African Journal of Emerging Issues
Peer reviewed | Double blind | Interdisciplinary

African Journal of Emerging Issues (AJOEI)
Online ISSN: 2663 - 9335
Available at: https://ajoeijournals.org

ECONOMIC

DIGITALIZATION AND TOTAL FACTOR PRODUCTIVITY OF SELECTED FIRMS LISTED AT THE NAIROBI SECURITIES EXCHANGE IN KENYA

[*1]Godfrey Ochola Oyugi & [2]Dr. Isaac Kimunio,

[1]School of Business, Economics and Tourism, Kenyatta University, Kenya

[2]School of Business, Economics and Tourism, Kenyatta University, Kenya

***Email of the Corresponding Author: godfreyaloise@email.com**

Publication Date: April 2025

ABSTRACT

Purpose of the Study: The study's main objective was to determine the effect of digitalization on the Total Factor Productivity of Nairobi Security Exchange listed firms.

Problem Statement: Despite significant firm investment in advance digital technology, the overall contribution of digitalization to the performance and total factor productivity of firms listed in the Nairobi Securities Exchange has been inconsistent.

Method/methodology: To achieve the objective the study adopted the Growth Accounting Equation Approach and Generalized Method of Moments to analyze the effect of digitalization on Total Factor Productivity of selected listed firms in NSE

Results of the study: The study reveals that digitalization as a key driver of productivity among NSE-listed firms.

Conclusion and policy recommendation: The study concludes digitalization is a critical driver of Total Factor Productivity among firms listed in NSE and forward-oriented tech policies should be prioritized to build a tech savvy working environment

Keywords: *Digitalization, Total Factor Productivity, Nairobi Securities Exchange.*

INTRODUCTION

The world economy stands on the cusp of a digital transformative revolution, often dubbed the Fourth Industrial Revolution (4IR) (Skilton & Hovsepian, 2018). Digitalization has emerged as the transformative juggernaut of modern economic growth, reshaping industries and enhancing productivity across the globe. The adoption of cutting-edge digital technologies such as artificial intelligence (AI) is fundamentally reshaping global economies, industries, and societies (George & George, 2024). This transformation has enabled economies, firms, and industries to streamline operations, cut costs, overcome global supply chain barriers, and innovate at unprecedented speeds. While digital technologies can accelerate productivity gains, firms operating in digital-intensive sectors tend to exhibit higher total factor productivity (TFP) growth compared to those in less digital-intensive sectors (Gal, Peter, et al., 2019). Even when firms have identical quality of capital, labor, and other input factors, their output levels can vary due to differences in TFP (Li & Tian, 2023). Market conditions, regulatory environments, and firm-specific factors such as management practices and resource availability can cause significant variations in TFP even within the same industry.

However, despite tremendous investments in digital technologies as a modern game-changer to spur firm productivity and aggregate economic growth, a productivity gap persists. The level of ICT investment and firm productivity has shown inconsistent trends alongside GDP growth. This gap raises critical questions about the effectiveness of digitalization investment efforts in translating into productivity gains for firms listed on the Nairobi Securities Exchange (NSE). The primary focus is understanding why rapid ICT investment in Kenya is disproportionate to firm productivity and economic output. Therefore, this research seeks to explore the total factor productivity of NSE-listed firms and how digitalization affects their TFP. This will provide in-depth insights into how Kenya and its firms can harness ICT investment to bridge the productivity gap and achieve sustainable economic growth at both firm and aggregate levels.

