary and necessary complement in the understanding of how skill-replacing and skill-enhancing technologies affect societies (Albuquerque and Albuquerque 2023). We believe that existing theories were developed to explain patterns of technological progress that were typical of the period following the Industrial Revolution, during which skill-enhancing technological innovations and labor-complementing capital were predominant. We postulate that the rise of cognitive cybernetic technologies starting around 1980 creates a structural break and changes the nature of technological progress in ways that were never previously observed, with a predominance of skill-replacing technological innovations and labor-replacing capital.

2.1. Physical and Cognitive Characteristics of Cybernetic Technologies

As an example, if we focus our attention on the cybernetic characteristics of technological innovations, this allows us to borrow from Vinge (1993) the concepts of weak (physical) and strong (cognitive) superhumanity (Albuquerque and Albuquerque 2024). As Vinge (1993) explains, “I call [the] ‘fast thinking’ form of superintelligence ‘weak superhumanity’ … [while] ‘strong superhumanity’ would be more than cranking up the clock speed on a human-equivalent mind.” [1]

By extension and more precisely, following Albuquerque and Albuquerque 2024, we offer the following definitions:

Proposition 1: cybernetic technological innovations may have physical and cognitive characteristics.

Definition 1.1: a physical technological innovation allows a new technology to perform with superior physical capabilities (e.g. superior speed or strength) at the same cognitive capability levels of the previous technology.

Definition 1.2: a cognitive technological innovation allows a new technology to perform with superior cognitive capabilities (e.g. superior reasoning or learning) at the same physical capability levels of the previous technology.

Making the distinction between physical and cognitive capabilities is therefore essential to the analysis of the socio-economic effects of technological disruptions. For example, physical improvements can lead to labor replacement because they increase the effective supply of artificial labor available to entrepreneurs, while cognitive improvements may lead to labor replacement because they create cognitively superior alternatives to human cognitive skills.

2.2. The Occupational Singularity

We also borrow from cybernetics and Vinge (1993; 2008) the phase transition concept of singularity. In mathematics, a singularity is “the value or range of values of a function for which a

1 Vinge originally applied the concepts of weak and strong superhumanity to entities. They should not be confused with Searle (1980)’s concepts of weak and strong artificial intelligence (Sloman 1987).

derivative does not exist." [2] Similarly, Vinge defines the "[technological singularity as] a point where our old models must be discarded and a new reality rules, a point that will loom vaster and vaster over human affairs until the notion becomes a commonplace." Another sense popularized by Kurzweil (2005) is that the singularity is "a future period during which the pace of technological change will be so rapid, its impact so deep, that human life will be irreversibly transformed." Nordhaus (2021) for example applies the concept of singularity to general contemporary economic trends. Accordingly, we define:

Definition 2: the occupational singularity is the point in time when cybernetic technologies achieve cognitive capability levels that can produce unprecedented, fast and accelerating destruction, disruption, and creation of human labor and nonlabor occupations.

3. The Occupational Singularity Model

To formalize the ideas presented in the previous section, we build a Solow-inspired growth model with two sectors and two types of labor skills. To keep it as parsimonious as possible, we assume that the total population does not grow.

3.1. The Legacy Sector and the Cybernetics Sector

We segment the two sectors according to how they use skill-enhancing (labor-augmenting) and skill-replacing (labor-saving) technologies, and two types of labor skills. The legacy sector and the cybernetics sector use labor-complementing capital embodying skill-enhancing technologies, but only the cybernetics sector uses labor-replacing capital embodying skill-replacing technologies.

We assume that goods and services are fully fungible in production and consumption so we can concentrate on the analysis of time allocation, technologies and production factors. Only real variables are considered. We label the technology vintage v according to its creation time period t, so $v = t$, therefore we omit time t from now on. We omit references to v as the determinant of other variables to reduce cluttering, but when necessary we include v in parentheses. The saving rate σ is constant.

The legacy sector employs unalienable legacy-skilled labor. Child-rearing skills are examples of legacy skills. Meanwhile, the cybernetics sector employs alienable (MacKenzie 1984) cybernetics-skilled labor. Machinery control skills and calculation skills are examples of alienable cybernetics skills. Factors are paid the equivalent of their marginal products.

3.1.1. The Legacy Sector

In the legacy sector, capital K_l complements legacy-skilled labor L_l:

2 See https://en.wiktionary.org/wiki/singularity (retrieved on April 16, 2022).

$$y_l = k_l^{\alpha} A_l^{1-\alpha}, \quad y_l = \frac{Y_l}{L_l}, \quad k_l = \frac{K_l}{L_l} \quad ,$$

so growth in the legacy sector is determined by the labor-augmenting productivity A_l, which is a function of technology vintage v with growth rate γ_l.

3.1.2. The Cybernetics Sector

The cybernetics sector employs two types of capital. The first type K_c complements cybernetics-skilled labor L_c, and the second type K_r partially replaces L_c:

$$y_c = k_c^{\beta} (A_r k_r + A_c)^{1-\beta}, \quad y_c = \frac{Y_c}{L_c}, \quad k_c = \frac{K_c}{L_c}, \quad k_r = \frac{K_r}{L_c} \quad , \quad (1)$$

where the labor-augmenting productivity A_c is a function of v with growth rate γ_c, and the labor-saving productivity A_r is a function of v with growth rate γ_r. Growth in the cybernetics sector is therefore determined by increasing values of A_c and A_r. The cybernetics sector is assumed to be more intensive in labor-complementing capital than the legacy sector, so $\beta > \alpha$.

3.1.3. Labor Demand and Supply

For analytical convenience, the representative human's quantity supplied of legacy-skilled labor is only limited by its time budget. Meanwhile, the quantity supplied of cybernetics-skilled labor is inversely related to the cybernetics skills level s.

