Economics Bulletin

Volume 45, Issue 3

Artificial Intelligence (AI), financial market and economic growth: A simple theoretical model

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Abstract

In this paper, we develop a theoretical model analyzing the role of financial development in the AI-economic growth nexus. Our theoretical framework is inspired by that of Zeira (1998) and Aghion et al. (2017), each articulated with that of Pagano (1993. The results show that AI affects economic growth through two channels: direct effects on the final product market via the productivity of automated tasks, indirect effects via financial market imperfections. In case of strong financial development, AI positively affects economic growth. But in case of weak financial development, AI can reduce economic growth. Taking the financial market into account thus avoids underestimating or overestimating the effect of AI on economic growth. In addition to labor market and education system reforms, our study recommends financial reforms that can improve financial development and more effectively allocate investments to finance AI. More specifically, African countries must invest in AI, holistically, in order to increase their shares in the global AI market.

We thank anonymous reviewers for helpful feedback.
Citation: Thiédjé Gaudens-Omer Kouakou, (2025) "Artificial Intelligence (AI), financial market and economic growth: A simple theoretical model", *Economics Bulletin*, Volume 45, Issue 3, pages 1297-1307
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Submitted: January 06, 2025. **Published:** September 30, 2025.

1. Introduction

Artificial intelligence (AI) refers to the ability of a machine to imitate intelligent human behavior using algorithms and computing power. Based on advances in Machine Learning (ML), and in particular, Deep Learning (DL), AI performs tasks that normally require human intelligence. Various studies have theoretically analyzed the potential effect of AI on economic growth. Recently, Gonzalez (2023) draws inspiration from Romer (1990) to develop an endogenous growth model which explains economic growth by an indicator of research effort approximated by innovations in AI (AI patents). Other works are rather inspired by Zeira (1998) to take into account the effect of AI on economic growth via its capacity to automate tasks. This is the case of Acemoglu and Restrepo (2016) who extend the theoretical framework of Zeira (1998) to the case where the automation of existing tasks is compensated by the creation of new labor-intensive productive tasks. Aghion et al. (2017) are also inspired by the Zeira model (op. cit.) and model the case of AI which increases the share of automated tasks over time, due to a lack of new labor-intensive tasks to compensate for the automation of existing tasks. Aghion et al. (op. cit.) show that AI stimulates economic growth through its ability to replace labor, a limited resource, with capital, an unlimited resource.

Economic analysis explains the effect of AI on economic growth by its direct impact on labor and capital factors via the automation of the production of goods and ideas, and by its influence via total factor productivity. This effect of AI can be ambiguous when we take into account the depreciation of capital incorporating AI (speed at which capital becomes obsolete), investments in AI compared to savings made, new jobs created in relation to the jobs destroyed. In fact, the economic effect of AI varies greatly from one economic sector to another. Furthermore, the effect of AI on economic growth may be muted because the diffusion of AI is not always smooth, with gains in global productivity potentially taking a long time to materialize in official statistics (Brynjolfsson et al., 2018; Acemoglu, 2024). The effect of AI on economic growth can be attenuated or even inhibited by institutional obstacles: an inappropriate competitive policy in the AI production sector, a lack of labor market reforms, an inadequate education system (Aghion, 2019). Our objective in this article is to show the role of the financial market in the AI-economic growth nexus. Additionally, we aim to identify the conditions under which the level of financial development in a country can either stimulate or attenuate the effect of AI on long-run economic growth.

Analyzing the effect of AI on economic growth without taking into account the financial markets carries the risk of underestimating or overestimating this effect. Indeed, the deployment of AI appears to be faster in the financial sector, facilitated by the adoption of big data, cloud computing and the expansion of the digital economy (Kearns, 2023). A survey of financial institutions shows that 77% of financial institutions surveyed consider AI to be very important to them (WEF, 2020). According to a 2019 survey by the Bank of England and the Financial Conduct Authority (FCA), 100% of insurance companies and 75% of banks say they use Machine Learning (ML). McKinsey (2020) estimated that the potential value of AI in banking could reach more than $1.5 trillion by 2025. Academic work has studied these indirect effects of AI on economic growth. According to Chouh (2023), AI has the potential to disrupt and refine the existing financial services industry, from approving loans, to managing assets, to assessing risks.