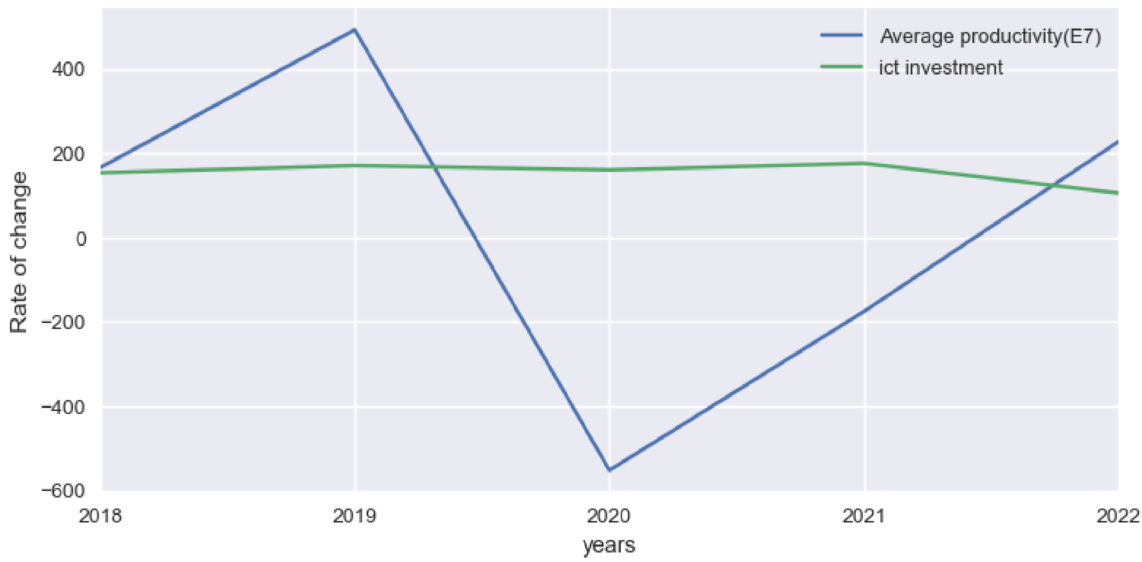

Figure 1: Selected Firm-level ICT investment and Average Productivity of NSE-listed firms trend 2018-2022

The Figure 1 illustrates the rate of change in average productivity of NSE-listed firms and the ICT investment from 2018 to 2022. Average productivity shows a sharp increase from 2018 to 2019, followed by a drastic decline to 2020. After this period, productivity gradually recovers with a sharp rise although on the marginal negative boundary through 2021, and transition into slight positive trajectory above the negative marginal line to 2022. On the other hand, ICT investment trend exhibits a consistent, positive marginal trajectory from 2018 to 2022. Specifically, it shows a modest increase from 2018 to 2019, followed by a slight dip in 2020. The trend is then succeeded by a gradual decline and a moderate rise in 2021 at the peak before taking a subtle decline into 2022.

LITERATURE REVIEW

Gal et al. (2019) examined digitalization and productivity—the "Holy Grail" for firms from European countries—and the impact of adopting various digital technologies on firm productivity. By integrating cross-country firm-level data with industry-based information on digital technology adoption, the analysis incorporates firm heterogeneity in its empirical framework. The findings provide compelling evidence that digital adoption within industries correlates with productivity enhancements at the firm level. Furthermore, digital technologies are statistically significant in high-performing firms. Consequently, the study highlights that disparity in productivity among firms is contributed to by digital technologies. However, the study is only focused at the industry level.

Li and Tian (2023) examined digital transformation's significant impact on firm-level TFP, focusing on a sample of 2,913 publicly listed companies in China between 2012 and 2018. The research findings showed a positive interplay between digital transformation and corporate firm TFP, suggesting that digitalization efforts contribute to productivity gains within Chinese firms. The study could potentially act as an inspiration for developing nations to emulate. However, the research focuses only on China-listed companies, which may limit viability for other countries.

Anderton et al. (2023) examined whether digitalization is indeed a transformative game-changer or merely a sideshow driving substantial productivity gains among firms. Utilizing a large panel dataset of over 19 million European firm-level observations, they analyzed the impacts of digitalization on productivity growth through previously unexplored channels and mechanisms. The findings reveal that while digital technologies can act as a transformative force for select firms, for the majority of others, digitalization remains a dwindling force, insufficient to drive substantive productivity gains. Therefore, digital investment should not be used as a universal solution for productivity enhancement. However, the scope of the study was only based on European firms, negating other firms across the globe, which could potentially raise bias.

Gaglio et al. (2022) examined how digital transformation impacts innovation and productivity through firm-level analysis of SMEs in South Africa's manufacturing sector. Embracing an expanded version of the Crepon-Duguet-Mairesse (1998) model, the study looks at the interconnection that exists between the usage of digital communication technologies, innovation, and productivity performance. This analysis employed data from 711 MSEs in Johannesburg's manufacturing sector, according to a 2019 survey. The findings depicted that digital channels, such as social media and mobile phone internet usage in business, positively influence innovation. Consequently, innovation that capitalizes on the adoption of these digital tech channels positively influences labor productivity. The findings showcase that public intervention to foster inclusive digitization should encompass digital technologies that are adequately accessible and beneficial to small firms, including those operating in the informal sector. However, the research was limited to manufacturing firms in a particular country.

