Cognitive Aging and Labor Share

Kausik, B.N.

Independent

24 August 2023

Cognitive Aging and Labor Share

B.N. Kausik[1]

Aug 24 2023

Abstract

Labor share, the fraction of economic output accrued as wages, is inexplicably declining in industrialized countries. Whilst numerous prior works attempt to explain the decline via economic factors, our novel approach links the decline to biological factors. Specifically, we propose a theoretical macroeconomic model where labor share reflects a dynamic equilibrium between the workforce automating existing outputs, and consumers demanding new output variants that require human labor. Industrialization leads to an aging population, and while cognitive performance is stable in the working years it drops sharply thereafter. Consequently, the declining cognitive performance of aging consumers reduces the demand for new output variants, leading to a decline in labor share. Our model expresses labor share as an algebraic function of median age, and is validated with surprising accuracy on historical data across industrialized economies via non-linear stochastic regression.

JEL D63, E22, E23, E24, J24, O33, O41

Introduction

Labor share, the fraction of economic output accrued as wages, is inexplicably declining in industrialized countries, raising the question of whether automation will displace human labor. Prior work, such as Frey and Osborne (2013), Korinek and Stiglitz (2020), Brynjolfsson (2022) and Acemoglu (2022) are pessimistic, while others such as Arntz, Gregory and Zierahn (2017), Bessen (2019), Autor et al (2020a), and Basu (2022) offer reasons for optimism. Nevertheless, there is sustained evidence that labor's share of economic output is declining in industrialized countries. Fig. 1 shows US labor share per the series "Shares of gross domestic income: Compensation of employees, paid: Wage and salary accruals: Disbursements: to persons (W270RE1A156NBEA)" from the St. Louis Federal Reserve.
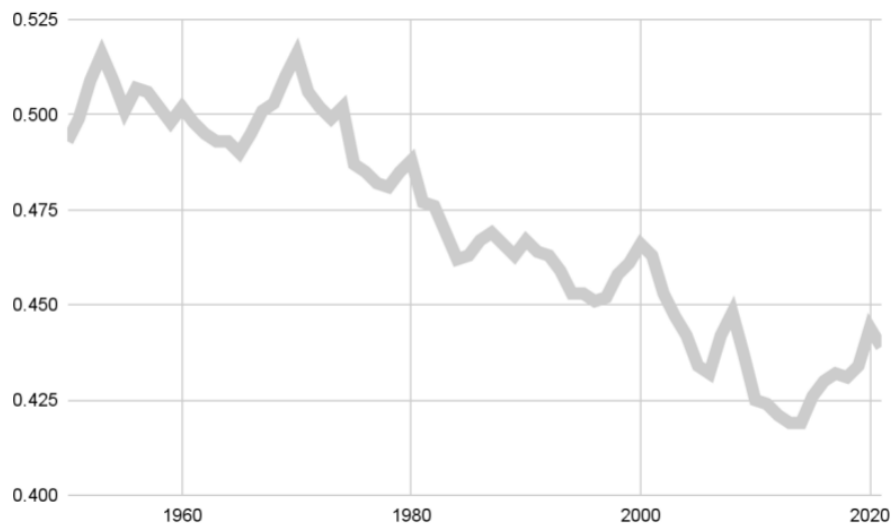

Fig. 1. US labor share 1948-2021 (data source: St. Louis Fed)

Fig. 1 suggests that US labor share was stable between 1948 and 1970 but declined since then. A similar decline is observed in other industrialized countries.

The cause of the decline is the subject of thousands of papers as surveyed by Grossman and Oberfeld (2021), ranging across (1) technological change, e.g., Karabarbounis and Neiman (2014), Oberfield and Raval (2014); (2) globalization, e.g., Elsby et al. (2013), Autor et al. (2020b); (3) concentration of market power, e.g., Barkai (2020), Autor et al. (2020b); (4) decline in unionization, e.g, Bentolila and Saint Paul (2003), Benmelech et al. (2020); (5) demographic changes in the workforce, e.g., Glover and Short (2020), Hopenhayn et al. (2018); with the conclusion that an explanation for the decline in labor share remains elusive.