AI algorithms execute financial transactions in milliseconds, reducing costs and increasing liquidity. IA improve algorithmic trading, generating 50-70% of equity market equity trades, 60% of futures trades and 50%of Treasuries (Buchanan, 2019). Biais et al. (2011) assert that algorithmic speed has a positive effect on the informativeness of prices. Hendershott et al. (2013) find that algorithmic trades improves liquidity and enhances the informational content of quotes. AI algorithms also help anticipate market movements and identify potential risks, helping investors make informed decisions (Bauguess, 2017). Banks are also engaging chatbots to improve their self-services interfaces, increasing the productivity of banking labor (Brummer and Yadav, 2019). Many financial services companies are exploring AI-based fraud prevention alternatives (van Liebergen, 2017).

These indirect effects of AI on economic growth concern the reduction of financial market imperfections via better allocation of resources and risks and greater efficiency of financial regulation. Indeed, AI could improve portfolio management, banking scoring methods, insurance segmentation, household financial education and the effectiveness of financial regulation. Resources and risks are then better allocated in the economy towards the most productive uses for the national economy, with a positive effect on economic growth.

With chatbots, robo-advisors, and automated loan and insurance underwriting, AI is reshaping the customer experience, optimizing investing and borrowing, and enabling financial institutions to realize significant savings in risk management and regulatory compliance (Arner et al., 2017). Robo-advisors automatically manage clients' asset portfolios, providing better investment performance at minimum cost (Schwab, 2018; McCann, 2020). AI banking scoring tools make it possible to better discriminate between good borrowers and bad borrowers, reducing credit risks. In the insurance sector, AI makes it possible to refine customer segmentation and better compensate claims. AI also facilitates financial literacy, thereby minimizing investment and financial management errors (Lusardi and Mitchell, 2014). AI provides central banks and supervisory authorities with new tools to improve the monitoring of systemic risks and strengthen prudential supervision (di Castri et al. 2019). Central banks use AI to detect financial risks, anomalies in transactions, predict market fluctuations and make informed decisions on monetary and financial policy (Kearns, 2023). However, it is known that improving the effectiveness of supervisory activities positively affects economic growth (OECD, 2006; Serres et al., 2006).

We develop a model inspired by those of Zeira (1998) and Aghion et al (2017) to which we add a financial market in the style of Pagano (1993). In that model, AI operates on two levels: on the one hand, it makes it possible to automate tasks in the goods market using capital from the transformation of savings into investment; on the other hand, it makes it possible to automate tasks in financial markets with the aim of improving the allocation of savings towards the most productive uses for the national economy. This model strives to reproduce the following stylized facts: the stability of the capital share; AI affects both the productivity of automated tasks, including in finance (direct effect) and the allocative, operational and informational efficiency of financial markets (indirect effect). We postulate that this indirect effect of AI can be negative due to biases in the learning data used by AI (inaccurate and/or insufficient informations). More precisely, countries with low financial development suffer from algorithmic bias due to the fact that most of the data used to train AI algorithms comes from Europe and the United States (UNESCO, 2021). These data, not adapted to local realities, generate AI algorithms likely to induce poor allocation of capital, in terms of asset management, banking scoring, insurance segmentation, regulation financial, leading to a decline in economic growth (Friedman and Nissenbaum, 1996). Algorithmic biases distort AI-based resource allocation or financial regulation decisions.

Our study makes two original contributions to the literature: to our knowledge, it is one of the first to theoretically analyze the effect of AI on economic growth through the financial market; then, using the financial market makes it possible not to underestimate or overestimate the effect of AI on economic growth. Our results show that the effect of AI on economic growth depends on the level of financial development. This is useful for defining national AI policies. These must not only be based on reforms of the labor market or the education system, but also on reforms of the financial markets. Our article is structured as follows: we develop the models according to the perspective of Zeira (section 2) and the approach of Aghion et al. (section 3). Section 4 concludes the paper.

