Artificial Intelligence Based Technologies and Economic Growth in a Creative Region

Batabyal, Amitrajeet and Kourtit, Karima and Nijkamp, Peter

Rochester Institute of Technology, USA, Open University, Heerlen, The Netherlands, AI Cuza University, Iasi, Romania

11 December 2023

Artificial Intelligence Based Technologies and Economic Growth in a Creative Region [1]

by

Amitrajeet A. Batabyal, [2]

Karima Kourtit, [3]

and

Peter Nijkamp [4]

[1] For their helpful comments on a previous version of this paper, we thank the Managing Editor Cristiano Antonelli, three anonymous referees, and session participants in (i) the Western Regional Science Association Hybrid Annual Meeting, Monterey, California, February 2024, and (ii) the Southern Regional Science Association Annual Conference, Arlington, Virginia, April 2024. Batabyal acknowledges financial support from the Gosnell endowment at RIT. The usual disclaimer applies.

[2] Departments of Economics and Sustainability, Rochester Institute of Technology, 92 Lomb Memorial Drive, Rochester, NY 14623-5604, USA. E-mail: aabgsh@rit.edu

[3] Open University, Heerlen, The Netherlands, and AI Cuza University, Iasi, Romania. E-mail: k_kourtit@hotmail.com

[4] AI Cuza University, Iasi, Romania. E-mail: pnijkamp@hotmail.com

Artificial Intelligence Based Technologies and Economic Growth in a Creative Region

Abstract

We analyze economic growth in a stylized, high-tech region $\mathbb{A}$ with two key features. First, the residents of this region are high-tech because they possess skills. In the language of Richard Florida, these residents comprise the region's creative class and they possess creative capital. Second, the region is high-tech because it uses an artificial intelligence (AI)-based technology and we model the use of this technology. In this setting, we first derive expressions for three growth metrics. Second, we use these metrics to show that the economy of $\mathbb{A}$ converges to a balanced growth path (BGP). Third, we compute the growth rate of output per effective creative capital unit on this BGP. Fourth, we study how heterogeneity in initial conditions influences outcomes on the BGP by introducing a second high-tech region $\mathbb{B}$ into the analysis. At time $t = 0$, two key savings rates in $\mathbb{A}$ are twice as large as in $\mathbb{B}$. We compute the ratio of the BGP value of income per effective creative capital unit in $\mathbb{A}$ to its value in $\mathbb{B}$. Finally, we compute the ratio of the BGP value of skills per effective creative capital unit in $\mathbb{A}$ to its value in $\mathbb{B}$.

Keywords: Artificial Intelligence, Creative Capital, Regional Economic Growth, Skills

JEL Codes: R11; O33

1. Introduction

1.1. Preliminaries

The 21st century has witnessed an unprecedented surge in technological advancements, with artificial intelligence (AI) emerging as a world-wide transformative force across various sectors (Bak-Coleman *et al.* 2021, Korinek and Stiglitz 2021, Sjodin *et al.* 2023). Like any new technology, AI has spatially discriminating effects depending on access conditions and integration with existing production modes and human cognitive abilities (Tariq *et al.* 2023). The integration of AI-based technologies into regional economies has sparked significant changes, leading to increased efficiency, innovation, and economic growth (Li *et al.* 2022).

One of the primary ways in which AI contributes to regional economic growth is through enhanced productivity (Czarnitzki *et al.* 2023). The automation of routine tasks, data analysis, and decision-making processes enables businesses to operate more efficiently. As AI-based technologies continue to evolve, industries can optimize their operations, reduce costs, and allocate resources more effectively. This heightened productivity, in turn, leads to increased output, new products and services, and economic expansion of geographical markets.

In manufacturing, for example, AI-powered robotics streamline production processes, resulting in higher output levels and improved product quality (Hedelind and

Jackson 2011). This not only boosts the competitiveness of local industries but also attracts foreign investment, fostering economic growth within a region. Similarly, the incorporation of AI in agriculture through precision farming techniques maximizes crop yields, contributing to food security and supporting rural economies (Bhat and Huang 2021).

AI acts as a catalyst for innovation, fostering a climate conducive to entrepreneurship and economic development. Start-ups and established businesses alike leverage AI technologies to create novel products and services, disrupting traditional industries and generating economic value (Brem *et al.* 2023). Regions that actively embrace AI-driven innovation often experience a surge in entrepreneurial activities, leading to job creation and economic diversification. In addition, the ability of AI-based technologies to augment rather than replace human capabilities has led to the creation of new job opportunities (Jarrahi *et al.* 2022). As a result, roles such as AI specialists, data scientists, and machine learning engineers have become integral components of the evolving job market. This means that regions that actively support the development of these skills are likely to witness a positive correlation between workforce transformation and economic growth.

Given this background about AI-based technologies, it is important to note two significant points made by the urbanist Richard Florida (2002, 2005). First, regions that want to thrive economically in this era of globalization need to do all they can to attract members of the creative class.[5] Second, attracting these members is important because they possess creative capital, which is the "intrinsically human ability to create new ideas, new technologies, new business models, new cultural forms, and whole new industries that really [matter]" (Florida, 2005, p. 32). Put differently and as pointed out by Batabyal and Nijkamp (2023), the creative capital possessing members of the creative class are a basic driver of regional economic growth and development.

If one subscribes to this Floridian view of regional economic growth and development then it seems natural to ask about the prospects for regional economic growth when entrepreneurial creative class members use transformative AI-based technologies to manufacture knowledge goods in a region. Will the use of AI-based technologies contribute positively to economic growth? If yes then what are the properties of this kind of growth? Finally, can one say anything meaningful quantitatively about the impact that the use of AI-based technologies is likely to have on regional growth? We maintain that even though these are very interesting questions to analyze from a research perspective, unfortunately, to the best of our knowledge, they have received *no theoretical attention* in the economic geography and regional science literatures. Therefore, we now proceed to review the related

---

[5] The creative class "consists of people who add economic value through their creativity" (Florida, 2002, p. 68). This class is composed of professionals such as doctors, lawyers, scientists, engineers, university professors, and, notably, bohemians such as artists, musicians, and sculptors.

issues that have been addressed in the literature and then we state our specific objectives in this paper.

1.2. Literature review and objectives

1.2.1. Review

In a relatively early "taking stock" paper, the late British geographer Stan Openshaw (1992) first reviews the development of AI methods in the late 1980s and the early 1990s and then discusses how these developments can improve our understanding of spatial pattern description, relationship seeking, and genetic optimization. Moore (1994) shows how associative memory techniques drawn from the AI literature can be gainfully employed to identify the parameters of dynamical spatial systems.

Sivramkrishna and Panigrahi (2003) point to the urgent need to reduce regional imbalances in economic development and contend that AI-based technologies such as the Kohonen Self-Organizing Map can be used by development planners and practitioners to explore patterns in economic development. Tolidis and Dimopoulou (2012) focus on land use planning and land policy in mountainous areas. They point out that AI-based tools give rise to multiple benefits for multi-site land use allocation procedures. Chain *et al.* (2019) assess the literature on interindustry interdependence and the geographical concentration of firms. They point out that what they call the traditional methods of regional science are increasingly been supplanted by techniques from spatial statistics, econophysics, and AI.