A popular perspective is that human labor and automation compete for their respective share of economic activity, e.g. Acemoglu and Restrepo (2018), Acemoglu and Restrepo (2019), Autor et al (2022), and that automation inexorably wins, driving down labor's share of economic output. In contrast, our perspective is that labor share is determined via a competition between human consumers[2] and human suppliers, and

---

[2] We use the term "consumers" to refer to all participants in the economy.

is influenced by biological factors related to the median age of the population, which is increasing in industrialized countries as shown in Figs. 2a and 2b (data source: https://ourworldindata.org/).
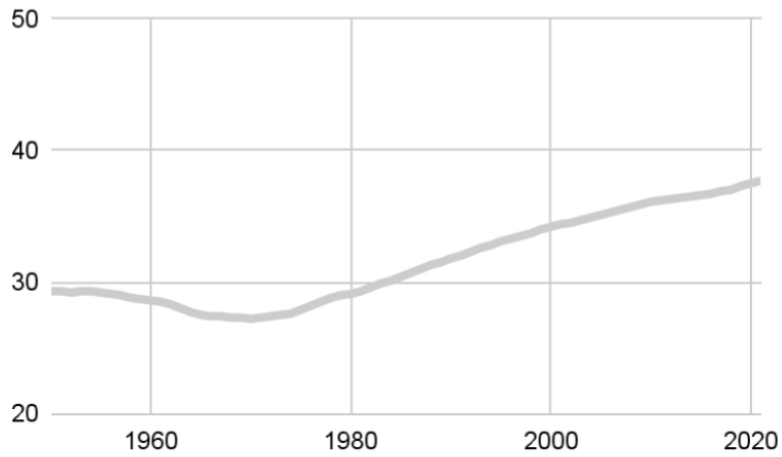