2. The effect of AI on economic growth: a theoretical framework inspired by the model of Zeira (1998)

Our first model is inspired by that of Zeira (1998), in which we integrate the financial market *à la* Pagano (1993), assuming that the capital used to automate tasks via AI comes from the financial market via the transformation of savings. Part of this savings disappears when transformed into investment due to financial market imperfections. AI affects production in two ways: first, by automating tasks, helping to strengthen the ratio of capital to labor; then, by affecting financial market imperfections through an improvement or deterioration in the allocation of capital and the effectiveness of financial regulation.

Consider an economy in which the final product (final output) is produced using the factors of production X_i according to the production function:

$$Y = AX_1^{\alpha_1}X_2^{\alpha_2}\dots X_n^{\alpha_n} \quad \text{where} \sum \alpha_i = 1 \qquad (1)$$

These factors of production X_i are tasks (Acemoglu and Autor, 2011)[1]. The X_i are produced thanks to the stock of capital (K_i) and labor supply (L_i) according to the equation:

$$X_i = \begin{cases} L_i & \text{if not automated} \\ K_i & \text{if automated} \end{cases} \qquad (2)$$

Thus, a task not yet automated can be accomplished by one unit of labor. As soon as a task is automated, a unit of capital can be used in its place. Aggregate production is obtained through the aggregate capital stock K and the global labor force, given the global share of automated tasks α and A total factor productivity, according to the following Cobb-Douglas production function :

$$Y = AK^{\alpha}L^{1-\alpha} \qquad (3)$$

Denoting $y = Y/L$, the GDP per capita, we have $y = Ak^{\alpha}$ with $k = K/L$ the capital per capita. We obtain: $dlny = dlnA + \alpha dlnk \;\Rightarrow\; g_y = g_A + \alpha g_k$. In the long term, we suppose, according to Zeira (op. cit.), that $g_y = g_k$. This hypothesis is that of Zeira (1998) whose Cobb-Douglas production function means that capital contributes to growth in proportion α; labor contributes in proportion $(1-\alpha)$. Automation spurs economic growth as it replaces labor – which is in finite supply – by capital which is in unbounded supply. In the long run, Zeira assumes that a very large part of labor will have been replaced by capital via AI automation, so that capital contributes 100% to the economic growth. The rate of growth of production then corresponds to the rate of growth of capital. Then, Zeira (op. cit.) postulates that, in the long run, $g_y = g_k$. Then, we obtain the long run economic growth rate.

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[1] At Zeira (1998), the factors of production X_i are intermediate inputs.

$$g_y^D = g_A/(1-\alpha) \quad (4)$$

Task automation via AI is increasing α, which in turn leads to a direct increase in g_y as long as total factor productivity growth is positive. We express E_D, the direct effects of AI on economic growth as follows :

$$E_D = \partial g_y^D/\partial\alpha = g_A/(1-\alpha)^2 \quad (5)$$

These direct effects are interpreted as the rate of acceleration of income per capita (or variation in growth rate) generated when the share of capital allowing both to automate tasks via AI and to generate the final product, increases by one percentage point.

The second channel through which AI affects production is the influence on capital allocation and the effectiveness of financial regulation via the effect on financial market imperfections. It is assumed that the capital used to automate tasks via AI comes from the transformation of savings into investment in the financial market. This financial market is assumed to be imperfect so that a part ψ of the savings disappears when it is transformed into investment. The coefficient $\psi \in [0;1]$ measures financial market imperfections (inefficiency, banking intermediation margins, tax levies, etc.). The degree of imperfections in the financial market defines the level of financial development of this market[2]. The more the coefficient ψ tends towards 1, the higher the level of financial development. The more ψ tends towards 0, the lower the level of financial development.