In a thought-provoking paper, Acemoglu and Restropo (2019a) point out that recent technological change has been biased towards automation and this has led to stagnating labor demand, rising inequality, and lower productivity growth. In spite of this, current AI is being developed to further increase the amount of automation in the economy. This needs to be corrected to generate better economic and social outcomes. Continuing this line of inquiry, Acemoglu *et al*. (2022) utilize establishment level data to study how AI affects labor markets. Their empirical analysis demonstrates that the substitution of labor by AI that many have worried about is visible at the establishment level but this effect is still very small in exposed industries and occupations.

Leigh *et al*. (2020) study some of the ways in which advances in robotics and AI-based technologies have influenced jobs in economies. Their analysis reveals that robots have contributed positively to manufacturing employment at the metropolitan level in the United States. Schintler and McNeely (2022) analyze the nature of the relationship between urban resilience and AI, coupled with big data. Focusing on job losses stemming from the use of AI-based technologies in Ireland, Crowley and Doran (2022) compare the results obtained from the use of "occupational" versus "task-based" methodologies. Both methodologies give rise to non-trivial job losses and therefore these authors urge caution when formulating local and regional urban development policy.

Does the use of AI-based technologies contribute to green economic growth? Zhao *et al.* (2022) answer this query by concentrating on China. Their econometric analysis shows that the use of such technologies has a salient but “U-shaped” effect on green total factor productivity (GTFP). These authors go on to show that improving AI in the resource rich areas of China is likely to have a particularly salubrious impact on GTFP. Once again focusing on China, Lin *et al.* (2024) argue that the use of AI promotes innovation, reduces resource use, and is conducive to the development of a green economy. On a related note, Cicerone *et al.* (2023) ask whether regions can use AI to further the goal of specializing in green technologies? They contend that the answer is yes, but only if the region under consideration is already somewhat specialized in the use of green technologies.

Gonzales (2023) utilizes a panel data set of nations from 1970 to 2019 and shows that AI has a definite positive impact of economic growth. In addition, this impact is greater than the collective impact of the entire population of patents. Li *et al.* (2023) study whether AI is related to the higher performance of new ventures in emerging economies. Using panel data, these authors demonstrate that having what they call an AI orientation is positively related to new venture performance. Finally, Calzada *et al.* (2023) empirically explore what it means for the citizens of a city to have the right to have digital rights where digital rights include the right to adopt AI.

Our review of the contemporary literature on the use of AI-based technologies in a variety of regional settings yields two main conclusions. First, this literature is overwhelmingly either empirical or based on case studies. That said, the reader should understand that we are *not* focusing only on empirical and case study based contributions. Instead, we contend that the extant literature is disproportionately made up of empirical and case studies and contains almost *no theoretical* studies. Second and consistent with our claim in the last paragraph of section 1.1, this literature has paid virtually *no theoretical attention* to the connections between the use of AI-based technologies and economic growth in a region that is creative in the sense of Richard Florida.

1.2.2. Objectives

Given this lacuna in the literature, our basic contribution in the present paper is as follows: To the best of our knowledge, we provide the first theoretical analysis of economic growth in a stylized, high-tech region with two distinct features. Specifically, the residents of this region are themselves high-tech because they possess appropriate technological skills. In other words, these residents comprise the region's creative capital possessing creative class. Second, the region under study is high-tech because it uses an AI-based technology and we model the use of this technology.

Our goal in conducting this analysis is twofold. First, we wish to demonstrate that the economy of our high-tech region converges to a so-called balanced growth path (BGP). Second, we wish to compare and contrast the economic performance of our high-tech region with the economic performance of a second region that is also high-tech but different from our region in that two specific ways that we describe in more detail in section 4 below.

We now describe our dynamic model which is adapted from Mankiw *et al.* (1992) and Batabyal and Nijkamp (2019) and then we derive analytic or closed-form expressions for three growth metrics. Second, we use these metrics to show that the economy of high-tech region $\mathbb{A}$ converges to a BGP. Third, we compute the growth rate of output per effective creative capital unit on this BGP. Fourth, we study how heterogeneity in initial conditions affects outcomes on the BGP by introducing a second high-tech region $\mathbb{B}$ into the analysis. At time $t = 0$, two key savings rates in $\mathbb{A}$ are twice as large as in $\mathbb{B}$. We compute the ratio of the BGP value of income per effective creative capital unit in $\mathbb{A}$ to its value in $\mathbb{B}$. Finally, we compute the ratio of the BGP value of skills per effective creative capital unit in $\mathbb{A}$ to its value in $\mathbb{B}$.

The remainder of this paper is organized as follows. Section 2 describes our theoretical model of high-tech region $\mathbb{A}$ in detail. Section 3.1 derives analytic expressions for three growth metrics. Section 3.2 first uses these metrics to demonstrate that the economy of high-tech region $\mathbb{A}$ converges to a BGP and then computes the growth rate of output per effective creative capital unit on this BGP. Section 3.3 computes the BGP values of the AI-based technology and skills per effective creative capital unit. Section 4.1 begins the study of heterogeneity in initial conditions. Specifically, this section first introduces a second high-tech region $\mathbb{B}$ into the analysis. At time $t = 0$, two salient savings rates in $\mathbb{A}$ are set twice as large as in $\mathbb{B}$. In this setting, this section computes the ratio of the BGP value of income per creative capital unit in $\mathbb{A}$ to its value in $\mathbb{B}$. For the values of the four savings rates in section 4.1, section 4.2 computes the ratio of the BGP value of skills per creative capital unit in $\mathbb{A}$ to its value in $\mathbb{B}$. Section 5 concludes and then discusses three ways in which the research presented in this paper might be extended.

2. The Theoretical Structure

Consider a stylized creative region that we denote by $\mathbb{A}$. At any time t, this region produces a high-tech good that is produced, *inter alia*, by using an AI-based technology. Examples of such goods include, but are not limited to, smartphones, autonomous vehicles, smart speakers, and personal assistants. AI-based technologies are integrated into the production of smartphones to augment features such as facial recognition and camera capabilities. These devices use AI-based algorithms for image processing, language understanding, and personalization. The manufacture of autonomous vehicles relies heavily on AI-based technologies. From the design and simulation phases to the production of components, AI-based technologies play a key role. Advanced driver-assistance systems

(ADAS) and self-driving capabilities are made possible through the integration of AI-based technologies in the production process. Finally, smart speakers and personal assistants such as Amazon's Alexa or Google Assistant, are produced using AI-based technologies. Natural language processing (NLP) and machine learning algorithms enable these devices to comprehend and respond to user commands, making them an integral part of "smart" home ecosystems.[6]

Let us denote the output of the high-tech good under consideration by $Y(t)$. This high-tech good is also the final consumption good whose price is normalized to unity at all points in time. To clearly model the nexus between the creative class and the working of creative regions discussed in section 1, we assume that the high-tech good mentioned above is produced by creative capital units $C(t)$ working with an AI-based technology denoted by $A(t)$.

In addition, we suppose that the total amount of *skills* possessed by the individual creative capital units is given by $S(t)$. Observe that we are *not* using the word

[6] It is true that we are modeling the AI-based technology in a relatively general manner. This is because we would like the story we tell in this paper about the impacts of using an AI-based technology to be as general as possible. Even so, a dynamic model that is very general *cannot* be solved analytically and hence this feature will *not* allow us to obtain interesting, closed-form results. This is a key reason for modeling the production of the high-tech good with a Cobb-Douglas production function in equation (1) below. That said, it is *untrue* that there are no conditions that follow from specific features of our definition of the AI-based technology. This can be seen most clearly by focusing on the way in which we model the temporal evolution of the AI-based technology in equation (4) below. All the results we obtain in sections 3 and particularly 4 below depend on this equation (4) specification. To conclude this point, our analysis, we believe, is an appropriate mix of general and specific features that permit us to come up with concrete and meaningful results within the context of an *analytically tractable* model.