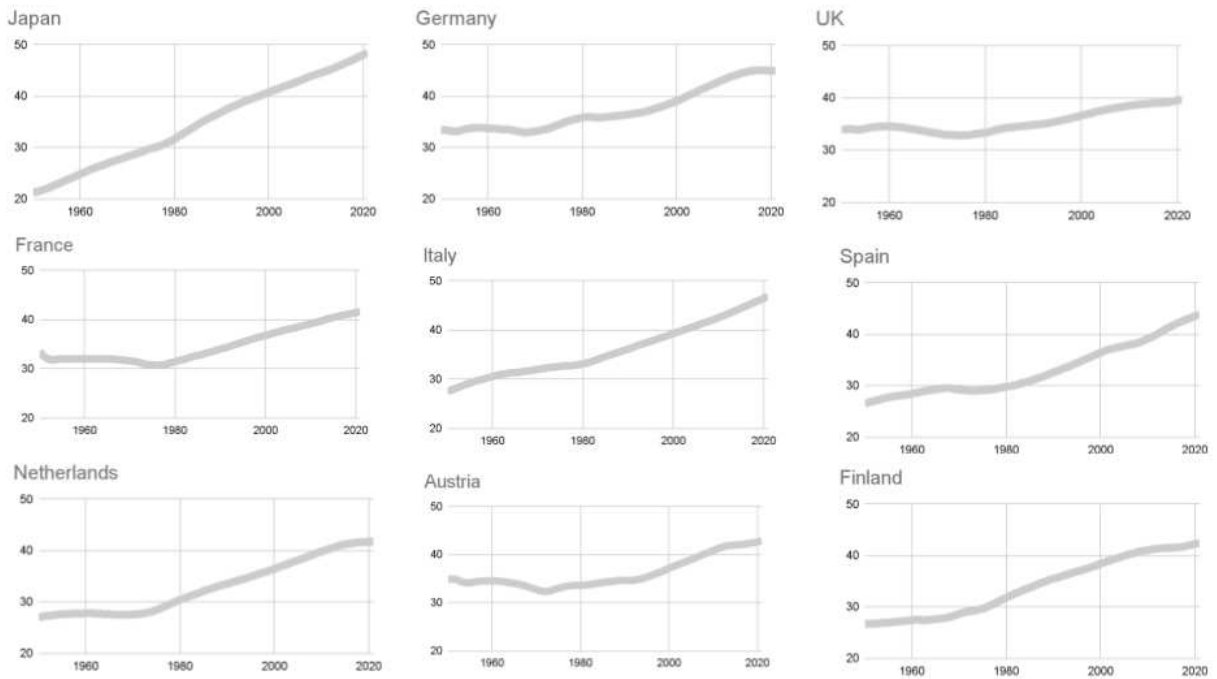Fig. 2a. US median age 1950-2021

Fig. 2b. Median age of select industrialized countries 1950-2021

The following example illustrates our approach:

Consider an economy where plain hats sell for $4 each, and carry a labor share of 0.2. Hats with customizable messages sell for $8 each. Consumers innovate on custom messages continuously, for sporting events, elections, alumni reunions, etc, leaving suppliers unable to automate the production process for custom hats beyond a labor share of 0.4. In short, consumers compete with suppliers to determine labor share.

Younger consumers prefer custom hats. Older consumers find crafting custom messages onerous and prefer plain hats. Initially, both types of hats sell equally and the overall labor share is

(0.5*0.2*4+0.5*0.4*8)/(0.5*4+0.5*8) = 0.33

Now suppose the median age of the population increases, with relatively more older consumers, shifting the mix of hats to 60% plain hats. The overall labor share declines to

(0.6*0.2*4+0.4*0.4*8)/(0.6*4+0.4*8) = 0.31

In short, aging consumers demand fewer output variants, leading to a decline in labor share.

Our paper is organized is as follows:

1. We observe that human needs favor long tail distributions, demanding the same from goods and services that fulfill those needs, following Anderson (2004), Anderson (2006), Brynjolfsson et al (2007), Goel et al (2010) and Kausik (2023a). Based on this observation, we propose a theoretical model of economic activity on a long tail distribution, where innovation in demand for output variants on the long tail competes with innovation in supply automation at the head of the distribution. In other words, on the demand side, human consumers innovate in seeking new, niche variants of items that require human labor. While on the supply side, human producers innovate on automation to drive down the cost of mature, popular items.
2. We observe that human cognitive performance is stable in the working years, declining sharply thereafter, e.g., Salthouse (2010, Kobayashi et al, (2014), Murman, (2015), and Eikelbloom et al. (2020). We invoke this observation to model innovation in supply and demand as a function of the median age of the population, then obtain an algebraic expression for labor share in a dynamic equilibrium.
3. We validate the model on historical data across industrialized economies via non-linear stochastic regression.

Model of Economic Activity

We propose a theoretical macroeconomic model where economic activity follows a long tail distribution. Referring to Fig. 3, the horizontal axis is all available tasks in the economy ranked in decreasing order of economic output, where the rank fraction of a task is the ratio of the rank of the task over the total number

of tasks. The vertical axis is the cumulative economic output share $P(r)$ of tasks with rank fraction between 0 and r. At any point in time, there exists rank fraction a such that tasks in $[0, a]$ are performed by automation while tasks in $(a, 1]$ are performed by labor. We refer to a as the automation fraction.
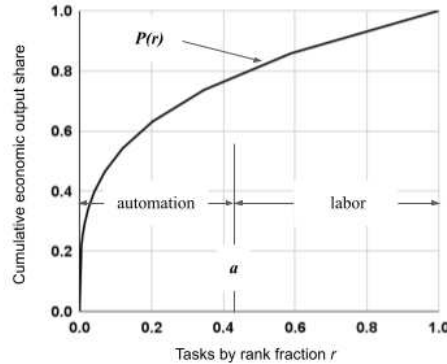

Fig. 3. Long tail model of economy

Assumption 1: The cumulative economic output share is given by $P(r) = r^n$ where n is a constant model parameter. Automation's share of the output is a^n and labor's share is $(1 - a^n)$.

