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Extension of Endogenous Growth Theory: Artificial Intelligence as a Self-Learning Entity

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ABSTRACT: The Artificial Intelligence (AI) evolution is a broad set of methods, algorithms, and technologies making software human-like intelligent that is encroaching our contemporary workplace. Thinking like humans but acting rational is the primary goal of AI innovations. The current market disruption with AI lies at the core of the IT-enhanced economic growth driven by algorithms – for instance enabled via the sharing economies and big data information gains, self-check outs, online purchases and bookings, medical services social care, law, retail, logistics and finance to name a few domains in which AI leads to productivity enhancement. While we have ample account of AI entering our everyday lives, we hardly have any information about economic growth driven by AI. Preliminary studies found a negative relation between digitalization and economic growth, indicating that we lack a proper growth theory capturing the economic value imbued in AI. We also have information that indicates AI-led growth based on ICT technologies may widen an inequality-rising skilled versus unskilled labor wage gap. This paper makes the theoretical case of AI as a self-learning entity to be integrated into endogenous growth theory, which gives credit to learning and knowledge transformation as vital economic productivity ingredients. Future research may empirically validate the claim that AI as a self-learning entity is a driver of endogenous growth. All these endeavors may prepare for research on how to enhance human welfare with AI-induced growth based on inclusive AI-human compatibility and mutual exchange between machines and human beings.

KEYWORDS: Algorithms, Artificial Intelligence (AI), Digitalization, Digitalization disruption, Digital inequality, Economic growth, Endogenous growth, Gross Domestic Product (GDP), Innovation, Learning, Productivity, Self-Learning, Software, Technology

Introduction

The Artificial Intelligence (AI) evolution as a broad set of methods, algorithms, and technologies making software human-like intelligent has revolutionized modern economies. Thinking like humans but acting rational is the goal of self-learning entities. To this day, the clear effect of AI on economic growth is not captured sufficiently. Preliminary studies found a negative relation between digitalization and economic growth, indicating that we lack a proper economic growth theory fully capturing the productive value imbued in AI (Puaschunder 2022a). This paper therefore theoretical introduces AI as a self-learning entity to be integrated into endogenous growth theory. The discussion stresses the need for further research to empirically validate the claim that AI as a self-learning entity is a driver of endogenous growth in order to prepare for research on how to enhance human welfare with AI-induced growth.

Artificial Intelligence

AI is "a broad set of methods, algorithms, and technologies that make software 'smart' in a way that may seem human-like" (Noyes 2016). The Oxford Dictionary defines AI as "the theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages." AI describes the capacity of a computer to perform like human beings including the ability to review, discern meaning, generalize, learn from past experience and find patterns and relations to respond dynamically to changing situations. AI is perceived as the sum of different technological advancements with currently developing regulation (Dowell 2018). Machine learning is based on computational algorithms that learn from big data sources in order to derive inferences for constantly improving future decisions and choices.

The self-learning nature of AI makes it different from any other previous industrialization revolution as this time human beings give up decision-making autonomy and train another species to take over control of their everyday tasks and human choices. To this day, no clear account exists on the economic role of AI encroaching economic space and human beings giving up decision-making control to this novel entity, which has components of technology as it has human features. This paper presents the first introduction of endogenous growth theory with respect for self-learning credentials of AI and discusses novel inequalities arising from AI-led growth.

Growth theory

Historical foundations of economic growth calculus date back to the economics classics in the work of Adam Smith, Thomas Robert Malthus, David Ricardo and Karl Marx. The early accounts of labor theories of value and theories of land rent prepare first ideas on how input factors generate economic productivity.

Modern growth theory (MGT) starts in the 20th century. The starting point of MGT can be attributed to Roy Harrod (1939) and Evsey Domar (1946), who studied business cycles as drivers of growth. MGT is thus primarily focused on capital with constant marginal product and constant returns to scale. From Sir Roy Harrod to Robert Solow and Paul Michael Romer, growth theory in the 20th century became more apolitical, equilibrium-focused with an application of a set of mathematical tools in the development of the ideas of the classicals.

Robert Merton Solow and Trevor Swan introduced the Solow-Swan model as a hallmark of neoclassical growth theory (Solow 1956, 1957; Swan 1956). The Solow-Swan growth model is based on the neoclassical Cobb-Douglas production function of capital and labor assumed to be freely substitutable. The Solow Growth Model uses the Aggregate Production Function, in which net national product Y is a function of Capital K and Labor L in $Y = F(K, L)$. The aggregate production function is fixed, meaning how the product depends on capital and labor does not change over time. In Solow's model differences (in the short-run) in income levels across countries are explained by rich countries having higher saving (investment) rates in relation to population growth than poorer countries. Permanent (long-run) cross-country differences can only result from differences in the rate of technological progress and access to the same technology.