"technological" to delineate these skills and, indeed, these skills may but they do *not* have to be technological in nature. The skills we have in mind represent characteristics that the individual creative capital units possess that are specific to the production of the high-tech good $Y(t)$. Hence, the possession of these skills enables the individual creative capital units to produce this high-tech good efficiently. As in Acemoglu and Restrepo (2019), these skills certainly impact the production of the final good $Y(t)$. They also affect our results discussed in section 4 below through the $s(t)$ variable that is defined precisely later on in this section.

Advanced engineering skills are an example of what we mean by skills. Subsumed in this category would be the ability to design and develop electrical systems and components such as circuits and microchips. Being able to analyze data and to possess knowledge about machine learning is a second example of what we mean by skills. Subsumed in this category would be the ability to implement algorithms that enable products to learn from and adapt to user interactions. As a final example of what we mean by skills, consider the ability to collaborate in interdisciplinary settings. Subsumed in this category would be the ability to convey complex technical information to non-specialists and stakeholders.[7]

---

[7] These and other such skills held by the creative capital possessing members of the creative class have been discussed by Florida (2002, 2006), Batabyal and Nijkamp (2010), and Leslie and Rantisi (2012).

Along with the AI-based technology in our creative region, we presume that there also exists a different kind of technology or *knowledge* and that this knowledge enhances or makes more productive the individual creative capital units. Let us denote this creative capital enhancing knowledge by $K(t)$ and let $K(t)C(t)$ denote an *effective* creative capital unit.[8]

The output $Y(t)$ of the high-tech good is given by a production function that has the Cobb-Douglas form. We can write this function as

$$Y(t) = A(t)^{\alpha} S(t)^{\beta} \{K(t)C(t)\}^{1-\alpha-\beta}, \tag{1}$$

where the parameters $\alpha > 0, \beta > 0,$ and $\alpha + \beta < 1.$[9] The equations of motion for the four factors of production---the four state variables---that are used to manufacture the high-tech good are given by the differential equations

---

8

This way of modeling an effective creative capital unit is similar to the way in which Harrod-neutral or labor-augmenting technological progress is modeled when studying, for instance, the Solow growth model with technological progress. See a standard textbook such as Acemoglu (2009, pp. 58-59) for more details on this point.

9

There is a long tradition of using the Cobb-Douglas production function to study economic growth in the literature. See Acemoglu (2009) for a more detailed corroboration of this claim. The same is true in regional science as well. See Shibusawa *et al.* (2008), Zhang (2008), Accetturo *et al.* (2014), Porter and Batabyal (2016), and Stavropoulos *et al.* (2020) for additional details. As such, our use of the Cobb-Douglas production function is certainly *not* precedent setting. That said, we would like to reiterate a point that we have already made in a preceding footnote and that is the following: our analysis, is an apposite mix of general and specific features that permit us to obtain concrete and meaningful results within the context of an analytically tractable model. The final point to make here is that our way of modeling the impact of the AI-based technology $A(t)$ on the output of the high-tech good $Y(t)$ is distinct. As noted by Gries and

$$\frac{dK(t)}{dt} \equiv \dot{K}(t) = gK(t), \tag{2}$$

$$\frac{dC(t)}{dt} \equiv \dot{C}(t) = nC(t), \tag{3}$$

$$\frac{dA(t)}{dt} \equiv \dot{A}(t) = \zeta_A Y(t) - \delta A(t), \tag{4}$$

and

$$\frac{dS(t)}{dt} \equiv \dot{S}(t) = \zeta_S Y(t) - \delta S(t), \tag{5}$$

and we have $g > 0, n > 0,$ and $\delta > 0.$ [10]

Naude (2022), there are other ways of modeling the impact of AI-based technologies on the production of final consumption goods. One such approach is the task-approach to labor markets initiated by Autor (2013).

[10] What makes the AI-based technology input in our model *unlike* a non-AI technological input is the way in which we have modeled its evolution over time in equation (4). Equations (2) and (3) represent the more traditional way of modeling the temporal evolution of a non-AI technological input. In this regard, note that the temporal evolution of non-AI technological inputs such as labor or land generally does *not* depend on a savings rate as shown in equation (4). The *specific* feature of the AI-based technology input that we are interested in concerns the disparity in the economic performance of heterogeneous regions that invest differentially in the enhancement of AI-based technologies. That study is conducted in detail in section 4 below. In principle, we could study additional features of AI-based technology use in one or more regional economies but doing so would make our dynamic model *intractable*. In other words, there is a clear *tradeoff* between increasing the complexity of the underlying dynamic model and being able to solve this model analytically. The reader needs to appreciate that we already have *four state variables* in our model and, generally speaking, optimal control models with this many state variables are *insoluble*. Even so, we are able to obtain closed-form solutions to our model. As shown in equation (1), skills are linked to the AI-based technology in a *multiplicative* manner in our model. They jointly and multiplicatively contribute to the production of the high-tech good $Y(t)$. Note that both inputs are *necessary* to produce the high-tech good. If we set the value of skills or $S(t) = 0$ then it does not

In our subsequent analysis, we shall be particularly interested in the coefficients $\zeta_A \in (0,1)$ and $\zeta_S \in (0,1)$. Specifically, ζ_A is the *constant* proportion of the output of the final consumption good that is *saved* to create a more powerful AI-based technology in creative region $\mathbb{A}$. Similarly, ζ_S is the *constant* proportion of the output of the final consumption good that is *saved* to create more skills in the same region. The initial values of the four factors of production $K(0), A(0), C(0),$ and $S(0)$ are given exogenously and they are all positive. Finally, let the values of output, the AI-based technology, and skills per effective creative capital unit (sometimes called the intensive values) be given by $y(t) = Y(t)/K(t)C(t)$, $a(t) = A(t)/K(t)C(t)$, and $s(t) = S(t)/K(t)C(t)$.

The reader will note that there are two underlying effects at play in our stylized creative region. To see this, observe that this region produces high-tech goods that involve the use of skills and an AI-based technology. Therefore, there is a "demand effect" at work that is all about attracting the individual creative capital units into this region. This demand effect is what we are studying, in part, in our analysis of economic growth in the creative region. However, in addition to this demand effect, there is also a "supply effect" that determines the supply of creative capital units to our creative region. This "supply effect" is the outcome of an *optimal job choice problem* which we are *not* analyzing in the

matter how much of the AI-based technology input is used, output is zero and the same can be said about output if we set the value of the AI-based technology or $A(t) = 0$. Finally, the AI-based technology input affects our results in section 4 below by means of the $a(t)$ variable and the ζ_A saving rate.

present paper. In this sense, our analysis is partial equilibrium in nature. That said, this last point does mean that there is no "potential endogeneity issue" to worry about. This concludes the description of our stylized creative region. We now proceed to derive closed-form expressions for three growth metrics and these metrics are $y(t), \dot{a}(t) = da(t)/dt$, and $\dot{s}(t) = ds(t)/dt$.