It is further assumed that the automation of tasks in financial markets generates two types of effects on financial markets depending on the level of financial development. According to a UNESCO report, countries with low financial development, mainly African, suffer from algorithmic bias due to the fact that most of the data used to train AI algorithms comes from Europe and the United States (UNESCO, 2021). Thus, in this report, only 9 of the 32 African countries analyzed claim to have a legal framework for protection against bias and the discriminatory nature of algorithms. Not being adapted to local realities, this data generates AI algorithms likely to induce poor allocation of capital, in terms of asset management, banking scoring, insurance segmentation, while altering the effectiveness of regulation financial (Friedman and Nissenbaum, 1996). This could lead to a decline in economic growth.

Thus, denoting $\hat{\psi}$ the threshold below which there is weak financial development and beyond which there is strong financial development, it follows that when $\psi \in [0, \hat{\psi}]$, the adoption of AI induces a drop in the coefficient ψ. In other words, the more tasks AI automates, the more the α share increases, the more the imperfections of the financial market are increased: $\psi'(\alpha) < 0$ when $\psi \in [0, \hat{\psi}]$ (case of weak financial development).

Let's clarify the function $\psi'(\alpha)$: we assume that the coefficient ψ of financial market imperfections depends on the share α expressing the degree of AI adoption. Thus, the function $\psi'(\alpha)$ is the derivative of the function $\psi(\alpha)$ with respect to α. When this function $\psi'(\alpha) < 0$, this means that the more tasks AI automates, the more α increases and $\psi(\alpha)$ decreases, that is, a smaller part of the savings is transformed into investment, due to financial market imperfections. This happens in countries with low financial development. For example, in African countries, automation of tasks in financial markets suffer from algorithmic bias. Indeed,

[2] A financial market with fewer imperfections is compatible with strong financial development. Indeed, such a market is characterized by its depth (liquidity, volume of financial transactions, credits granted to the private sector, book value of investments, market capitalization), its efficiency (capacity to provide financial services at low cost by ensuring sustainable profitability) and its accessibility (financial inclusion) (Sahay et al., 2015).

AI algorithms designed and trained using data from advanced economies may lead to inefficient capital allocation when applied to different market realities, potentially misdirecting investment and dampening economic growth. Another source of financial market imperfections is structural inequalities and digital divides in Africa that limit the adoption of AI, especially generative AI.

On the other hand, in countries with strong financial development, in Europe and the United States, algorithmic biases are minimized so that AI can significantly improve the allocation of capital (UNESCO, op. cit.). Formally: $\psi'(\alpha) > 0$ when $\psi \in [\hat{\psi}, 1]$ (case of strong financial development). We summarize the functional relationship transforming savings per capita ($s \equiv S/Y = ey$ where e is the savings rate) into gross investment per capita ($i \equiv I/Y$) on the imperfect financial market as follows:

$$i = \psi(\alpha)s \quad \text{where} \begin{cases} \psi'(\alpha) < 0 & \text{in case of weak financial development} \\ \psi'(\alpha) > 0 & \text{in case of strong financial development} \end{cases} \tag{6}$$

From there, we calculate the economic growth generated thanks to the financial market, when savings are transformed into investment. We know that savings per capita, ey, are allocated by the financial markets towards a gross investment per capita $i = \psi(\alpha)ey$ which is broken down into net investment per capita Δk and replacement investment per capita δk where δ: capital depreciation rate: $i = \Delta k + \delta k$. We obtain $\psi(\alpha)ey = \Delta k + \delta k \Rightarrow \Delta k = \psi(\alpha)ey - \delta k \Rightarrow g_k = \psi(\alpha)\, s/k - \delta$. In the long term, we have $g_y = g_k$ and we calculate the long run economic growth rate g_y^{IND}. We define g_y^{IND} as the economic growth obtained from indirect effects of AI on production. This second channel through which AI affects production is the influence on capital allocation and the effectiveness of financial regulation via the effect on financial market imperfections.