Assumption 2: Tasks leftmost in the labor component are newly automated at a nominal rate $\sigma \geq 0$, in that the automation fraction a nominally increases to $a + \sigma\tau$ after infinitesimal time interval τ. See Fig. 4. We refer to σ as the *supply innovation rate*.
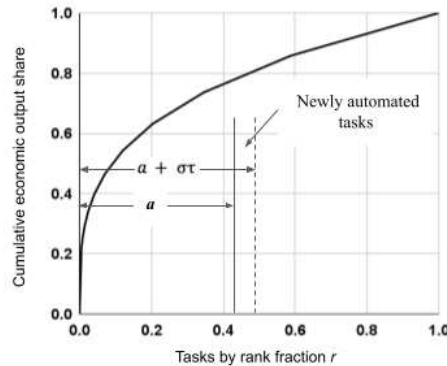

Fig. 4. Supply innovation: expanded automation of tasks

Assumption 3: As existing tasks become obsolete and new niche tasks are created, the rank fraction of tasks improves at a nominal rate $\delta > 0$, in that each point r on the horizontal axis nominally shifts to $r(1 - \delta\tau)$ after infinitesimal time interval τ. See Fig. 5. We refer to δ as the *demand innovation rate*.
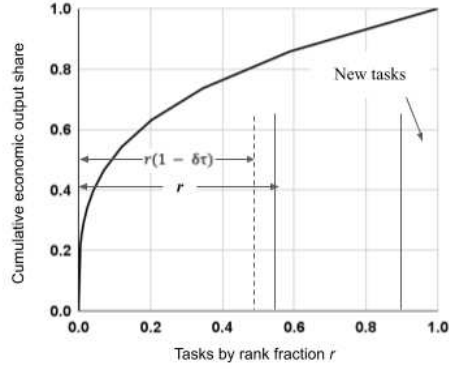
5

Fig. 5. Demand innovation: obsolescence and new niche tasks

Assumption 4: We assume that at time t,

$$\frac{\sigma}{\delta} = \left(\frac{\sigma_0}{\delta_0}\right)^{\frac{1}{1-k(\mu-\mu_0)}}$$

where σ_0 and δ_0 are the innovation rates at initial time t_0, μ and μ_0 are the median age of the population at time t and t_0 respectively, and $k \geq 0$ is a constant model parameter.

Assumption 4 is motivated by Fig. 6, which abstracts the literature on cognitive aging, e.g., Salthouse, (2010), Kobayashi et al, (2014), Murman (2015), and Eikelbloom et al. (2020). Per Fig. 6, cognitive performance, except vocabulary, is relatively stable during the working years but declines sharply thereafter. Since the supply innovation rate σ pertains to the workforce and the demand innovation rate δ pertains to the entire population, Assumption 4 attenuates only the demand innovation rate δ by a factor linear in the median age of the population. We note that physical fitness also declines with age, but can impact the items consumed rather than the ability to demand variants of those items. In earlier work, Kausik (2023b), we assume (σ/δ) is constant over the interval of interest, i.e., $k = 0$, leading to asymptotic transitions between static equilibria.
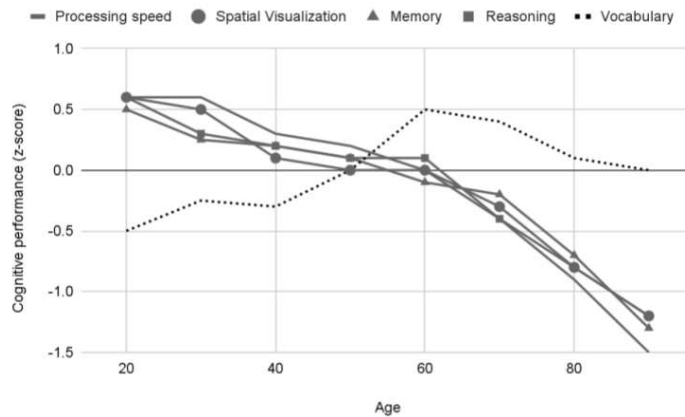