The following time budget restrictions apply:

$$T = \begin{cases} L_{l0} + L_{c0} + O_0 & \text{for } v \leq v_0 \\ L_l + L_c + O & \text{for } v > v_0 \end{cases} \quad , \quad (2)$$

where T is the per period constant endowment of time available to all humans. Before the **occupational singularity vintage v_0** (to be determined in the next subsection) L_{l0}, the total amount of legacy-skilled labor, and L_{c0}, the total amount of cybernetics-skilled labor, are constants. The amount of labor-replacing capital k_r is equal to zero, and productivity growth rates are equal and constant:

$$\gamma_c = \gamma_l = \gamma_0 \quad \text{for } v \leq v_0 \quad .$$

Consequently, humans allocate a constant amount of time O_0 to nonlabor occupations, such as sleep, leisure, housekeeping, nurturing, self-care, etc. For periods following v_0, k_r partially replaces L_c in increasing amounts, as cognitive technological innovations allow skill-replacing technologies to perform with an increasing skills level s. When replaced, labor time in the cybernetics sector is freed up. Humans can use the freed up time to join the legacy sector by an amount L_{cr}, or to engage in nonlabor occupations by an amount O_c, according to the optimization of the following well-being function:

$$\max_{L_{cr},O_c} \psi\left(L_{cr}, O_c \middle| \frac{w_c}{w_l}, v, \Phi\right) \text{ s.t. } L_c(v) = L_{c0} - L_{cr}(v) - O_c(v) \quad , \quad (3)$$

where L_c is exogenously determined by new technology vintages, $\psi(\cdot)$ is a monotonic and convex well-being function on L_{cr} and O_c, and the following are conditioning factors: w_c/w_l is the cybernetics skill premium and Φ represents all other conditioning occupational substrates, such as form, function, and meaning (Clark et al. 1991). Well-being optimization leads to L^*_{cr}, the optimal amount of freed up time that moves to the legacy sector, and O^*_c, the optimal amount of freed up time that moves to nonlabor occupations. Notice that the technology vintage can affect time allocations.

Because of the occupational singularity, legacy-skilled labor L_l in the legacy sector increases in size after v_0 due to labor inflows, as given by:

$$L_l(v) = L_{l0} + L^*_{cr}(v) \text{ for } v > v_0 \quad , \quad (4)$$

where L^*_{cr} is the inflow due to the replacement of cybernetics sector labor. In summary, after v_0, the total amount of labor hours continuously falls, as humans increase the amount of time devoted to nonlabor occupations, ultimately due to skills replacement and complementarities between new cybernetic technologies and nonlabor occupations, as exemplified by new modalities of digital entertainment such as media streaming and video gaming. In the limit, as labor-replacing capital asymptotically replace all cybernetics-skilled labor, we have the following:

$$\lim_{v\to\infty} L_c = 0, \quad \lim_{v\to\infty} L^*_{cr} + \lim_{v\to\infty} O^*_c = L_{c0} \quad .$$

3.1.4. Physical and Cognitive Technological Innovations

Firstly, physical technological innovations drive up A_r because they increase the speed or strength of k_r (see Definition 1.1). We assume for analytical convenience that A_r is a concave, differentiable, and monotonically increasing function of v with the properties:

$$A_r \in [0, \infty), \quad A_r' > 0, \quad A_r'' < 0, \quad \lim_{v\to\infty} A_r' = 0 \quad . \quad (5)$$

A possible relation between A_r and the technology vintage v is seen in Figure 1.

[Figure 1 appears around here]

Secondly, cognitive technological innovations do not directly drive up productivity but allow k_r to perform with superior skills (see Definition 1.2), making cybernetics-skilled labor redundant by establishing an increasing **skill alienability floor s_f** for L_c. We assume that s_f is a concave, differentiable, and monotonically increasing function of v for $v > v_0$ with the properties:

$$s_f = 0 \text{ for } v \le v_0, \quad s_f \in [0, \infty) \quad \text{, and}$$

$$s_f' > 0, \quad s_f'' < 0, \quad \lim_{v\to\infty} s_f = \infty, \quad \text{and} \quad \lim_{v\to\infty} s_f' = 0 \text{ for } v > v_0 \quad .$$

A possible relation between s_f and the technology vintage v is seen in Figure 2.

[Figure 2 appears around here]

Because the reduced remaining pool of cybernetics-skilled labor has skills superior to the floor set by new technology vintages, A_c shifts to higher productivity levels as labor is replaced, increasing γ_c during the transition period. At the same time, because of skills adaptation, A_l is assumed to shift to lower productivity levels as a result of legacy sector labor inflows, reducing γ_l during the transition period. We assume consequently that productivity growth rates γ_l and γ_c have the following additional properties:

$$\gamma_0<\gamma_c<\gamma_{max},\ \lim_{v\to v_0^+}\gamma_c=\gamma_{max},\ \lim_{v\to\infty}\gamma_c=\gamma_0,\ \ \gamma_c'<0,\ \text{and}\ \lim_{v\to\infty}\gamma_c'=0\ \ \text{for}\ v>v_0\ \ \text{, and}$$

$$\gamma_{min}<\gamma_l<\gamma_0,\ \lim_{v\to v_0^+}\gamma_l=\gamma_{min},\ \lim_{v\to\infty}\gamma_l=\gamma_0,\ \ \gamma_l'>0,\ \text{and}\ \lim_{v\to\infty}\gamma_l'=0\ \ \text{for}\ v>v_0\ \ .\ (6)$$

Figure 3 shows a possible trajectory for γ_c.

[Figure 3 appears around here]

3.1.5. Capital Markets and Cyber-Entrepreneurs

We assume that, for all time periods, there is arbitrage between capital rates of return r in all capital markets. Because capitalists are indifferent between investing amounts I_l in the legacy sector and I_c in the cybernetics sector, they allocate funds according to each sector's output:

$$I_l=\sigma Y_l\ \ \text{and}\ \ I_c=\sigma Y_c\ \ .$$

To invest in the cybernetics sector, capitalists lend capital to cybernetic technology entrepreneurs, from now on called cyber-entrepreneurs. Due to market power (see discussion in the next section), cyber-entrepreneurs receive a cybernetics entrepreneurship premium r_c that is equal to the difference between the rate of return on capital in the cybernetics sector and the arbitrage rate of return r determined in the legacy sector. Before the occupational singularity, with both sectors on their balanced growth paths, this premium can be shown to be equal to:

$$r_{c0}=(\beta-\alpha)\frac{\gamma_0+\delta}{\sigma},\ \ \beta>\alpha\ \ ,$$

where δ is a constant depreciation rate.

The skill-replacement process starts with the occupational singularity vintage v_0, when $k_r > 0$. To keep the model dynamics simple, cybernetics sector k_c and k_r are assumed to be fungible, and the cybernetics premia on k_c and k_r are by arbitrage equal, $r_c = r_r$. Cyber-entrepreneurs decide how total cybernetics sector capital is allocated between k_c and k_r.

In summary, capitalists receive a rate of return r determined in the legacy sector, while cyber-entrepreneurs receive a cybernetics premium r_c determined in the cybernetics sector.

3.2. Determination of the Occupational Singularity Vintage v_0

To find the value of the singularity vintage v_0 we first postulate that k_r is equal to zero and k_c follows a balanced growth path before v_0. This postulate is confirmed below to be consistent with the following solution to the v_0 determination problem.