$$g_y^{IND} = \psi(\alpha)\, s/k - \delta = Ae\psi(\alpha)k^{\alpha-1} - \delta \tag{7}$$

Automating tasks via AI increases α, which in turn leads to a variation in $\psi(\alpha)$ and g_y, i.e. an indirect variation in growth. We express E_{IND} the indirect effects of AI on economic growth as follows:

$$E_{IND} = \partial g_y^{IND}/\partial\alpha = Ae[\psi'(\alpha)k^{\alpha-1} + \psi(\alpha)(\alpha - 1)k^{\alpha-2}] \tag{8}$$

These indirect effects are interpreted as the rate of acceleration of income per capita generated when the share of capital allowing both to automate tasks via AI and to transform savings into investment, increases by one percentage point.

In case of strong financial development ($\psi'(\alpha) > 0$), the direct and indirect effects of AI on economic growth are positive, so that the global effects are positive. In case of weak financial development ($\psi'(\alpha) < 0$), the direct effects of AI on economic growth are positive but the indirect effects are negative. The global effects of AI on growth are then assessed by comparing the direct effects and the absolute value of the indirect effects:

- If $E_D > |E_{IND}|$, the global effects are positive: AI positively affects long run economic growth;
- If $E_D = |E_{IND}|$, the direct effects and the indirect effects compensate each other exactly: AI does not affect long run economic growth.
- If $E_D < |E_{IND}|$, the global effects are negative: AI negatively affects long run economic growth.

As noted by Aghion et al. (2017), a limitation of the Zeira (1998) model is that it predicts an increase in the share of capital. This result contradicts Kaldor's observation that the share of capital tends to remain stable over time. Aghion et al. (2017) overcomes this limitation by postulating the complementarity between automated tasks and labor-intensive tasks, combined with the fact that labor becomes scarcer relative to capital over time. The share of capital then remains stable over time. Furthermore, in the financial sector, complementarity between tasks automated via AI and tasks requiring sufficient productive labor seems to be the rule. This makes it necessary to analyze the potential effect of AI on economic growth via the theoretical framework of Aghion et al. (2017) in order to verify whether the intuitive results obtained previously still hold.

3. The effect of AI on economic growth: a theoretical framework inspired by the model of Aghion, Antonin and Bunel (2017)

Our second model, inspired by Aghion et al. (op. cit.), considers an economy in which the final product (final output) is produced thanks to the production factors which are the complementary tasks X_i with $\rho < 0$, where knowledge A progress at a constant rate g_A, according to the production function:

$$Y_t = A_t\left(\int_0^1 X_{it}^{\rho}\, di\right)^{\frac{1}{\rho}} \qquad (9)$$

As before, a task not yet automated can be accomplished by one unit of labor. As soon as a task is automated via AI, a unit of capital can be used in its place. We formalize this idea by positing that the X_i are produced by stock of capital (K_i) and labor supply (L_i):

$$X_{it} = \begin{cases} L_{it} & \text{if not automated} \\ K_{it} & \text{if automated} \end{cases} \qquad (10)$$

The share of automated tasks increases over time, due to a lack of new labor-intensive tasks to compensate for the automation of existing tasks. Assuming that a fraction β_t of the tasks is automated at date t, we can reformulate the production function above as follows:

$$Y_t = A_t\left(\beta_t^{1-\rho} K_t^{\rho} + (1-\beta_t)^{1-\rho} L^{\rho}\right)^{\frac{1}{\rho}} \qquad (11)$$

With K_t : aggregate stock of capital; $L_t \equiv L$ aggregate labor supply. In accordance with Aghion et al. (2017), at the equilibrium point, the ratio between the share of capital and the share of labor is equal to:

$$\frac{\alpha_{K_t}}{\alpha_L} = \left(\frac{\beta_t}{1-\beta_t}\right)^{1-\rho}\left(\frac{K_t}{L_t}\right)^{\rho} \qquad (12)$$