Fig. 6. Cognitive aging

The decline of human innovation with age is the subject of prior works, e.g Simonton (1988) and Jones (2010), who observe that innovation in science and technology, which is a combination of training and cognitive performance, peaks around age 40 and declines sharply thereafter. Likewise, in the context of internet search engines where query formulation is a measure of demand innovation and search results are output variants, prior works, e.g. Karanam and van Oostendorp (2016) and Kordovski et al. (2021), find that older adults have a lower accuracy and lower rate of query formulation.

Theorem 1: In dynamic equilibrium, labor share is

$$1 - \left[\left(\frac{\sigma_0}{\delta_0} \right)^{\frac{1}{1-k(\mu-\mu_0)}} \right]^n$$

Proof: Combining Assumptions 2 and 3, we get
$$\partial a / \partial t = \sigma - a\delta.$$
Rearranging, we get

$$\partial a / \partial t = - \delta \left(a - \frac{\sigma}{\delta} \right)$$

Setting $\partial a / \partial t = 0$ and noting $\delta > 0$, we get $a - \frac{\sigma}{\delta} = 0$, which implies $a = \frac{\sigma}{\delta}$ at equilibrium, i.e.

$$a = \left[\left(\frac{\sigma_0}{\delta_0} \right)^{\frac{1}{1-k(\mu-\mu_0)}} \right]$$

Per Assumption 1, it follows that in dynamic equilibrium, the labor share is

$$1 - \left[\left(\frac{\sigma_0}{\delta_0} \right)^{\frac{1}{1-k(\mu-\mu_0)}} \right]^n$$

Validation

We now validate our model against historical economic data.

Data Set 1: We apply TensorFlow non-linear stochastic gradient descent regression to the time series of Figs. 1 and 2a to extract the three parameters $\frac{\sigma_0}{\delta_0}$, k and n, in the labor share formula of Theorem 1. Each run consists of 100 iterations of stochastic gradient descent and Mean Square Error loss, starting with the three parameters randomly initialized in the interval [0,1]. We average the three parameters across 20 runs to obtain the values shown below.

$$n = 7.86E - 01; \ \frac{\sigma_0}{\delta_0} = 4.24E - 01; \ k = 1.75E - 02$$

Fig. 7 plots the results. The thick gray line is the actual historical data 1950-2021. The solid black line is the model's fit across the same period. The Root Mean Squared error of the model in the period is ~2.4%.
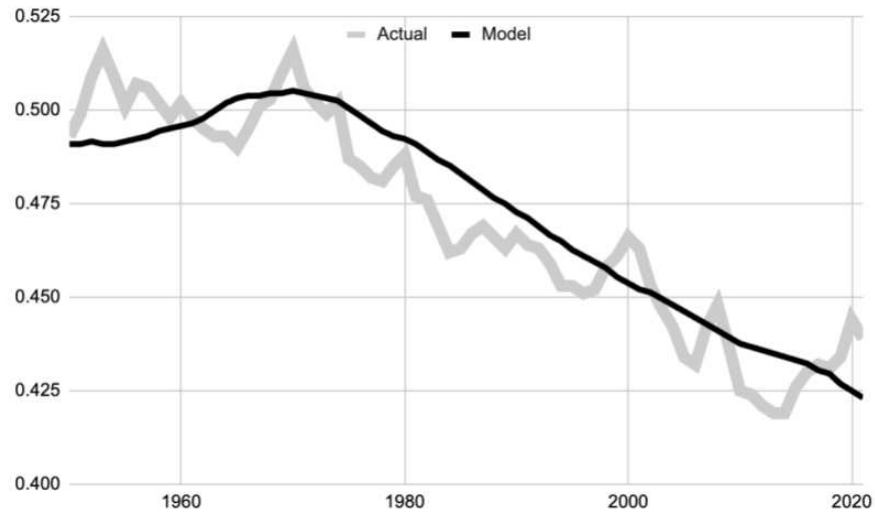