We start by observing that, in the pre-singularity period, due to balanced growth, the ratio of labor-complementing capital to labor-augmenting productivity in the cybernetics sector is a constant:

$$\frac{k_c}{A_c}=\frac{k_{c0}}{A_{c0}} \quad \text{for}\, v\leq v_0 \quad .$$

After the singularity takes place, the cybernetics premia for k_c and nonzero k_r can be determined from equation (1) as:

$$r_c=\beta\left(\frac{A_r k_r+A_c}{k_c}\right)^{1-\beta}-\delta-r \quad , \ (7)$$

$$r_r=(1-\beta)\left(\frac{k_c}{A_r k_r+A_c}\right)^{\beta} A_r-\delta-r \quad . \ (8)$$

Due to arbitrage in the cybernetics sector capital market, these two premia must be identical when $k_r > 0$. This equality can be used to determine v_0, since for all $v > v_0$:

$$\lim_{v\to v_0+} k_r=0 \ \text{ and } \ \lim_{v\to v_0+}\frac{k_c}{A_c}=\frac{k_{c0}}{A_{c0}} \ \Rightarrow \ \lim_{v\to v_0+} A_r=A_{r0}=\frac{\beta}{1-\beta}\frac{A_{c0}}{k_{c0}} \quad .$$

The occupational singularity vintage v_0 is thus the vintage that raises the value of A_r above the constant threshold value A_{r0}. The solution works as follows: there is a discontinuity (singularity) in the growth dynamics before and after v_0. Before v_0, k_r does not produce a high enough cybernetics premium to justify its use. In such a situation, all capital in the cybernetics sector k_c complements L_{c0}. But after v_0 is reached, k_r is increasingly employed.

Notice that the model produces a single occupational singularity event because it relies on representative agents. Real phenomena is better described as a complex sequence of occupational singularity events that take place at different moments for different firms, industries, and sectors, making the occupational singularity dynamics more convoluted and protracted than the one predicted by the model. However, there is no reason to believe that the main qualitative predictions of the model would change.

3.3. Capital Rates of Return and Wage Rates

3.3.1. Legacy Sector before v_0

The balanced growth path capital rate of return and wage rate are:

$$r=\alpha\gamma_0+\frac{\delta}{\sigma}-\delta \text{ for } v\leq v_0 \quad ,$$

$$w_l=(1-\alpha)(\frac{\sigma}{\gamma_0}+\delta)^{\frac{\alpha}{1}-\alpha} A_l \text{ for } v\leq v_0 \quad . \text{ (9)}$$

3.3.2. Cybernetics Sector before v_0

The balanced growth path cybernetics premium and the wage rate are:

$$r_c=\beta\gamma_0+\frac{\delta}{\sigma}-\delta-r \text{ for } v\leq v_0 \quad ,$$

$$w_c=(1-\beta)(\frac{\sigma}{\gamma_0+\delta})^{\frac{\beta}{1-\beta}} A_c \text{ for } v\leq v_0 \quad . \text{ (10)}$$

3.3.3. Legacy Sector after v_0

As shown in equation (4), the labor amount in the legacy sector grows once it starts to receive inflows from the cybernetics sector. The legacy-skilled labor growth n_l is thus assumed to have the following properties:

$$n_l=0 \text{ for } v\leq v_0,\ n_l\in[0,n_{max}) \text{ , and}$$

$$n_l'<0,\ n_l''>0,\ \lim_{v\to\infty} n_l=0, \text{ and } \lim_{v\to\infty} n_l'=0 \text{ for } v>v_0 \quad .$$

Consider now the following approximations for k_l, r, and w_l after v_0:

$$k_l\approx(\frac{\sigma}{\gamma_l+n_l+\delta})^{\frac{1}{1-\alpha}} A_l \text{ for } v>v_0 \quad ,$$

$$r\approx\alpha\frac{\gamma_l+n_l+\delta}{\sigma}-\delta \text{ for } v>v_0 \text{ , and}$$

$$w_l\approx(1-\alpha)(\frac{\sigma}{\gamma_l+n_l+\delta})^{\frac{\alpha}{1-\alpha}} A_l \text{ for } v>v_0 \quad . \text{ (11)}$$

These equations assume that capital is always in equilibrium for changing values of n_l and γ_l during the transition to the balanced growth path. Although approximate, their qualitative results are expected: on the one hand, labor inflows in the legacy sector always lead to a temporary decrease of w_l, as A_l temporarily falls. On the other hand, if the negative effects of labor inflows on γ_l are more (less) important than the positive effect on n_l, then they lead to temporary decreases (increases) of r.

The legacy sector returns to the original balanced growth path dynamics once labor inflows approach zero:

$$\lim_{v\to\infty} r = \alpha\frac{\gamma_0+\delta}{\sigma}-\delta \text{ , and}$$

$$\lim_{v\to\infty} w_l = (1-\alpha)(\frac{\sigma}{\gamma_0+\delta})^{\frac{\alpha}{1-\alpha}} A_l \quad .$$

3.3.4. Cybernetics Sector after v_0

From equations (7) and (8), and applying the arbitrage condition, we find that:

$$\frac{A_r k_c}{A_r k_r + A_c} = \frac{\beta}{1-\beta} \quad . \ (12)$$

Plugging this equation back into (7) allows us to find the cybernetics premium:

$$r_c = \ \beta^{\beta}(1-\beta)^{1-\beta} A_r^{1-\beta} - \delta - r \quad \text{for } v > v_0 \quad , \ (13)$$

and the wage rate:

$$w_c \ = \ \beta^{\beta}(1-\beta)^{1-\beta} A_c A_r^{-\beta} \quad \text{for } v > v_0 \quad . \ (14)$$

Notice from the equation above that:

$$\frac{w_c{}'}{w_c} = \gamma_c - \beta \gamma_r \quad ,$$

so the wage rate growth in the cybernetics sector depends on the relative effects of physical and cognitive technological innovations, since:

(a) physical technological innovations make $-\beta\gamma_r$ more negative, while

(b) cognitive technological innovations make γ_c more positive.

If γ_c is larger than a share β of γ_r, then the cybernetics sector wage rate rises. This happens when labor in the cybernetics sector strongly benefits from cognitive technological innovations and is weakly penalized by physical technological innovations. On the other hand, if labor benefits weakly from cognitive technological innovations and is strongly penalized by physical technological innovations, then the wage rate falls. In summary, in the cybernetics sector, the effect of physical technological innovations on the wage rate is always negative, while the effect of cognitive technological innovations on the wage rate is always positive.

3.4. Income Inequality

3.4.1. Income Inequality before v_0

Inequality is constant because the two sectors follow balanced growth paths with the same growth rates equal to γ_0.