Neoclassical growth theory literature was superseded by endogenous growth theory or the new growth theory. Endogenous Growth Theory (EGT) emerged during the apparent sudden rise of a new group of inter-related Asian 'Tigers' (Singapore, Hong Kong, Taiwan, Korea) as fully fledged members of the league of developed nations that could not be explained with exogenous growth theory. The idea of externalities and spillover effects was originally formalized by Arrow (1962) who argued that externalities arising from learning-by-doing and knowledge spillovers positively affect labor productivity on the aggregate level of the economy. Endogenization of knowledge and technology actually led to an explanation of endogenous growth. In the late 1980s, Romer and Lucas incept EGT, in which economic growth is determined by the production of knowledge and ideas. Building on Uzawa (1965), Lucas (1988) emphasized human capital creation as a source of growth. Knowledge and technology are characterized by increasing returns unlike physical capital. In Romer's New Growth Theory (1986) persistent growth is explained by the impact of externalities on economic development. Romer (1990) considered the creation of new knowledge as a source of growth. Qualitative ideas – such as Schumpeter's creative destruction – are later mathematically formalized in growth theories and models of Solow (1973), Lucas (1988), Aghion and Howitt (1992). In

Aghion and Howitt (1992, 1998), the Schumpeterian process of creative destruction becomes central to growth.

Both Lucas and Romer include knowledge of human capital in their respective models to embody technological change. The growth in human capital is what spurs technological change within the model. There are little defining characteristics of the process in which knowledge transforms into technological change. Romer suggests that investment in research and development (R&D), along with the given state of technology, will spur innovation that leads to economic growth. The use of existing ideas and the creation of new innovations is introduced as the driver of growth in the long-run. Lucas emphasizes that human capital can grow from education as well as learning-by-doing. Endogenous growth models are built on microeconomic foundations, where households maximize utility subject to budget constraints, while firms maximize profits subject to production constraints. Policy implications are a mix of goods to accumulate human capital, subsidies for skills development and create incentives for workers to accumulate human capital.

Over the entire world and in the prospect of time, for thousands of years, growth in population and per capita GDP has accelerated, rising from virtually zero to the relatively rapid rates observed in the last century. Romer (1986, 1990) adds new stylized facts in pointing at rising flows of goods, ideas, finance, and people — via globalization as well as urbanization — have driven the extent of the market for all workers and consumers. Variation in the rate of growth of per capita GDP increases with the distance from the technology frontier.

Most recent developments and additions to growth theory include health precautions as experienced during the COVID-19 pandemic to enhance labor productivity (Puaschunder 2022b), climate change impacts on economic growth outlooks (Puaschunder 2020, 2021) and digitalization's relation to growth, which is surprisingly negative indicating that contemporary growth theory does not fully capture AI's impact on economic growth (Puaschunder 2020).

Growth theory and technical change

We currently live in a transition period from factor-neutral to factor-biased technical change. The traditional measure of economy-wide technological change, introduced by Solow (1957), is aggregate total factor productivity (TFP). Solow defines a TFP advancement as an increase in output that leaves marginal rates of transformations untouched for given inputs; thus, a change in TFP is a form of factor-neutral technical change. There used to be an overwhelming consensus that neutral technological improvements are the primary source of growth in income per capita. However, recent data highlights the limits of this conceptualization of technical change. In the last three decades, the rental price of skilled labor has soared dramatically relatively to that of unskilled labor despite a major uprise in the relative supply of skills. Given the observed movements in the relative quantities, these price changes could not be generated by movements "along the production function." Neutral technical change is, by definition, silent on changes in relative prices. To make sense of these recent developments, one must introduce the concept of factor-biased technical change.

There is a skill-bias of IT-led growth. In the past 30 years in the wake of the IT revolution, technological change in the production process has been skill-biased with the rise in a disproportionate skills-premium. The rapid diffusion of ICT in the workplace, expenditures in information processing equipment and software, as a share of U.S. private nonresidential fixed investment, rose from 6% in 1960 to 40% in 2000 due to semiconductors. Ample micro-econometric research and several case studies document a statistical correlation between the use of new technologies, like computers, and either the employment share of skilled workers or their wage share across industries. Skill-biased technical change (SBTC) occurs as shifts in production technology that favors skilled (hence more educated, able, experienced) labor over unskilled labor by increasing its relative productivity and relative demand for and rise in skills-premium, defined as the skilled:unskilled wages ratio.

Technology skill complementarity takes three alternative formulations: (1) Postwar U.S. economy sharp decline of the constant-quality relative price of equipment investment, especially evident for information technologies whose prices fell at 10% per year. (2) Nelson-Phelps view of human capital (1966), "educated people make good innovators, so that education speeds the process of technological diffusion." The more educated, able or experienced labor deals better with technological change. (3) Milgrom and Roberts (1990) argue that information technologies reduce costs of data storage, communication, monitoring and supervision activities within the firm which triggers a shift towards a skill-biased organizational design. Microeconomic evidence consistent with all these formulations of the technology-skill complementarity hypothesis exists.