Fig. 7. Actual and model labor share of the United States

Data Set 2: We apply TensorFlow non-linear stochastic gradient descent regression to the time series of Fig. 2b and KLEMS 2013 economic data at http://www.euklems.net/. Each run consists of 100 iterations of stochastic gradient descent and Mean Square Error loss, starting with the three parameters randomly initialized in the interval [0,1]. We average the three parameters across 20 runs for each country to obtain the values shown in Table 1.

Fig. 8 plots the results. For each country, the thick gray line is the actual historical data available between 1970 and 2012. The solid black line is the model's fit across the same period. The Root Mean Squared error of the model in the period is ~3% for each country.

n	σ_0/δ_0	k	n	σ_0/δ_0	k	n	σ_0/δ_0	k
Japan			Germany			UK		
8.99E-01	2.63E-01	2.08E-02	9.04E-01	2.10E-02	2.38E-01	8.89e-1	2.51E-01	4.68E-03
France			Italy			Spain		
9.62E-01	2.51E-01	4.10E-02	9.65E-01	2.41E-01	3.44E-02	8.85E-01	2.90E-01	1.33E-02
Netherlands			Austria			Finland		
9.40E-01	2.54E-01	2.95E-02	9.65E-01	2.59E-01	3.70E-02	9.70E-01	2.28E-01	2.74E-02

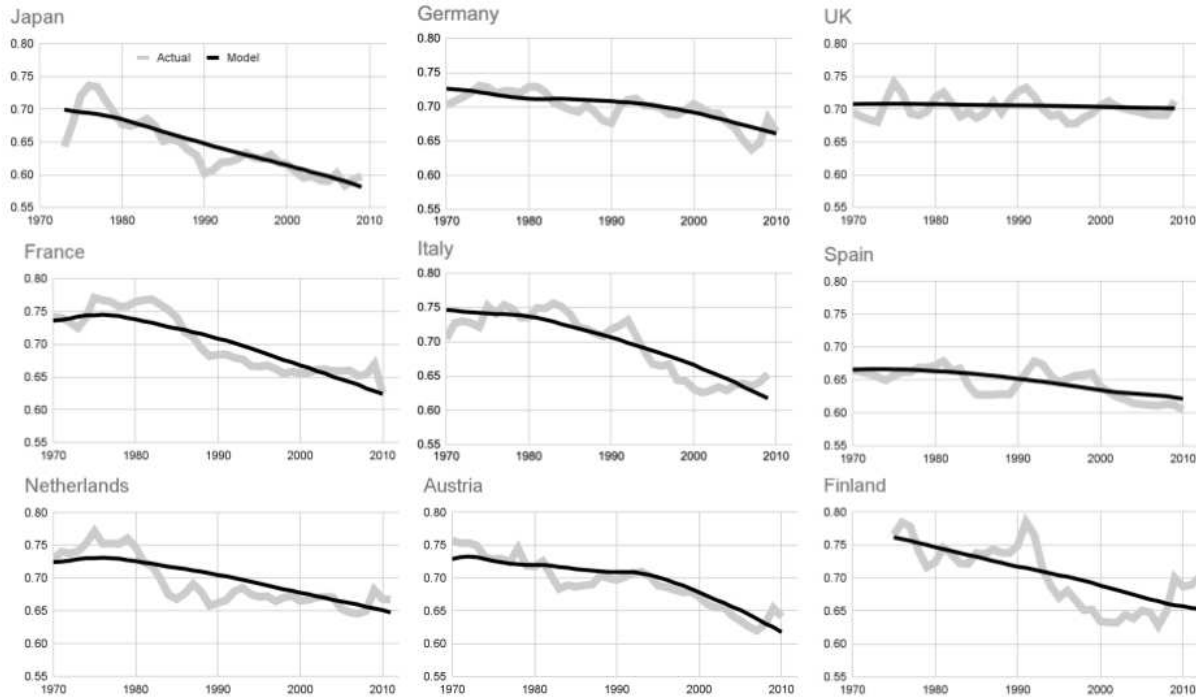Table 1. Model parameters for select industrialized countries