3.4.2. Legacy Sector Balanced Growth Path after v_0

The balanced growth path of the legacy sector is:

$$k_l = \left(\frac{\sigma}{\gamma_0 + \delta}\right)^{\frac{1}{1-\alpha}} A_l \quad \text{for } v > v_0 \quad ,$$

$$r = \alpha \frac{\gamma_0 + \delta}{\sigma} - \delta \quad \text{for } v > v_0 \quad ,$$

$$r k_l = \left(\alpha \frac{\gamma_0 + \delta}{\sigma} - \delta\right)\left(\frac{\sigma}{\gamma_0 + \delta}\right)^{\frac{1}{1-\alpha}} A_l \quad , \text{ and } \ (15)$$

$$w_l = (1-\alpha)\left(\frac{\sigma}{\gamma_0 + \delta}\right)^{\frac{\alpha}{1-\alpha}} A_l \quad \text{for } v > v_0 \quad . \ (16)$$

3.4.3. Cybernetics Sector Asymptotically Balanced Growth Path after v_0

Due to the properties of A_r described in (5), and to equations (12). (13) and (14), the asymptotically balanced growth path of the cybernetics sector after the occupational singularity vintage v_0 and, as $v \rightarrow \infty$, can be found as:

$$k_c = \beta\left(\frac{\sigma}{\gamma_0+\delta}\right)^{\frac{1}{1-\beta}} A_c \quad \text{for } v > v_0 \quad ,$$

$$k_r = (1-\beta)\left(\frac{\sigma}{\gamma_0+\delta}\right)^{\frac{1}{1-\beta}} A_c \quad \text{for } v > v_0 \quad ,$$

$$r(k_c+k_r) = \left(\alpha\frac{\gamma_0+\delta}{\sigma} - \delta\right)\left(\frac{\sigma}{\gamma_0+\delta}\right)^{\frac{1}{1-\beta}} A_c \quad \text{for } v > v_0 \quad , \quad (17)$$

$$r_c(k_c+k_r) = \left(\beta^{\beta}(1-\beta)^{1-\beta} A_r^{1-\beta} - \delta - r\right)\left(\frac{\sigma}{\gamma_0+\delta}\right)^{\frac{1}{1-\beta}} A_c \quad \text{for } v > v_0 \quad \text{, and} \quad (18)$$

$$w_c = (1-\beta)\left(\frac{\sigma}{\gamma_0+\delta}\right)^{\frac{\beta}{1-\beta}} A_c \quad \text{for } v > v_0 \quad . \quad (19)$$

3.4.4. Income Inequality after v_0

From *3.4.2* and *3.4.3* we conclude:

(a) From (15) and (16), that income inequality between capitalists and workers is stable in the legacy sector in the long run.

(b) From (16) and (19), and the discussion in previous subsections, that changes in income inequality between cybernetics sector and legacy sector workers depend on the relative strengths of the effects of physical technological innovations, cognitive technological innovations, and legacy sector labor inflows. Nonetheless, inequality stabilizes in the long term.

(c) From (15), (16), (17), (18) and (19), that income inequality between cyber-entrepreneurs and all other economic agents diverges to infinity due to the always beneficial effects of improving physical and cognitive technological innovations on the cyber-entrepreneurs rent (**cybernetics rent**) shown in equation (18) (see discussion in the next section).

(d) That the income inequality divergence between cyber-entrepreneurs and all other economic agents mentioned in item (c) happens at decreasing rates with new technology vintages *v*, due to the properties of A_r described in (5) and the properties of γ_c described in (6), which create an asymptotically balanced growth path. Notice however that this balanced result does not hold if the conditions imposed on the trajectory of A_r are relaxed to produce asymptotically divergent growth paths.

3.5. Labor Share of Income

3.5.1. Before v_0

The labor share of income is constant because the two sectors follow balanced growth paths with the same growth rates γ_0.

3.5.2. After v_0

The labor share of income converges to zero, as the relative income of cyber-entrepreneurs increases ad infinitum due to results discussed in item *3.4.4.*(c).

4. Interpretation and Evidence

In this section we offer further interpretation of the occupational singularity theory and present the evidence in its favor, by comparing its predictions with socio-economic puzzles and stylized facts of the last four decades. The latter are taken from the United States because its economic system is arguably the most affected by physical and cognitive technological innovations, thanks to its leadership in R&D, and also due to its less generous and less comprehensive social welfare system, at least when compared to other advanced economies.

4.1. The Cybernetics Age

The first pillar of the occupational singularity theory is the growing importance of the cybernetics sector (see e.g. Grinin and Grinin, 2020). We use data concerning patents in the United States to demonstrate that this is indeed happening. We proxy the number of **cybernetics patents** as the number of patents issued in the NBER fields of (a) Communications, (b) Computer Hardware and Software, (c) Computer Peripherals, (d) Information Storage, (e) Electronics Business Methods and Software, and (f) Semiconductor Devices. We compare the evolution of cybernetics patents with that of total patents in Figure 4.

[Figure 4 appears around here]

The data indicate that a change in technological innovation patterns happens around the 1980s. Cybernetics patents grow faster than total patents, becoming an increasingly larger share of the latter. Cybernetics patents represents around 43% of the total number of patents in 2014, the latest year in the database. These same observations were previously made in Marco et al. (2015).[3]

In summary, we state the following:

Proposition 2: the socio-economic context of the last few decades is marked by cybernetic technological innovations, which sprout at a higher growth rate than other technological innovations.

3 “Between 1981 and 2014 … filings in Computers & Communications clearly stand out, having grown in absolute number at significantly higher rates than all other categories.”

4.2. The Rise of Cyber-Entrepreneurs

The second pillar of the occupational singularity theory is that it predicts the rise of cyber-entrepreneurs. Since the 1980s, cyber-entrepreneurs have rapidly acquired extreme amounts of wealth, arguably in a manner not seen since the Gilded Age and its robber barons, as pointed out by Krugman (2012). For instance, in the latest *The Richest People in the World* by Forbes Magazine,[4] six out of the ten richest people made their fortunes almost exclusively out of cyber-entrepreneurship, and the other four have direct or strong ties to cyber-entrepreneurship.[5]

For instance, Glaeser (2014) observed that "perhaps, we are just experiencing an era in which innovation benefits the few rather than the many." A similar point is made in Mian, Straub, and Sufi (2020): "there is substantial evidence in the literature that the rise in top income shares reflected shifts in technology and globalization that began in the 1980s." The influence of cyber-entrepreneurs on world affairs is still growing fast. Consider Birch, Cochrane, and Ward (2021)'s calculation that the market capitalization of Big Tech, the five largest technology firms (Apple, Amazon, Facebook, Google/Alphabet and Microsoft), has risen from about 8% of the S&P500 total capitalization in 2014 to about 25% by mid 2020 (see also Brynjolfsson, Rock, and Syverson 2018). Even more important, cyber-entrepreneurs are central to the creation of the physical and cognitive technological innovations that give origin to the occupational singularity.