3. A Single Creative Region

3.1. Three growth metrics

3.1.1. An expression for y(t)

Our first task is to derive an expression for output per effective creative capital unit or $y(t)$ as a function of the AI-based technology per effective creative capital unit $a(t)$ and skills per effective creative capital unit $s(t)$. Substituting equation (1) into the definition of $y(t)$, we get

$$y(t) = \frac{A(t)^{\alpha} S(t)^{\beta} \{K(t)C(t)\}^{1-\alpha-\beta}}{K(t)C(t)}. \tag{6}$$

Now using the definitions of $a(t)$ and $s(t)$ given above, we can rewrite equation (6) as

$$y(t) = \frac{\{K(t)C(t)a(t)\}^{\alpha}\{K(t)C(t)s(t)\}^{\beta}\{K(t)C(t)\}^{1-\alpha-\beta}}{K(t)C(t)}. \tag{7}$$

Canceling the term $K(t)C(t)$ from the numerator and the denominator of equation (7), we obtain the expression for $y(t)$ that we seek. That expression is

$$y(t) = a(t)^{\alpha} s(t)^{\beta}. \tag{8}$$

Equation (8) expresses the production function in equation (1) in its intensive form.

3.*1.2. An expression for the derivative* $\dot{\boldsymbol{a}}(\boldsymbol{t})$

Taking the derivative of both sides of the defining equation for $a(t)$ with respect to time t, we get

$$\dot{a}(t) = \frac{\dot{A}(t)K(t)C(t) - A(t)\{\dot{K}(t)C(t) + K(t)\dot{C}(t)\}}{\{K(t)C(t)\}^2}. \tag{9}$$

Utilizing the definition $a(t) = A(t)/K(t)C(t)$ we can rewrite equation (9) to give us

$$\dot{a}(t) = \frac{\dot{A}(t)}{K(t)C(t)} - \left\{\frac{\dot{K}(t)}{K(t)} + \frac{\dot{C}(t)}{C(t)}\right\} a(t). \tag{10}$$

Substituting from equations (2), (3), and (4) into equation (10) and then rewriting, we get

$$\dot{a}(t) = \zeta_A y(t) - (g + n + \delta)a(t). \tag{11}$$

Let us now substitute the value of $y(t)$ from equation (8) into equation (11). This gives us the expression for $\dot{a}(t)$ that we seek. Specifically, we obtain

$$\dot{a}(t) = \zeta_A a(t)^{\alpha} s(t)^{\beta} - (g + n + \delta)a(t). \tag{12}$$

Equation (12) describes the temporal evolution of the AI-based technology input when this input is expressed in its intensive form $a(t) = A(t)/K(t)C(t)$.

3.*1.3. An expression for the derivative* $\dot{\boldsymbol{s}}(\boldsymbol{t})$

Let us begin by differentiating both sides of the defining equation for skills per effective creative capital unit or $s(t)$ with respect to time t. Doing this, we get

$$\dot{s}(t) = \frac{\dot{S}(t)K(t)C(t) - S(t)\{\dot{K}(t)C(t) + K(t)\dot{C}(t)\}}{\{K(t)C(t)\}^2}. \tag{13}$$

Using the definition $s(t) = S(t)/K(t)C(t)$, equation (13) can be rewritten as

$$\dot{s}(t) = \frac{\dot{S}(t)}{K(t)C(t)} - \left\{\frac{\dot{K}(t)}{K(t)} + \frac{\dot{C}(t)}{C(t)}\right\} s(t). \tag{14}$$

Now, substituting from equations (2), (3), and (5) into equation (14) and then rewriting, we obtain

$$\dot{s}(t) = \zeta_S y(t) - (g + n + \delta)s(t). \tag{15}$$

Let us now substitute the value of $y(t)$ from equation (8) into equation (15). This gives us the expression for $\dot{s}(t)$ that we seek. That expression is

$$\dot{s}(t) = \zeta_S a(t)^{\alpha} s(t)^{\beta} - (g + n + \delta)s(t). \tag{16}$$

Equation (16) delineates the temporal evolution of the skills input when this input is expressed in its intensive form $s(t) = S(t)/K(t)C(t)$. This completes the derivation of closed-form expressions for $y(t), \dot{a}(t)$, and $\dot{s}(t)$. Our next task is to demonstrate that the economy of creative region $\mathbb{A}$ converges to a BGP and to then calculate the growth rate of output per creative capital unit on the BGP.

3.2. BGP convergence

To demonstrate that creative region $\mathbb{A}$ converges to a BGP, we need to first comprehend the attributes of the set of points in (a, s) space where $\dot{a}(t) = \dot{s}(t) = 0$. To this end, let us first work with equation (12). To obtain the $\dot{a}(t) = 0$ locus, we set the right-hand-side (RHS) of this equation equal to zero and then perform a couple of steps of algebra to isolate $a(t)$. Doing this, we obtain

$$a(t) = [\zeta_A\{g+n+\delta\}^{-1}]^{1/(1-\alpha)} s(t)^{\beta/(1-\alpha)}. \tag{17}$$

We can now use equation (17) to calculate the first and the second derivatives of $a(t)$ with respect to $s(t)$. Doing this, we deduce that $da(t)/ds(t) > 0$ and that $d^2a(t)/ds(t)^2 < 0$. These last two results together tell us that the $\dot{a}(t) = 0$ locus is upward sloping and *concave* in (a, s) space.

We work with equation (16) next. To find the $\dot{s}(t) = 0$ locus, we set the RHS of this equation equal to zero and then isolate $s(t)$. Doing this, we get

$$a(t) = [\zeta_S^{-1}\{g+n+\delta\}]^{1/\alpha} s(t)^{(1-\beta)/\alpha}. \tag{18}$$

Once again, we use equation (18) to ascertain the first and the second derivatives of $a(t)$ with respect to $s(t)$. Upon finishing the needed calculations, we observe that $da(t)/ds(t) > 0$ and that $d^2a(t)/ds(t)^2 > 0$. Given the signs of these two derivatives, we infer that the $\dot{s}(t) = 0$ locus is upward sloping and *convex* in (a, s) space.

The information we have just ascertained about the $\dot{a}(t) = 0$ and the $\dot{s}(t) = 0$ loci can be presented together in a phase diagram. This is shown in figure 1. This figure clearly

Figure 1 about here

demonstrates that the economy of creative region $\mathbb{A}$ converges to a stable BGP at the point marked E. Inspecting this figure, we obtain three additional results. First, if we exclude the origin where $a = s = 0$, we see that the stable BGP at point E is *unique*. Second, $a(t) = A(t)/K(t)C(t)$ is constant on the BGP. This tells us that the AI-based technology per creative capital unit or $A(t)/C(t) = a(t)K(t)$ must be growing at the *same* rate as the creative capital enhancing technology or knowledge, which is g. Third, skills per effective creative capital unit or $s(t) = S(t)/K(t)C(t)$ is also constant on the BGP. Hence, skills per creative capital unit or $S(t)/C(t) = s(t)K(t)$ must also be growing at the *same* rate as the creative capital augmenting technology, which is, once again, g.

Our last task in this section is to compute the growth rate of output per creative capital unit on the above described BGP. To do so, we divide both sides of the production function given in equation (1) by $C(t)$. This gives us

$$\frac{Y(t)}{C(t)} = \{\frac{A(t)}{C(t)}\}^{\alpha}\{\frac{S(t)}{C(t)}\}^{\beta}K(t)^{1-\alpha-\beta}. \tag{19}$$

We already know that the ratios $A(t)/C(t)$, $S(t)/C(t)$, and the creative capital enhancing knowledge $K(t)$ all grow at rate g on the BGP. Also, the production function in equation (1) displays constant returns to scale. These last two points collectively tell us that the output of the high-tech good per creative capital unit in creative region $\mathbb{A}$ also grows at rate g on the BGP. We now move on to calculate the BGP values of the AI-based technology and skills per effective creative capital unit in terms of the savings rates ζ_A, ζ_S, and the other parameters of our model.