Fig. 8. Actual and model labor share of select industrialized countries

Summary

Labor share, the fraction of economic output accrued as wages, is inexplicably declining in industrialized countries. Whilst numerous prior works attempt to explain the decline via economic factors, our novel approach links the decline to biological factors. Specifically, we propose a theoretical macroeconomic model where labor share reflects a dynamic equilibrium between the workforce automating existing outputs, and consumers demanding new output variants that require human labor. Industrialization leads to an aging population, and while cognitive performance is stable in the working years it drops sharply thereafter. Consequently, the declining cognitive performance of aging consumers reduces the demand for new output variants, leading to a decline in labor share. Our model expresses labor share as an algebraic function of median age, and is validated with surprising accuracy on historical data across industrialized economies via non-linear stochastic regression.

References

1. C. Frey, M.A. Osborne, "The Future of Employment: How Susceptible are Jobs to Computerization?" https://www.oxfordmartin.ox.ac.uk/downloads/academic/The_Future_of_Employment.pdf (2013)

2. A. Korinek, J. Stiglitz, "Steering Technological Progress," https://conference.nber.org/conf_papers/f143989.pdf (2020)

3. E. Brynjolfsson, "The Turing Trap: The Promise & Peril of Human-Like Artificial Intelligence,"https://digitaleconomy.stanford.edu/news/the-turing-trap-the-promise-peril-of-human-like-artificial-intelligence/ (2022)

4. D. Acemoglu, "The Harms of AI," https://economics.mit.edu/files/21848 (2022)

5. J.E. Bessen,"Automation and Jobs: When Technology Boosts Employment" https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2935003 (2019).

6. M. Arntz, T. Gregory, U. Zierahn, U., "Revisiting the Risk of Automation," Economics Letters 159:157-160 (2017).

7. D. Autor, D.Mindell, and E. Reynolds, "The Work of the Future: Building Better Jobs in an Age of Intelligent Machines" Cambridge: MIT Press https://workofthefuture.mit.edu/wp-content/uploads/2021/01/2020-Final-Report4.pdf (2020a).

8. K. Basu, "An inclusive future? Technology, New Dynamics and Policy Challenges" Brookings Institute, https://www.brookings.edu/wp-content/uploads/2022/05/Inclusive-future_Technology-new-dynamics-policy-challenges.pdf (2022).

9. Grossman, Gene M. and Oberfield, Ezra, The Elusive Explanation for the Declining Labor Share (August 2021). NBER Working Paper No. w29165, https://www.nber.org/system/files/working_papers/w29165/w29165.pdf

10. Karabarbounis, L., and Neiman, B. "The Global Decline of the Labor Share." Quarterly Journal of Economics 129 (1): 61–103. (2014).

11. Oberfield, E., and Raval, D. "Micro Data and Macro Technology." National Bureau of Economic Research Working Paper 20452 (2014).