Furthermore, cyber-entrepreneurship is characterized by a very unique combination of market power advantages: (a) incumbent advantages from strong brand recognition (Elliott 2014); (b) capture of public services and cybernetic networks like the Internet (Moore and Tambini 2018); (c) power to set technological and business standards and universal platforms (Moore and Tambini 2018); (d) access to low-cost financing and ample cash reserves that facilitate preemptive (killer) acquisitions (Bunworth 2021); (e) close relations to the political system (Lindsey and Teles 2017); (f) an excessively favorable and protective patents, trademarks, and copyrights system (Boldrin and Levine 2013; Moser 2016; Lindsey and Teles 2017); (g) tight ownership structures of command and control (Little and Winch 2021); and (h) the ability to collect, accumulate and own personal user and costumer data, and to use them to their own benefit (Moore and Tambini 2018; Birch et al.

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4 See https://www.forbes.com/billionaires/ (retrieved on April 28, 2022).

5 The top ten list: 1. Elon Musk (automotive); 2. Jeff Bezos (technology); 3. Bernard Arnault & family (fashion & retail); 4. Bill Gates (technology); 5. Warren Buffett (finance & investments); 6. Larry Page (technology); 7. Sergey Brin (technology); 8. Larry Ellison (technology); 9. Steve Ballmer (technology); 10. Mukesh Ambani (diversified). Musk is a cyber-entrepreneur; the Arnault family has ties to digital media, and actively promotes the use of technological innovations in the family's enterprises; Warren Buffett is well known for his direct and strong ties to Apple; and Ambani is a cyber-entrepreneur.

2021).

More precisely, cyber-entrepreneurs enjoy a cybernetics rent (Birch and Cochrane 2022). This happens because they own physical and cognitive technological innovations that allow them to break free from labor costs and labor supply limitations, furthering a winner-take-all society model (Frank and Cook 2010), as demonstrated in item *3.4.4.*(c). On the one hand, pyhsical technological innovations increase their cybernetics rent due to an always rising cybernetics premium extracted from each unit of borrowed capital, as shown in equation (13). On the other hand, cognitive technological innovations increase their cybernetics rent due to capital deepening, as shown in equation (18).

In summary, we propose the following:

Proposition 3: cyber-entrepreneurs play a unique historical role because they own technologies that allow them to break free from labor supply scarcity and to alienate increasingly superior human skills.

4.3. The Declining Average Number of Hours at Work

The third pillar of the occupational singularity theory is its assessment of the effects of technology disruptions on labor and nonlabor occupations (Wilcock and Hocking 2015, p. 304). Usually, the intrinsic value of nonlabor occupations is not fully accounted for in economics. On the one hand, nonlabor occupations can bear an individual and social value of tangible nature, based on improved or acquired skills or competences, producing a tangible but not necessarily marketable outcome. On the other hand, occupations of all kinds can be performed for their symbolic value, bearing personal and cultural dimensions, and enabling communication and relationships among humans (Persson et al. 2001). More recently, Asaba et al. (2021) critically describe how tensions between productivist occupational perspectives and broader human occupational interests restrict labor and nonlabor occupational choices, with negative consequences for well-being.

The occupational singularity theory proposes that freed up time due to skill-replacing technologies is increasingly devoted to nonlabor occupations, conform equation (3). Among the explanations for this phenomenon we cite: a high cybernetics skill premium (w_c/w_l) that discourages replaced labor from working in the legacy sector due to negative effects on self-esteem (Gardner et al. 2004), and the effects of conditioning occupational substrates $\mathbf{\Phi}$, such as reduced labor occupational meaning because of mismatched skills, or preference for meaning-making nonlabor occupations, such as raising a family or enjoying new digital entertainment occupations such as video gaming (Clark et al. 1991). In other words, humans increasingly choose nonlabor over labor occupations, as skill-replacing technologies put many meaningful labor occupations forever out of their reach, and offer alternative nonlabor occupations that may have higher meaning than legacy labor occupations.

The predictions of the occupational singularity theory presented in subsection *3.7* are confirmed by United States data. Consider for example the average number of hours at work of men 25 to 54 years old (labor active age) from the Current Population Survey (CPS) in Figure 5. We avoid using women data because of the transitional positive effect of the secular increase in women emancipation on the total averages. The average trends down and falls more strongly during recessions, and this pattern is related to the adoption of skill-replacing technologies (Jaimovich and Siu 2020), but we add that this is also the consequence of occupational meaning reevaluation among American men.

[Figure 5 appears around here]

In summary, we state the following:

Proposition 4: according to the occupational singularity theory, technological innovations lead to a downtrending average number of hours at work. United States data confirm these predictions.

4.4. The Contextual Instability of the Skill Premium

The skill-biased technology and the skill-replacing technology hypotheses were developed as a response to frequent skill premium pattern changes during the last four decades. The skill-biased technology hypothesis stopped matching US data around the 2000s, because of the disappearance of the skill premium, particularly after 2010, as shown in Figures 7 and 8.

[Figures 6 and 7 appears around here]

Interestingly, the disappearance of the skill premium did not stop wage inequality from rising, as seen in Figure 8

[Figure 8 appears around here]

This apparent paradox can be explained by the occupational singularity theory, which predicts the contextual instability of the skill premium, since the alienability of human skills by skill-replacing technological innovations should have only incidental and temporary contextual connections to years of schooling or training. For example, wage inequality may rise because of a rising cybernetics skill premium, while the skill premium based on academic achievements may not change, because labor skills affected by skill-replacing technological innovations may in certain contexts and periods have little relation to academic or training achievements.

4.5. Cyber-Entrepreneurs and Rising Inequality

There was an undeniable increase in income inequality within advanced and emerging economies during the last four decades (Alvaredo et al. 2018). For example, Alvaredo et al. (2013)

state that “the top 1 percent income share has more than doubled in the United States over the last 30 years, drawing much public attention in recent years.” This pattern of rising income and wealth inequality in the United States can be seen in Figure 9.

[Figure 9 appears around here]

Kopczuk (2015) mentions that cyber-entrepreneurs have been among the greatest beneficiaries of recent technological disruptions: “wealthy individuals may in fact be those who received what, in retrospect, appears to be a very high rate of return. Obvious examples include successful technology companies – say Microsoft, Apple, or Google – that made their owners into billionaires.” A broader political perspective on these socio-economic developments is offered by Korinek and Stiglitz (2017), where they suggest that a new form of technology-driven Malthusian dynamics may be in progress.

We propose therefore the following, based on the discussion in item *3.4.4.*(c):

Proposition 5: the occupational singularity theory predicts that, after the occupational singularity takes place, inequality between cyber-entrepreneurs and all other agents should uptrend, what is in agreement with United States data and stylized facts.