3.3. BGP values of $a(t)$ and $s(t)$

We begin by denoting the two BGP values we seek by $a^{BGP}$and s^{BGP} respectively. Upon solving equations (17) and (18) simultaneously, we obtain

$$\{s^{BGP}\}^{\frac{1-\beta}{\alpha}-\frac{\beta}{1-\alpha}} = [\zeta_A\{g+n+\delta\}^{-1}]^{\frac{1}{1-\alpha}}[\zeta_S\{g+n+\delta\}^{-1}]^{\frac{1}{\alpha}}. \tag{20}$$

Observe that the exponent on s^{BGP} in equation (20) can be written as $(1-\alpha-\beta)/\{\alpha(1-\alpha)\}$. Hence, raising both sides of equation (20) to the reciprocal of this rewritten exponent, we obtain our desired expression for s^{BGP} as a function of ζ_A, ζ_S, and the other parameters of the problem. That expression is

$$s^{BGP} = \zeta_A^{\frac{\alpha}{1-\alpha-\beta}}\zeta_S^{\frac{1-\alpha}{1-\alpha-\beta}}[\{g+n+\delta\}^{-1}]^{\frac{1}{1-\alpha-\beta}}. \tag{21}$$

Equation (21) provides us with an expression for the BGP value of the skills input when this input is expressed in its intensive form $s(t) = S(t)/K(t)C(t)$.

To find the equivalent expression for a^{BGP}, we substitute the expression for s^{BGP} from equation (21) into equation (17). This gives us

$$a^{BGP} = \zeta_A{}^{\frac{1}{1-\alpha}}[\{g+n+\delta\}^{-1}]^{\frac{1}{1-\alpha}}[\zeta_A{}^{\frac{\alpha}{1-\alpha-\beta}}\zeta_S^{\frac{1-\alpha}{1-\alpha-\beta}}[\{g+n+\delta\}^{-1}]^{\frac{1}{1-\alpha-\beta}}]^{\frac{\beta}{1-\alpha}}. \tag{22}$$

After a couple of steps of uncomplicated but tedious algebra, equation (22) can be rewritten as

$$a^{BGP} = \zeta_A{}^{\frac{1-\alpha-\beta+\alpha\beta}{(1-\alpha)(1-\alpha-\beta)}}\zeta_S{}^{\frac{\beta}{1-\alpha-\beta}}[\{g+n+\delta\}^{-1}]^{\frac{1-\alpha-\beta+\beta}{(1-\alpha)(1-\alpha-\beta)}}. \tag{23}$$

The exponent on ζ_A in equation (23) can be simplified because $(1-\alpha-\beta+\alpha\beta) = (1-\alpha)(1-\beta)$. Using this simplification, we get the sought after expression for a^{BGP} as a function of the savings rates ζ_A, $\zeta_{S,}$ and the other parameters of the problem. That analytical expression is

$$a^{BGP} = \zeta_A{}^{\frac{1-\beta}{1-\alpha-\beta}}\zeta_S{}^{\frac{\beta}{1-\alpha-\beta}}[\{g+n+\delta\}^{-1}]^{\frac{1}{1-\alpha-\beta}}. \tag{24}$$

Equation (24) provides us with an expression for the BGP value of the AI-based technology input when this input is expressed in its intensive form $a(t) = A(t)/K(t)C(t)$. Our next task is to analyze the effect of heterogeneity in certain initial conditions on the BGP values of some key variables.

4. Two Creative Regions

4.1. Ratio of BGP value of income in its intensive form in region $\mathbb{A}$ to region $\mathbb{B}$

To study the impact of heterogeneity on long run economic performance, we now focus on two creative regions. These two regions are region $\mathbb{A}$, which we have been studying thus far, and a second creative region $\mathbb{B}$. Creative region $\mathbb{B}$ is different from creative region $\mathbb{A}$ in two important ways. Specifically, both ζ_A and ζ_S are twice as large in region $\mathbb{A}$ as in region $\mathbb{B}$. To conduct the inquiry below in an analytically tractable manner, it will be necessary to make two assumptions. To this end, we first assume that apart from the differences in regions $\mathbb{A}$ and $\mathbb{B}$ that we have just mentioned, these two regions are identical in all other aspects. Second, we assume that $\alpha = 1/3$ and $\beta = 1/2$ in the remainder of this section.[11]

11

This method of working with specific values for the exponents of a Cobb-Douglas production function to conduct the underlying analysis is *not* new and it has clear precedents in the literature. See Batabyal and Beladi (2021, 2022) and Batabyal and Nijkamp (2022) for further details. In this regard, strictly speaking, the assumption of constant returns to scale *in the aggregate* is not necessary but because we do *not* have any information suggesting otherwise, this seems to us to be the most reasonable default assumption. More generally, we have chosen to work with specific values of the exponents to obtain closed-form results that are both intuitive in nature and hence *easily interpretable*. If, instead of working with specific values, we were to work with α and β directly then the expressions leading up to equations (28) and (29) below and these two equations themselves would be substantially more complicated and therefore *not* easily interpretable. That said, we acknowledge the following two points. First, the "price" we pay for obtaining closed-form results that are easily interpreted is reduced generality. We could "increase" the generality of our model by working with only two and not four state variables, but this approach would be intellectually unsatisfactory because it would *not* allow us to meaningfully capture the multiplicative and necessary interaction between the AI-based technology input $A(t)$, the skill input $S(t)$, and the effective creative capital input $(K(t)C(t))$. Second, an analysis conducted with a constant elasticity of substitution or CES production function would in principle be more general than the analysis in our paper, but we have been unable to obtain closed-form and interpretable results with a CES production function. The reader should understand that our goal in this paper is to make a *theoretical* contribution to the literature. Our objective is *not* to conduct empirical analysis or to conduct numerical simulations of our model. In this regard, we

Observe that because the creative capital enhancing technology $K(t)$ is the same in both the regions under study, we can compare the output of the high-tech (and final consumption) good per effective creative capital unit. Using equation (8), the ratio of the output of the high-tech good on the BGP in creative region $\mathbb{A}$ to creative region $\mathbb{B}$ is given by

$$\frac{y_{\mathbb{A}}^{BGP}}{y_{\mathbb{B}}^{BGP}} = \{\frac{a_{\mathbb{A}}^{BGP}}{a_{\mathbb{B}}^{BGP}}\}^{\alpha}\{\frac{s_{\mathbb{A}}^{BGP}}{s_{\mathbb{B}}^{BGP}}\}^{\beta}. \tag{25}$$

From the discussion above, we know that $\alpha = 1/3$ and that $\beta = 1/2$. Hence, substituting these two values in equations (24) and (21), we get

$$a^{BGP} = \zeta_A^3 \zeta_S^3 [\{g + n + \delta\}^{-1}]^6 \tag{26}$$

and

---

emphasize that numerical simulations are *unnecessary* because we obtain closed-form results even though we work with four state variables. In our opinion, this paper makes an unambiguous theoretical contribution to the extant literature. As such, the question of studying what impact varying levels of substitutability between the different inputs has on the production of the high-tech final good is beyond the scope of the paper. That said, we do point out in section 5 that this is a salient question that needs to be addressed in future research on the subject of this paper. In sum, it is worth emphasizing the point that our analysis here contains an *appropriate* mix of general and specific attributes that permit us to obtain concrete and meaningful results within the setting of an *analytically tractable* model.