12. Elsby MWL, Hobijn B, ¸Sahin A. 2013. The decline of the U.S. labor share. Brookings Pap. Econ. Activ. 2013(2):1-63

13. Autor D, Dorn D, Katz LF, Patterson C, Van Reenen J. 2020b. The fall of the labor share and the rise of superstar Örms. Q. J. Econ. 135(2):645-709

14. Barkai S. 2020. Declining labor and capital shares. J. Finance 75(5):2421-63

15. Bentolila S, Saint-Paul G. 2003. Explaining movements in the labor share. Contributions in Macroecon. 3(1)

16. Benmelech E, Bergman NK, Kim H. 2020. Strong employers and weak employees: How does employer concentration a§ect wages? J. Hum. Resour. 0119-10007R1

17. Glover A, Short J. 2020. Can capital deepening explain the global decline in laborís share? Rev. of Econ. Dyn. 35:35-53

18. Hopenhayn H, Neira J, Singhania R. 2018. From population growth to firm demographics: Implications for concentration, entrepreneurship and the labor share. NBER Work. Pap. 25382

19. Acemoglu, D., Restrepo, P., "Automation and New Tasks: How Technology Displaces and Reinstates Labor." Journal of Economic Perspectives—Volume 33, Number 2. (2019).

20. D. Autor, C. Chin, A.M. Salomons, and B. Seegmiller, "New Frontiers: The Origins and Content of New Work, 1940–2018," https://www.nber.org/papers/w30389 (2022).

21. Acemoglu, D., Restrepo, P., The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment, American Economic Review 2018, 108(6): 1488–1542 https://doi.org/10.1257/aer.20160696

22. C. Anderson, "The long tail." Wired Magazine, 12(10):170–177, (2004)

23. C. Anderson, "The Long Tail: Why the Future of Business is Selling Less of More." Hyperion, (2006).

24. E. Brynjolfsson, Y.J. Hu, and M.D. Smith, "Consumer surplus in the digital economy: Estimating the value of increased product variety at online booksellers." MIT Center for Digital Business Working Paper, (2007).

25. S. Goel, A. Broder, E. Gabrilovich, B. Pang, "Anatomy of the long tail: ordinary people with extraordinary tastes." Proceedings of the third ACM international conference on Web search and data mining, (2010)

26. Kausik, B.N. 2023a. Long Tails & the Impact of GPT on Labor https://ideas.repec.org/p/pra/mprapa/117063.html

27. Kausik, BN, Long Tails, Automation and Labor (2023b), https://ssrn.com/abstract=4520641

28. Salthouse TA. Selective review of cognitive aging. J Int Neuropsychol Soc. 2010 Sep;16(5):754-60. doi: 10.1017/S1355617710000706. Epub 2010 Aug 2. PMID: 20673381; PMCID: PMC3637655.

29. Kobayashi LC, Smith SG, O'Conor R, et al. The role of cognitive function in the relationship between age and health literacy: a cross-sectional analysis of older adults in Chicago, USA. BMJ Open 2015;5:e007222. doi:10.1136/bmjopen-2014- 007222

30. Murman DL. The Impact of Age on Cognition. Semin Hear. 2015 Aug;36(3):111-21. doi: 10.1055/s-0035-1555115. PMID: 27516712; PMCID: PMC4906299.

31. Eikelboom, W.S., Bertens, D., Kessels, R.P.C. (2020). Cognitive Rehabilitation in Normal Aging and Individuals with Subjective Cognitive Decline. In: DeLuca, J., Chiaravalloti, N.D., Weber, E. (eds) Cognitive Rehabilitation and Neuroimaging. Springer, Cham. https://doi.org/10.1007/978-3-030-48382-1_3

32. Simonton DK. Age and outstanding achievement: What do we know after a century of research. Psychological Bulletin. 1988;104:251–267.

33. Jones BF. Age and great invention. Review of Economics and Statistics. 2010;92(1):1–14.

34. Karanam, S., van Oostendorp, H.: Age-related Differences in the Content of Search Queries when Reformulating. Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems - CHI' ' '16. pp. 5720–5730. ACM Press, New York, New York, USA (2016).

35. Kordovski VM, Tierney SM, Rahman S, Medina LD, Babicz MA, Yoshida H, Holcomb EM, Cushman C, Woods SP. Older age and online health information search behaviors: The mediating influence of executive functions. J Clin Exp Neuropsychol. 2021 Sep;43(7):689-703.