This equation (12) shows that the ratio between the share of capital and the share of labor remains stable, despite the automation of tasks via AI. Indeed, when the share of automated goods β_t increases via AI, this positively affects the expression $(\beta_t/(1-\beta_t))^{1-\rho}$ and negatively the ratio $(K_t/L_t)^{\rho}$ since $\rho < 0$. When the ratio K_t/L_t increases, labor becomes more scarce than capital, which means that a significant part of total income will be generated by labor, given the complementarity between high-intensity tasks labor and automated tasks. This is Baumol's famous "cost disease". In the end, the two effects compensate each other such that the ratio α_{K_t}/α_L remains stable, thus confirming Kaldor's observation that the share of capital tends to remain stable over time.

The first channel through which AI affects production is the automation of tasks, helping to strengthen the ratio of capital to labor. We evaluate the effect of AI automation on long run economic growth, by comparing the long run growth rate in the case where $\beta_t = \beta < 1$ to the long run growth rate in the case where $\beta_t = 1$. In the first case, a constant fraction of tasks, not yet automated, become automated each period according to the expression:

$$\dot{\beta} = \theta(1 - \beta_t) \tag{13}$$

β_t is the fraction of automated tasks at period t. The term $\dot{\beta} = d\beta_t/dt$ is the rate of change of β over time. The term θ is the constant fraction of tasks, not yet automated, that become automated each period. Aghion et al. (2017) show that the growth rate converges to a long run constant $g_y^D = g$. In the second case, all tasks become automated in a finite time, according to the expression:

$$\beta_t \equiv 1 \ \forall\, t > T \tag{14}$$

When $t > T$, the aggregate production of final goods becomes $Y_t = A_t K_t \ \Rightarrow \ g_y = g_A/k + g_k/A$. In the long term, we have $g_y = g_k$ so that the long run economic growth rate is:

$$g_y^D = g_A/[k(1 - 1/A)] \tag{15}$$

Task automation via AI, β_t, affects economic growth through its effect of improving task productivity. AI stimulates economic growth through its ability to replace labor, a limited resource, with capital, an unlimited resource. The growth rate grows unlimitedly since A grows at the exponential rate g_A. We assess the direct effects of AI on economic growth by calculating $E_D = \left[g_y^D\{(\beta = 1)\} - g_y^D\{(\beta < 1)\}\right]/(1 - \beta)$. We obtain:

$$E_D = \{g_A/[k(1 - 1/A)] - g\}/(1 - \beta) \ > 0 \tag{16}$$

The second channel through which AI affects production is the transformation of savings into investment in the imperfect financial market. The more tasks AI automates, the more the share β_t increases, the more the imperfections of the financial market are increased or reduced depending on the functional relationship:

$$i = \psi(\beta_t)s \ \text{ where } \begin{cases} \psi'(\beta_t) < 0 & \text{in case of weak financial development} \\ \psi'(\beta_t) > 0 & \text{in case of strong financial development} \end{cases} \tag{17}$$

As capital accumulates over time according to $\Delta k_t = eAk\psi(\beta_t) - \delta k_t$, the economic growth rate then gives:

$$g_y^{IND} = g_A + eA\psi(\beta_t)A - \delta \tag{18}$$

The indirect effects of AI on economic growth are expressed as follows:

$$E_{IND} = \partial g_y^{IND}/\partial\beta_t = eA\psi'(\beta_t) \tag{19}$$

In case of strong financial development ($\psi'(\beta_t) > 0$), the direct and indirect effects of AI on economic growth are positive, so that the global effects are positive. In case of weak financial development ($\psi'(\beta_t) < 0$), the direct effects of AI on economic growth are positive but the indirect effects are negative. We then find the results of the previous model :

- If $E_D > |E_{IND}|$, the global effects are positive: AI positively affects long run economic growth;
- If $E_D = |E_{IND}|$, the direct effects and the indirect effects compensate each other exactly: AI does not affect long run economic growth.