$$s^{BGP} = \zeta_A^2 \zeta_S^4 [\{g + n + \delta\}^{-1}]^6. \tag{27}$$

Now, substituting equations (26) and (27) into equation (25) and then rewriting, we get

$$\frac{y_{\mathbb{A}}^{BGP}}{y_{\mathbb{B}}^{BGP}} = \left\{\frac{\zeta_{A\mathbb{A}}\zeta_{S\mathbb{A}}}{\zeta_{A\mathbb{B}}\zeta_{S\mathbb{B}}}\right\}\left\{\frac{\zeta_{A\mathbb{A}}\zeta_{S\mathbb{A}}^2}{\zeta_{A\mathbb{B}}\zeta_{S\mathbb{B}}^2}\right\}. \tag{28}$$

By assumption, we have $\zeta_{A\mathbb{A}} = 2\zeta_{A\mathbb{B}}$ and $\zeta_{S\mathbb{A}} = 2\zeta_{S\mathbb{B}}$. Except for these two key differences, the economies of creative regions $\mathbb{A}$ and $\mathbb{B}$ are identical in every other way. Therefore, substituting these assumptions about the two savings rates in equation (28), we get $y_{\mathbb{A}}^{BGP}/y_{\mathbb{B}}^{BGP} = 32$.

This result plainly demonstrates one powerful way in which initial differences in the two savings rates in the two creative regions matter. In particular, we see that even though creative region $\mathbb{A}$ saves only twice the amount that creative region $\mathbb{B}$ does to generate a more powerful AI-based technology and skills, this 2-fold initial difference between the two regions leads to a *32-fold* difference in the BGP output per effective creative capital unit between these same two regions. In other words, relatively *minor* initial differences in the two savings rates translate into a substantially *amplified* impact on the BGP values of output per effective creative capital unit.

The extent to which a region is creative can be measured by looking at the skills possessed by the various creative capital units in this region. In this regard, it is true that existing regions generally differ in the extent to which they are creative, and this difference can be ascribed to, *inter alia*, dissimilar skill acquisition processes. Therefore, consistent with the comparative exercise carried out in this section, we can examine how initial differences in ζ_A and ζ_S across the two regions $\mathbb{A}$ and $\mathbb{B}$ influence the ratio of the BGP value of skills per effective creative capital unit in these same regions. We now move on to answer this query.

4.2. Ratio of BGP value of skills in its intensive form in region $\mathbb{A}$ *to region* $\mathbb{B}$

Let us begin by recognizing that it is possible to compare the amount of skills per effective creative capital unit in the two creative regions because the creative capital enhancing technology $K(t)$ is, once again, the same in both regions. Using equation (27), the BGP ratio of skills in region $\mathbb{A}$ to those in region $\mathbb{B}$ is given by

$$\frac{s_{\mathbb{A}}^{BGP}}{s_{\mathbb{B}}^{BGP}} = \frac{\zeta_{A\mathbb{A}}^2 \zeta_{S\mathbb{A}}^4}{\zeta_{A\mathbb{B}}^2 \zeta_{S\mathbb{B}}^4}. \tag{29}$$

As in section 4.1, we postulate that $\zeta_{A\mathbb{A}} = 2\zeta_{A\mathbb{B}}$ and that $\zeta_{S\mathbb{A}} = 2\zeta_{S\mathbb{B}}$. Substituting these four values into equation (29), we get $s_{\mathbb{A}}^{BGP}/s_{\mathbb{B}}^{BGP} = 64.$

This result demonstrates a second powerful way in which initial differences in the two savings rates in the two creative regions affect BGP outcomes. In particular, we see that even though creative region $\mathbb{A}$ saves only twice the amount that creative region $\mathbb{B}$ does to generate a more powerful AI-based technology and skills, this 2-fold initial difference between the two regions leads to a *64-fold* difference in the BGP value of skills per effective creative capital unit between these same two regions. Consistent with the finding in section 4.1, once again we see that relatively *minor* initial differences in the two savings rates translate into a substantially *amplified* impact on the BGP values of skills per effective creative capital unit.

We prefer to refer to the outcome of the comparative exercises we have conducted thus far in section 4.1 and the present section as policy implications although this outcome can also be thought of as predictions emanating from the analysis of our model. That said, the policy implications for creative regions are threefold.

First, for a given creative region, *ceteris paribus*, increasing the proportion of the output of the final consumption good that is used to generate a more powerful AI-based technology and skills in the creative capital units *now* will lead to substantially *amplified* benefits in terms of increased output and skills per effective creative capital unit *later*.

Second, consider a creative region that is lagging behind another creative region in terms of output and skills per effective creative capital unit. For such a region to get ahead, it will need to *increase* the two constant proportions or, equivalently, the two savings rates denoted by ζ_A and ζ_S.[12]

Finally, the *size* of the amplification effect on output and skills that we have been discussing thus far can be easily calculated by a policy maker in a creative region for the *general case* of a *z-fold initial* difference between the relevant savings rates in any two creative regions. To see this, suppose that we have $\zeta_{A\mathbb{A}} = z\zeta_{A\mathbb{B}}$ and $\zeta_{S\mathbb{A}} = z\zeta_{S\mathbb{B}}$ where z is any arbitrary positive integer that is greater than two. In this instance, straightforward calculations reveal that $y_{\mathbb{A}}^{BGP}/y_{\mathbb{B}}^{BGP} = z^5$ and that $s_{\mathbb{A}}^{BGP}/s_{\mathbb{B}}^{BGP} = z^6$. In other words, the output (skills) amplification effect equals the fifth (sixth) power of the initial difference between the two creative regions. This completes our discussion of the nexuses between creative capital, an AI-based technology, and economic growth in creative regions.

5. Conclusions

In this paper, we examined the connections between creative capital, an AI-based technology, and economic growth in a stylized creative region $\mathbb{A}$. To reiterate a point we have made previously in section 1, to the best of our knowledge, this is the *first* paper to

---

12

Instead of working with the two savings rates, if we wanted to explore the impact that differences in productivity parameters such as g have on, say, the BGP output ratio studied in section 4.1 then one way to proceed would be as follows: First, for consistency, let $\alpha = 1/3$ and $\beta = 1/2$. Second, for analytical tractability, let $\zeta_{A\mathbb{A}} = \zeta_{A\mathbb{B}}$ and $\zeta_{S\mathbb{A}} = \zeta_{S\mathbb{B}}$. Finally, let $(g + n + \delta)_{\mathbb{A}} = 2(g + n + \delta)_{\mathbb{B}}$. Because $(g + n + \delta)$ in creative region $\mathbb{A}$ is *twice* its corresponding value in creative region $\mathbb{B}$, we expect BGP output in region $\mathbb{A}$ to be *lower* than the BGP output in region $\mathbb{B}$. But how much lower? Using the above numerical assumptions, calculations of the sort performed in section 4.1 tell us that $y_{\mathbb{A}}^{BGP}/y_{\mathbb{B}}^{BGP} = 1/32$. In words, even though $(g + n + \delta)$ in creative region $\mathbb{A}$ is twice what it is in creative region $\mathbb{B}$, this relatively minor initial difference leads to a 1/32 contraction in the BGP output of creative region $\mathbb{A}$ relative to creative region $\mathbb{B}$.

theoretically analyze economic growth in this sort of stylized, high-tech region. In addition, our analysis generates *three key conclusions*---discussed in the previous paragraph---that policy makers need to keep in mind to ensure that their region displays robust economic growth and that it does not become and remain a lagging region.