The current state-of-the-art conclusion on technology-driven growth is that traditionally, in the growth literature, technological progress is associated with productivity improvements that benefit all workers and it is viewed as the chief long-run determinant of average income levels. Preliminary research found growth theory not fully capturing AI-induced growth, demanding for an investigation of the contribution of AI to productivity. This paper attempts to introduce the self-learning capacities of AI as a driver of endogenous growth in order to make the case that inclusive human-AI compatibility grants the optimum conditions in order to flourish AI-led growth on a social-welfare enhancing path.

AI as a driver of endogenous growth

In today's economy, robots and algorithms are taking over human decision-making tasks and entering the workforce. Most recently, big data has evolved to become a source of major assets and governments around the world are endeavoring to tax wealth creation from information transfer. This trend currently challenges conventional economic theory to capture growth based on purely capital and labor components. Algorithms, machine learning, and big data gains but also the sharing economy do not seem to be represented accurately in conventional growth theory components of capital and labor.

It is therefore proposed that contemporary growth theory should be revised as for integrating growth related to AI. Micro-macro and endogenous and exogenous growth theories could hold a novel component for AI as comprised of machine learning, big data, and robotics-induced growth components that are self-learning.

The new growth theory proposed is

$$Yn(t) = (A(t)K(t))^{\propto}(A(t)L(t))^{\beta}(A(t)I(t))^{1-\propto-\beta}$$

whereby $Yn(t)$ denotes total new production function, $A(t)$ refers to capital and labor-augmenting technologies or AI knowledge, $K(t)$ is the capital, $L(t)$ is the labor, and $I(t)$ represents information gain, which Internet connectivity and self-learning capacities have made more accessible and available to flourish economically from.

Information sharing and big data storage as well as computation power are most novel features of AI. Access to information but also reaping benefits from information sharing through synergizing information and deriving inferences in relation to big data is an innovative value generation in the artificial age differing from conventional capital or labor. Having already a big data collection enhances the productivity of $I(t)$ due to network effects. In addition, information is a non-rivalrous good, with a marginal utility gain that is exponential. Information is non-rivalrous as the consumption of one piece of information does not decrease or deplete the opportunity for another person to consume the information. Network effects from information and connectivity increase per additional user. The more information one holds, the better—hence, the marginal utility of information rises exponentially with information gain. In all these features—network effect gains, non-rivalrous information consumption opportunities, and exponential marginal utility gains of knowledge—information is completely different from classical notions of capital and labor. Where capital and labor are exclusive, the knowledge economy and big data-driven growth are non-exclusive (Clancy 1998). A piece of information shared or written online does not take anything away or decrease utility; it actually increases people's utility non-depletable (Stiglitz 1998; Stroebe & Frey 1982).

Self-learning algorithms resemble learning entities that are capable to derive inferences from big data in order to make more rational decisions and plan strategically into the future. Therefore, it is proposed to measure AI as completely novel component to be considered in standard growth theory. Economically, the current AI revolution is thus believed to differ from conventional technology shocks by the knowledge economy obeying different laws of economic exchange (Lucas 2004).

Future research avenues

Future research on the role of AI as self-learning entity for endogenous growth may address the notion of skills-biases due to technology transitions as a prerequisite for societal inequality and obstacle of international development. Capturing the hidden inequalities and disparate impacts of AI-induced growth is targeted at alleviating technological frictions and socio-economic impediments of technological change.

Skills-biases have introduced the theoretical possibility that technological progress benefits only a sub-group of society, placing technical change also at the center stage of the income distribution debate. Technical change implies rising inequality depending on the nature of technical change as well as circumstances within which change takes place (e.g., production process, institutional conditions, endogenous or exogenous change factors). Labor-saving technical change in labor-intensive processes implies a reduction in demand for labor and lower wage, which lowers costs of production and means higher profits for capitalists.

Technical change can also restructure industries so labor does not get reduced. Newly created work could re-employ if workers adapt and gain necessary skills to work with new technology and equipment, which depends on institutional factors such as law, policy, motivation and incentives to capitalists and bargaining power of trade unions. Future research may focus on determining positive influences on the dissemination of new technology that shares AI-gains democratically in society that reduces inequality. When providing people with more equal economic opportunities and capabilities, for instance, technology-led growth can lead to a network of learning even if fundamental inequalities between ownership of large-scale industrial means of production remain in place (e.g., smartphones and computers with internet encourage people to set up their own enterprises, access to stock market investments etc.). Institutional factors – such as intellectual property rights and patents – add competitive market advantage over rivals, yet persist inequality between firms.

In the future, most important work is needed to address human-machine compatibility in order to increase and cultivate a vital flow between AI-led growth and human learning capacities. A bundling of AI with human beings may benefit both worlds: With human help, AI can be improved in creative thinking skills and human decision capabilities, which are complex and add an emotional and irrational humanistic touch to economic productivity. Human beings can benefit from reaping the value of AI in enormous data storage and analyzing capacities that offer to be efficient, rational and eternally exponentially growing. So, for growth to be productive and humanistic, a harmonized interaction between human and AI is called for to pave the way for future wealth of mutually AI-human-driven nations.

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