- If $E_D < |E_{IND}|$, the global effects are negative: AI negatively affects long run economic growth.

The economic growth rate depends on traditional factors (savings rate e, total factor productivity A, capital depreciation δ) and AI. AI has direct effects and indirect effects on long run economic growth via improving the productivity of automated tasks and indirect effects through the financial market channel. In the case of strong financial development, the overall effects of AI on long-term economic growth are positive: financial development then stimulates the positive effect of AI on growth. In the case of low financial development, these effects can be neutral or even negative: financial development attenuates the positive effect of AI on growth. There is a level of financial development ($\psi \in [0, \hat{\psi}]$) where the effect of AI on economic growth can become negative.

We have performed en empirical study in a separate paper, which examines the role of the financial market in the AI-economic growth nexus. This is a working paper intitled "Artificial Intelligence, financial development and economic growth: a panel data study". For reasons of robustness of the results, we capture AI investment through two proxies: AI patents (logarithm of the number of patents incorporating AI), AI score (based on 39 indicators distributed across the pillars "Government", "technology sector", "Data and infrastructure" and "Private sector"). The empirical methodology tests this theoretical result using a panel of 50 countries over the period 1980-2023 via fixed effects and GMM (generalized method of moments) estimations to control endogeneity bias. Empirical results show that AI drives long run economic growth. However, this positive effect is less for African countries compared to developed countries, and is attenuated in the event of low financial development. There is even a financial development threshold below which AI is likely to reduce economic growth.

4. Concluding remarks

By introducing the financial market as a key intermediary in the AI-economic growth nexus, this article addresses a significant gap in the current theoretical discourse. The model used synthesize the Zeira (1998) model (which links new technology to labor and capital), the Aghion et al. (2017) model (which links innovation to growth), and the Pagano (1993) model (which introduces financial imperfections). The central finding of the article is that the effect of AI on economic growth is contingent upon a country's level of financial development. This result is highly relevant for policymakers worldwide, especially in emerging and developing economies. Our study has economic policy implications aimed at strengthening the positive effect of AI on long run economic growth.

Certain measures concern all countries: reducing AI algorithm bias via incentives for AI research; reforming financial markets to integrate innovative, structured financial products serving as vehicles for investments in AI; establishing a legal framework for the protection of data against bias and the discriminatory nature of algorithms applied to financial markets (chatbots, robo-advisors, banking scoring algorithms and segmentation in insurance, etc.). This would strengthen the ability of financial markets to use AI to efficiently allocate capital to the most productive uses for the economy. Other measures are more specific to developing countries, particularly African countries: adopting an inclusive and holistic approach to concertedly increase investments in AI; establishing national AI strategies in each African country with a view to creating a coherent framework for implementing the reforms of the education system, the labor market and the financial market required by the adoption of AI. Beyond national strategies, African countries must invest in AI, holistically, in order to increase their shares in the global AI market.

Limitations of our study concern, on the one hand, the failure to take into account the indirect effects of AI on economic growth via the labor market, and on the other hand, the exogenous and constant nature of the savings rate. For example, modeling the savings behavior of households via the maximization of intertemporal utility under budgetary constraints and the behavior of financial institutions maximizing their intermediation profit, could make it possible to endogenize the contribution of the financial market and to better formalize the allocation of savings towards investment. Indeed, in the model, the savings rate is given exogeneously. It does not come from the optimizing behavior of households. A more realistic hypothesis could be this one: the incentives for households to save on the markets could depend on their attitude (trust, mistrust) concerning the capacity of AI to allocate their savings towards the most profitable investments. Furthermore, the presence of AI algorithms could reduce or increase frictions on financial markets (information asymmetries, agency costs) affecting the efficiency of financial institutions in their financial intermediation function. This approach could help to better model the effect of AI on economic growth via financial market. It could also allow us to assess the effect of AI on well-being and in terms of economic fluctuations. We reserve these points for future research. The purpose of this study was only to give first intuitions of the effect of AI on the real sphere via financial markets."

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