We first described our model and then derived closed-form expressions for three growth metrics. Second, we used these metrics to demonstrate that the economy of creative region $\mathbb{A}$ converged to a BGP and then we calculated the growth rate of output per effective creative capital unit on this BGP. Third, we computed the BGP values of the AI-based technology and skills per effective creative capital unit. Fourth, we analyzed how heterogeneity in initial conditions affected outcomes on the BGP by bringing into the analysis, a second creative region $\mathbb{B}$. At time $t = 0$, two key savings rates in region $\mathbb{A}$ were twice as large as in region $\mathbb{B}$. In this scenario, we calculated the ratio of the BGP value of income per effective creative capital unit in region $\mathbb{A}$ to its value in region $\mathbb{B}$. Finally, for the same values of the four savings rates, we calculated the ratio of the BGP value of skills per effective creative capital unit in region $\mathbb{A}$ to its value in region $\mathbb{B}$.

We note that the analysis contained in this paper can be extended in several directions. One of the questions concerning the use of AI-based technologies---similar to earlier technologies---is that their impacts on regional economic growth and development are likely to be probabilistic and *not* deterministic. As such, it would be useful to analyze an extension of the model used in this paper where the effects of using an AI-based technology on output are stochastic. Second, it would be useful to study policies that regional authorities can pursue to *diminish* the rather dramatic growth-related amplification effects we demonstrated here. Finally, in our model (see equation (1)) all the factors of production $\{A(t), S(t), K(t), C(t)\}$ were *essential* for producing the high-tech good $Y(t)$. In other words, it was not possible to produce the high-tech good by using none of the creative capital input $C(t)$. As such, it would be useful to ascertain whether there exist scenarios in which it makes economic sense to *substitute* an AI-based technology for the creative capital input, either at a point in time or over time. Studies that analyze these aspects of the underlying problem in creative regions will provide additional insights into the nexuses between alternate technological and regulatory factors on the one hand and sustainable economic growth and development on the other.

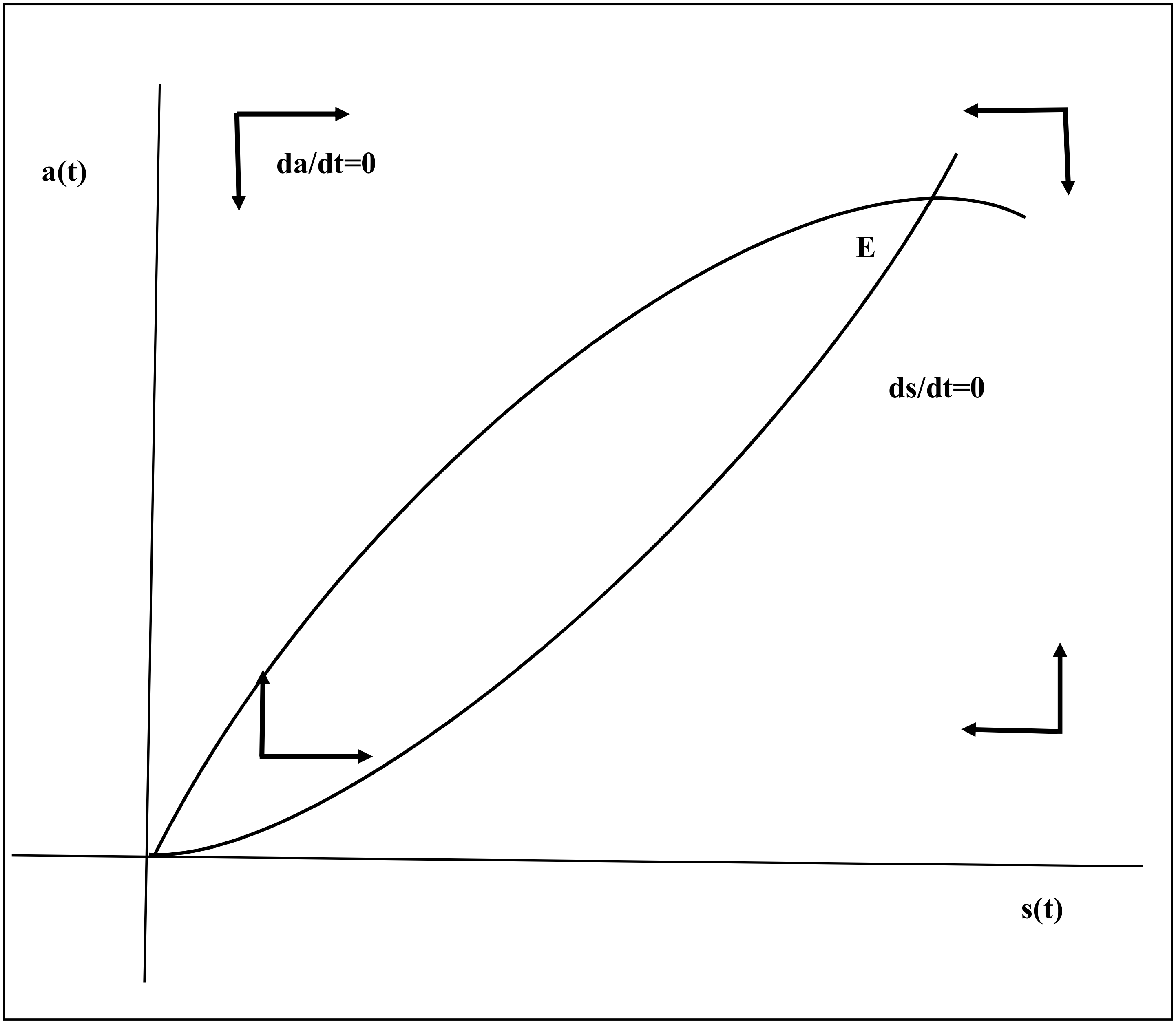

Figure 1: Economy of creative region $\mathbb{A}$ converges to a BGP

References

Accetturo, A., Dalmazzo, A., and de Blasio, G. 2014. Skill polarization in local labor markets under share-altering technical change, *Journal of Regional Science*, 54, 249-272.

Acemoglu, D. 2009. *Introduction to Modern Economic Growth*. MIT Press, Cambridge, MA.

Acemoglu, D., Autor, D., Hazell, J., and Restrepo, P. 2022. Artificial intelligence and jobs: Evidence from online vacancies, *Journal of Labor Economics*, 40, S293-S340.

Acemoglu, D., and Restrepo, P. 2019a. The wrong kind of AI? Artificial intelligence and the future of labour demand, *Cambridge Journal of Regions, Economy, and Society*, 13, 25-35.

Acemoglu, D., and Restrepo, P. 2019b. Artificial intelligence, automation, and work, in A. Agrawal, J. Gans, and A. Goldfarb, Eds., *The Economics of Artificial Intelligence*, 197-236. University of Chicago Press, Chicago, IL.

Autor, D. 2013. The task approach to labour markets, *Journal for Labour Market Research*, 46, 185-199.