4.6. The Declining Labor Share of Income

The labor share of income in the United States trends down since the 1970s, as shown in Figure 10, following the predictions of subsection *3.5*.

[Figure 10 appears around here]

Recent data analysis by Autor et al. (2020) finds that labor share of income patterns in the United States are related to what the authors call “the rise of superstar firms.” The authors also mention that these firms tend to be part of the high-tech, retail and transportation sectors, and typically have a “winner takes most” advantage. We argue that this kind of advantage, as discussed in previous subsections, is expected because it is caused by the adoption and ownership of physical and cognitive technological innovations. This leads to the following proposition:

Proposition 6: the occupational singularity theory predicts that, after the singularity takes place, the labor share of income should downtrend. United States data and stylized facts are in agreement with this prediction.

4.7. The Productivity Paradox

Solow (1987) famously declared that “you can see the computer age everywhere but in the productivity statistics.” We propose that the productivity paradox is explained by the fact that productivity statistics were not conceived to differentiate between legacy and cybernetics sectors. Once the differentiation is made, according to our theory, data seem to speak clearly. We offer three tentative examples, based on the assumed cybernetics nature of the skills used in selected industries taken from the North American Industry Classification System (NAICS). The graphs use logarithmic scales due to the extremely divergent patterns observed in the data.

In Figure 11 we compare labor productivity between the Semiconductor industry (cybernetics) and the Fabricated Structural Metals industry (legacy), both pertaining to the Manufacturing sector. An occupational singularity event seems to take place: the two industries, even though in the same sector, present astonishingly divergent labor productivity trajectories.

[Figure 11 appears around here]

The same can be observed in the Information sector: we compare labor productivity between the Telecommunications industry (cybernetics) and the Newspaper Publishers industry (legacy) in Figure 12, and the difference is equally impressive, in what seems to be another example of an occupational singularity event.

[Figure 12 appears around here]

Finally, in Figure 13 we compare two industries of the Retail Trade sector: the Electronic Shopping industry (cybernetics) and the Building Material Dealers industry (legacy). The same extraordinary occupational singularity labor productivity pattern is observed again.

[Figure 13 appears around here]

The problem with aggregate productivity statistics is that they have not been conceived to differentiate between industries that rely heavily on legacy-skilled labor and industries that rely heavily on cybernetics-skilled labor.

4.8. Piketty's Fundamental Inequality Empirical Observations

Piketty (2014)'s work on capitalism received significant attention not only due to its assessments on the history of capital but also because of the wealth of data presented. Among the many authors who debated it, we find Solow (2014), Acemoglu and Robinson (2015), Jones (2015), Mankiw (2015) and Piketty (2015) himself.

We concentrate on its most important assertion called the fundamental inequality $r > g$, where r stands for capital rate of return and g for output growth rate. According to Piketty (2014), "this fundamental inequality ... will play a crucial role in this book. In a sense, it sums up the overall logic of my conclusions." Piketty (2015) mentions that the fundamental inequality "is one of the important forces that can account for the historical magnitude and variations in wealth inequality [during the last many decades]."

The occupational singularity theory supports Piketty's analysis in what concerns the cybernetics sector. After the occupational singularity, the cybernetics premium r_c in equation (13) grows boundlessly and eventually becomes permanently larger than the output growth rate $g = \gamma_0$ in the asymptotically balanced growth path. It is also the cause of the diverging income inequality discussed in *3.4.4.*(c). Although this reasoning is not necessarily what Piketty had in mind, it can be an explanation for some of his empirical observations.

5. Conclusions

This article offers a few original contributions to the existing literature on the effects of technological innovations on socio-economic developments of the last four decades.

Firstly, we develop an occupational singularity theory of discontinuous technological disruption based on a legacy sector and a cybernetics sector that differently combine skill-enhancing technologies, skill-replacing technologies, and production factors. We also build a phase transition and overlapping generations occupational singularity model based on a Solow-inspired growth model with two sectors, two types of labor, and three generation periods, which supports the main features of the theory.

Secondly, we show that we live in the cybernetics age, and we use cybernetics science to study technological innovations. We propose based on the work of Vinge (1993, 2008) that disruptive skill-replacing technological innovations have two components: physical and cognitive, and we show that distinguishing between these two is essential to a better understanding of the socio-economic effects of technological innovations. We define the occupational singularity as the moment when cybernetic technological innovations become dominant and produce fast and accelerating destruction, disruption, and creation of labor and nonlabor human occupations.

Thirdly, we argue that current economic statistics have not been conceived to make the distinction between firms, industries, and sectors that employ legacy-skilled labor, and firms, industries, and sectors that employ cybernetics-skilled labor, impeding a better understanding of the socio-economic effects of technological innovations.

Finally, our theory is supported by data and helps to explain economic puzzles, empirical results, and stylized socio-economic facts of the past four decades, such as: (a) the coming of the cybernetics age, (b) the rise of cyber-entrepreneurs, (c) the declining average number of hours at work and the rising life cycle labor imbalance, (d) the contextual instability of the skill premium, (e) the rising inequality between cyber-entrepreneurs and other economic agents, (f) the declining labor share of income, (g) the productivity paradox, (h) secular stagnation, and (i) Piketty's fundamental inequality empirical observations.

Increasing income inequality due to cyber-entrepreneurs' ownership of physical and cognitive technological innovations, and the mounting destruction of highly meaningful human labor occupations, could be creating a politically and socially unsustainable outcome. New perspectives will be needed to address the detrimental effects of technological innovations on well-being. We intend to study these matters in future investigations.

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Figures

Figure 1: Labor-saving productivity A_r (physical technological innovations) as a function of technology vintage v

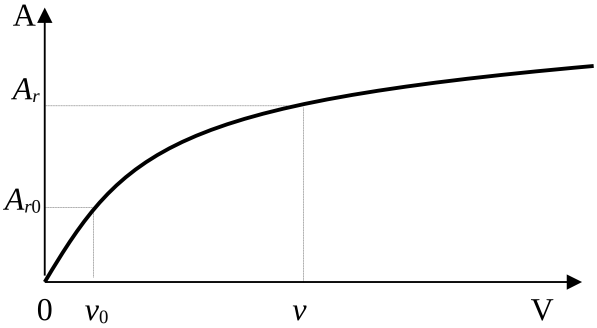


Figure 2: Skill alienability floor s_f (cognitive technological innovations) as a function of technology vintage v

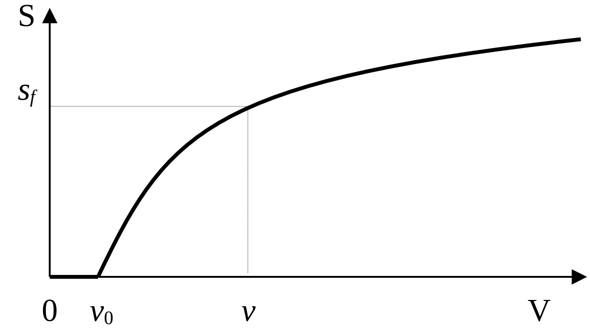


Figure 3: Labor-augmenting productivity growth rate γ_c as a function of technology vintage v