Bak-Coleman, J.B., Alfano, M., Barfuss, W., Bergstrom, C.T., Centeno, M.A., Couzin, I.D., and Weber, E.K. 2021. Stewardship of global collective behavior, *Proceedings of the National Academy of Sciences*, 118, e2025764118.

Batabyal, A.A., and Beladi, H. 2021. Interregional demand for workers and the effects of labour income taxation, *Regional Science Policy and Practice*, 13, 1042-1050.

Batabyal, A.A., and Beladi, H. 2022. The response of creative class members to regions vying to attract them with subsidies, *International Regional Science Review*, 45, 581-600.

Batabyal, A.A., and Nijkamp, P. 2010. Richard Florida's creative capital in a trading regional economy: a theoretical investigation, *Annals of Regional Science*, 44, 241-250.

Batabyal, A.A., and Nijkamp, P. 2019. Creative capital, information and communication technologies, and economic growth in smart cities, *Economics of Innovation and New Technology*, 28, 142-155.

Batabyal, A.A., and Nijkamp, P. 2022. Interregional competition for mobile creative capital with and without physical capital mobility, *International Regional Science Review*, 45, 58-73.

Batabyal, A.A., and Nijkamp, P. Eds. 2023. *The Creative Class Revisited*. World Scientific Publishing, Singapore.

Bhat, S.A., and Huang, N. 2021. Big data and AI revolution in precision agriculture: Survey and challenges, *IEEE Access*, 9, 110209-110222.

Brem, A., Giones, F., and Werle, M. 2023. The AI digital revolution in innovation: A conceptual framework of artificial intelligence technologies for the management of innovation, *IEEE Transactions on Engineering Management*, 70, 770-776.

Calzada, I., Perez-Batlle, M., and Batlle-Montserrat, J. 2023. People-centered smart cities: An exploratory action research on the cities' coalition for digital rights, *Journal of Urban Affairs*, 45, 1537-1562.

Chain, C.P., dos Santos, A.C., de Castro, L. G., and do Prado, J.W. 2019. Bibliometric analysis of the quantitative methods applied to the measurement of industrial clusters, *Journal of Economic Surveys*, 33, 60-84.

Cicerone, G., Faggian, A., Montressor, S., Rentocchini, F. 2023. Regional artificial intelligence and the geography of environmental technologies: Does local AI knowledge help regional green-tech specialization? *Regional Studies*, 57, 330-343.

Crowley, F., and Doran, J. 2023. The geography of job automation in Ireland: What urban areas are most at risk? *Annals of Regional Science*, 71, 727-745.

Czarnitzki, D., Fernandez, G., and Rammer, C. 2023. Artificial intelligence and firm-level productivity, *Journal of Economic Behavior and Organization*, 211, 188-205.

Florida, R. 2002. *The Rise of the Creative Class*. Basic Books, New York, NY.

Florida, R. 2005. *The Flight of the Creative Class*. Harper Business, New York, NY.

Florida, R. 2006. The flight of the creative class: The new global competition for talent, *Liberal Education*, 92, 22-29.

Gonzales, J.T. 2023. Implications of AI innovation on economic growth: A panel data study, *Journal of Economic Structures*, 12, Article 13.

Gries, T., and Naude, W. 2022. Modelling artificial intelligence in economics, *Journal for Labour Market Research*, 56, Article 12.

Hedelind, M., and Jackson, M. 2011. How to improve the use of industrial robots in lean manufacturing systems, *Journal of Manufacturing Technology Management*, 22, 891-905.

Jarrahi, M.H., Lutz, C., and Newlands, G. 2022. Artificial intelligence, human intelligence and hybrid intelligence based on mutual augmentation, *Big Data and Society*, 9, 1-6.

Korinek, A., and Stiglitz, J.E. 2021. Artificial intelligence, globalization, and strategies for economic development, *NBER Working Paper 28453*, Cambridge, MA.

Leigh, N.G., Kraft, B., and Lee, H. 2020. Robots, skill demand, and manufacturing in the US regional labor markets, *Cambridge Journal of Regions, Economy and Society*, 13, 77-97.

Leslie, D., and Rantisi, N.M. 2012. The rise of a new knowledge/creative economy: Prospects and challenges for economic development, class inequality, and work, in

T.J. Barnes, J. Peck, and E. Sheppard, Eds., *The Wiley-Blackwell Companion to Economic Geography*, 458-471, Wiley, Hoboken, NJ.

Li, B., Jiang, F., Xia, H., and Pan, J. 2022. Under the background of AI application, research on the impact of science and technology innovation and industrial structure upgrading on the sustainable and high-quality development of regional economies, *Sustainability*, 14, 11331.

Li, D., Pan, Z., Wang, D., and Zhang, L. 2023. A study on artificial intelligence orientation and new venture performance, *Asia Pacific Business Review*, 29, 967-989.

Lin, S., Wang, M., Jing, C., Zhang, S., Chen, J., and Liu, R. 2024. The influence of AI on the economic growth of different regions in China, *Scientific Reports*, 14, 9169.

Mankiw, N.G., Romer, D., and Weil, D.N. 1992. A contribution to the empirics of economic growth, *Quarterly Journal of Economics*, 107, 407-437.

Moore, J.E. 1994. Time series and turning point forecasts: A comparison of associative memories and Bayesian econometric techniques applied to LeSage's data, *Journal of Regional Science*, 34, 1-25.

Openshaw, S. 1992. Some suggestions concerning the development of artificial intelligence tools for spatial modelling and analysis in GIS, *Annals of Regional Science*, 26, 35-51.

Porter, A., and Batabyal, A.A. 2016. Physical capital mobility, the educational and quality aspects of creative capital, and output production, *Regional Science Policy and Practice*, 8, 167-175.

Schintler, L.A., and McNeely, C.L. 2022. Artificial intelligence, institutions, and resilience: Prospects and provocations for cities, *Journal of Urban Management*, 11, 256-268.

Shibusawa, H., Ding, L., and Haynes, K.E. 2008. The knowledge network and learning in a competitive environment: A learning region model, *Studies in Regional Science*, 38, 33-49.

Sivramkrishna, S., and Panigrahi, R. 2003. Articulating uneven regional development: Artificial intelligence as a tool in development planning, *Journal of Human Development*, 4, 437-456.

Sjodin, D., Parida, V., and Kohtamaki, M. 2023. Artificial intelligence enabling circular business model innovation in digital servitization: Conceptualizing dynamic capabilities, AI capacities, business models and effects, *Technological Forecasting and Social Change*, 197, 122903.

Stavropoulos, S., van Oort, F.G., and Burger, M.J. 2020. Heterogeneous relatedness and firm productivity, *Annals of Regional Science*, 65, 403-437.

Tariq, S., Iftikhar, A., Chaudhary, P., and Khurshid, K. 2023. Is the ‘technological singularity scenario’ possible? Can AI parallel and surpass all human mental capabilities? *World Futures*, 79, 200-266.

Tolidis, K., and Dimopoulou, E. 2012. Addressing complex spatial decision problems in mountainous areas: The intelligent spatial decision support systems (SDSS) approach, *Regional Science Inquiry*, 4, 51-67.

Zhang, W. 2008. Leisure, amenity, and capital accumulation in a multi-region model, *Annals of Regional Science*, 42, 183-207.

Zhao, P., Gao, Y., and Sun, X. 2022. How does artificial intelligence affect green economic growth?---Evidence from China, *Science of the Total Environment*, 834, 155306.