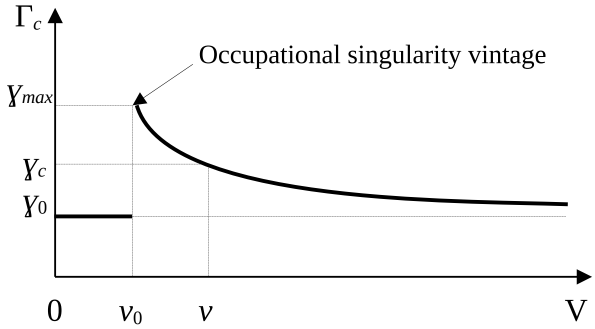
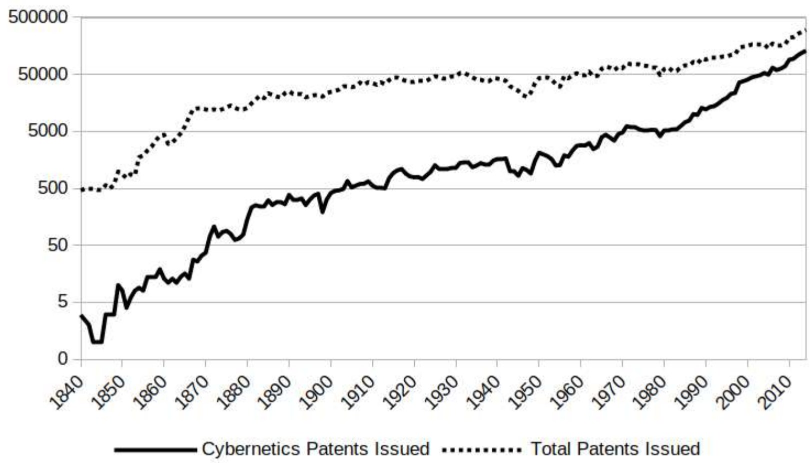
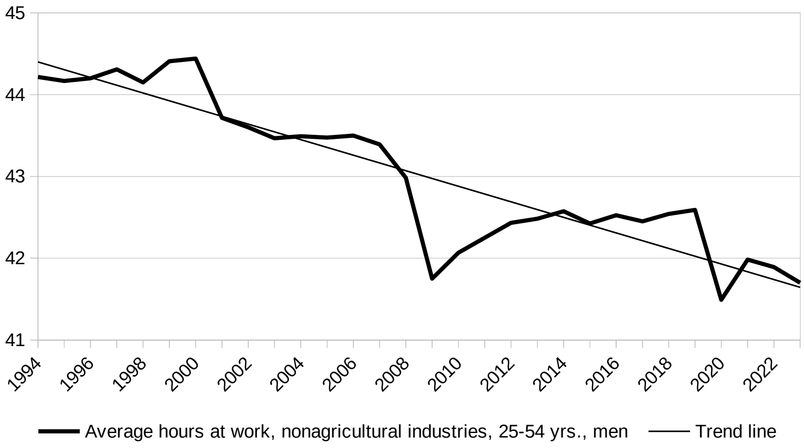


Figure 4: Yearly number of cybernetics and total patents issued in the US (log scale)



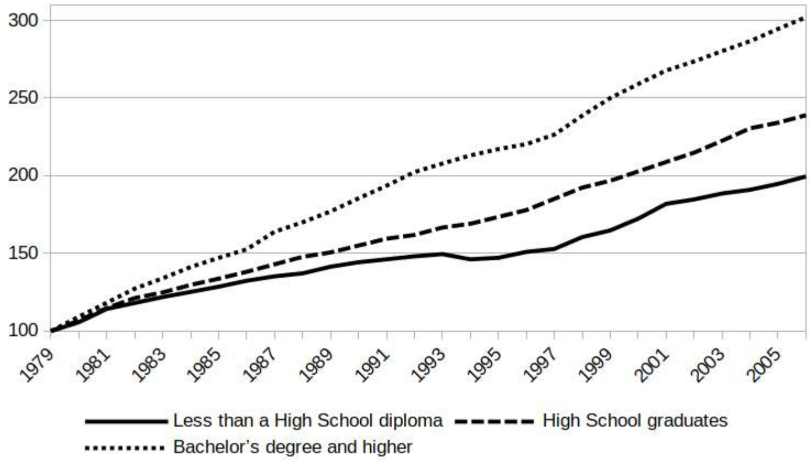
Source: United States Patent and Trademark Office

Figure 5: Average weekly number of hours at work for men 25 to 54 years old in the US (percent)



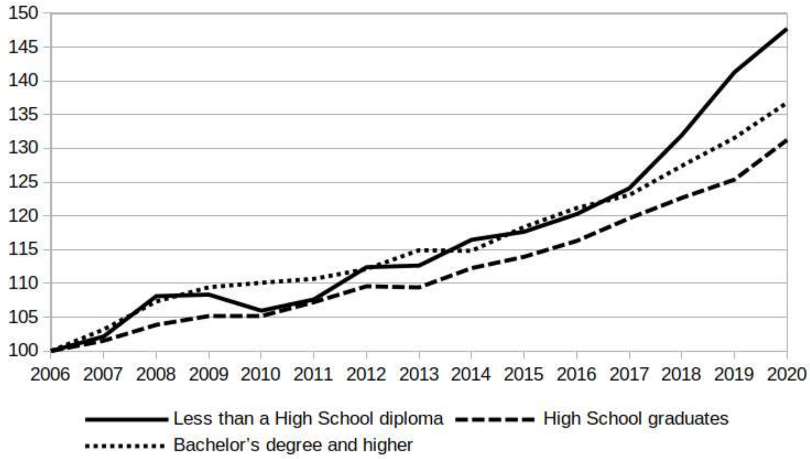
Source: Current Population Survey (CPS), U.S. Bureau of Labor Statistics

Figure 6: Median nominal earnings for workers 25 years and over in the US (base year 1979)



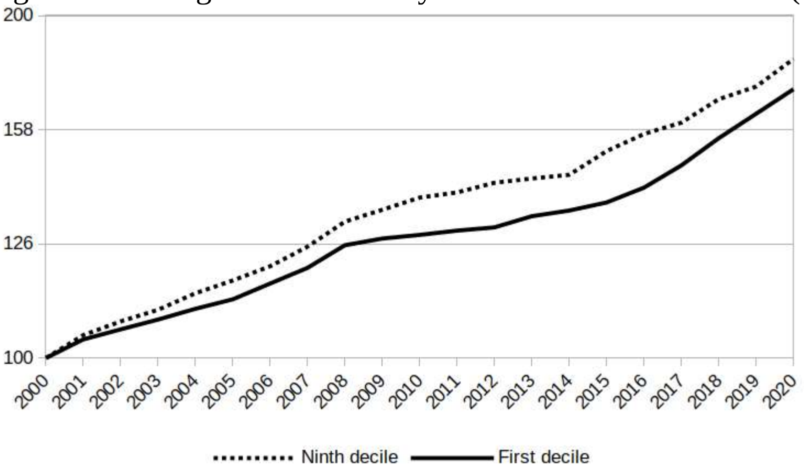
Source: U.S. Bureau of Labor Statistics

Figure 7: Median nominal earnings for workers 25 years old and over in the US (base year 2006)



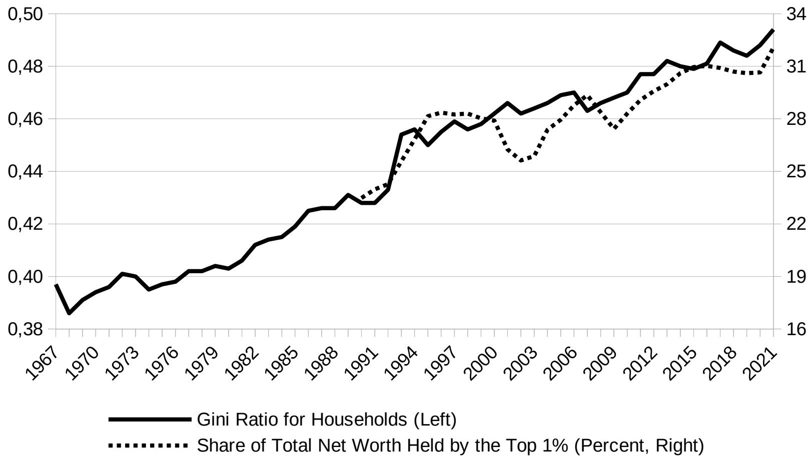
Source: U.S. Bureau of Labor Statistics

Figure 8: Earnings of workers 25 years old and over in the US (base year 2000, log scale)



Source: U.S. Bureau of Labor Statistics

Figure 9: Income and Wealth Inequality in the US

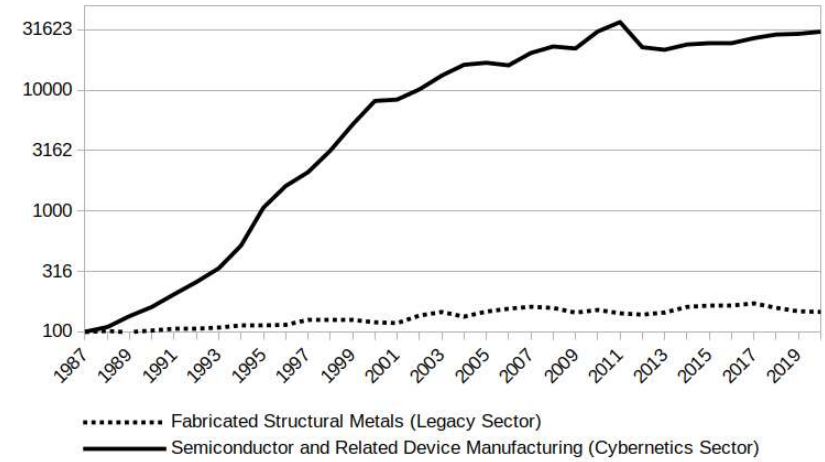


Source: U.S. Bureau of Labor Statistics

Figure 10: Labor share of income in the US (percent)

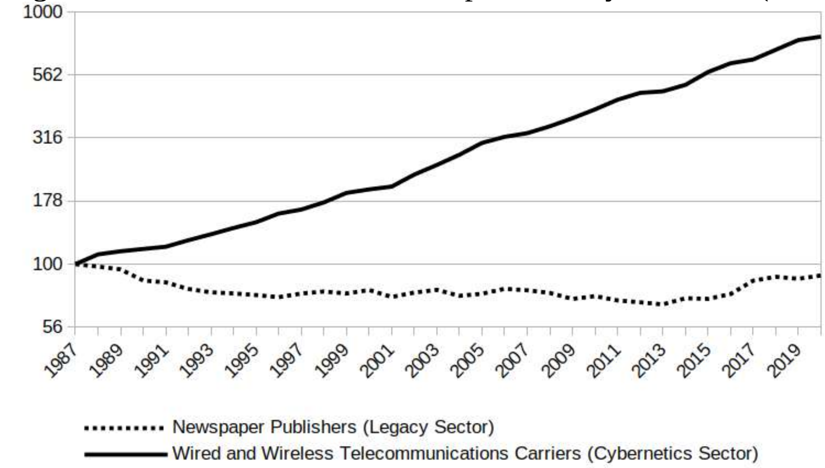
Source: Penn World Table 10.0

Figure 11: Manufacturing sector labor productivity in the US (base year 1987, log scale)



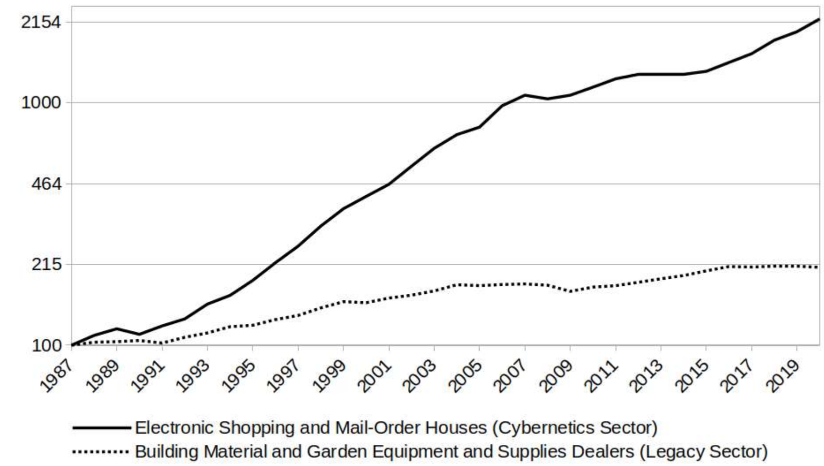
Source: U.S. Bureau of Labor Statistics

Figure 12: Information sector labor productivity in the US (base year 1987, log scale)



Source: U.S. Bureau of Labor Statistics

Figure 13: Retail Trade sector labor productivity in the US (base year 1987, log scale)



Source: U.S. Bureau of Labor Statistics