METHODOLOGY

The framework of Theoretical and Empirical models

The Cobb-Douglas Production function is thus the indispensable model for this analysis and it is expressed in the following form

$$Y_t = [A_t K_t^{\alpha} L_t^{\beta}] \tag{1}$$

Where **A** denotes technological progress, K represents capital, L stands for Labour, (***α)*** is the output elasticity w.r.t capital, β is the output elasticity w.r.t labour, and ***t*** denotes time factor. The model is based on the assumption of constant return to scale meaning the sum of the elasticity of capital and labour is equal to one ($\alpha + \beta = 1$). To estimate TFP, equation (1) is linearized by converting it to natural logarithms.

$$lnY_t = lnA_t + \alpha\, lnK_t + \beta\, lnL_t \tag{2}$$

By differentiating equation (2) based on the growth accounting approach w.r.t, it gives equation (3) as;

$$\frac{\partial lnY_t}{\partial_t} = \frac{\partial lnA_t}{\partial_t} + \alpha \frac{\partial lnK_t}{\partial_t} + \beta \frac{\partial lnL_t}{\partial_t} \tag{3}$$

$$\frac{Y_t^*}{Y_t} = \frac{A^*}{A_t} + \alpha \frac{K_t^*}{K_t} + \beta \frac{L_t^*}{L_t} \tag{4}$$

Where output growth rate-$\frac{Y_t^*}{Y_t}$, TFP growth rate-$\frac{A^*}{A_t}$, capital growth rate$\frac{K_t^*}{K_t}$, labour growth rate$\frac{L_t^*}{L_t}$ while α and β denotes elasticity or responsiveness of capital and labour. The TFP growth rate is thus equal to;

$$\frac{A^*}{A_t}(TFP) = \frac{Y_t^*}{Y_t} - \alpha \frac{K_t^*}{K_t} - \beta \frac{L_t^*}{L_t} \tag{5}$$

This is referred to as Solow Residual in the Solow Model Growth Accounting Equation (Romer, 2012). To determine the amount of total factor productivity of NSE-listed firms, the study will use the Cobb-Douglas production function following the specification in equation (1). For the econometric model, the study will modify equation (1) and the residuals will used as the estimates of the amount of TFP for Kenyan firms. The econometric model for this analysis, however, will use a dynamic panel data model.

According to Bond (2002) even in cases when the dynamics of variables are not of direct interest, it may be important to allow for their dynamics in the underlying process to get consistent estimates of other parameters. Moreover, the dynamic model encompasses within and between variations in the determining model coefficients, therefore capturing individual and time-specific effects more efficiently (Piper, 2014).

Guided by Blundell and Bond, (2001) a static panel data model for this study can be specified as:

$$lnY_{it} = \alpha + \beta_2 lnA_{it} + \beta_3 lnK_{it} + \beta_4 lnL_{it} + \varepsilon_{it} , \quad (6)$$

For i = 1, 2... N and t = 1, 2, ..., T

To introduce dynamism in the model in equation (6) $lnY_{i,t-1}$, which is the first lag of the log of output is added to give:

$$lnY_{i,t} = \beta_1 lnY_{i,t-1} + \beta_2 lnA_{it} + \beta_3 lnK_{it} + \beta_4 lnL_{it} + v_{it} , \quad (7)$$

Where $lnY_{i,t-1}$the first is lag of output and $v_{it} = \alpha_i + \varepsilon_{it}$ is the composite error term.

The study will use only one lag of the log of output in order to avoid losing more number of observations. The key assumption from equation (7) is that the expectation, $E\left(v_{it} \middle| lnY_{i,t-1}, lnK_{it}, lnA_{it}, lnL_{it}, \alpha_i\right) = 0$. It implies lack of autocorrelation in the composite error term. In addition, the strict exogeneity assumption for the explanatory variables is relaxed, hence allowing for the feedback from lagged values of the log of output to the current values for the explanatory variables.

Earlier, Arellano & Bond (1991) emphasized that the key assumption in equation (7) ensures consistency of the GMM estimator. Therefore, the study will use GMM estimation method for analysis with the model specified in equation (8) below.

$$lnY_{it} = \alpha + \beta_1 lnY_{i,t-1} + \beta_2 lnA_{it} + \beta_3 lnK_{it} + \beta_4 lnL_{it} + \varepsilon_{it} \quad (8)$$

The residual series obtained from equation (8) is equivalent to the Solow residual in equation (5), which can be expressed as follow:

$$TFP_{it} = lnY_{it} - \alpha - \beta_1 lnY_{i,t-1} - \beta_2 lnA_{it} - \beta_3\, lnK_{it} - \beta_4\, lnL_{it} \equiv \frac{Y_t^*}{Y_t} - \alpha \frac{K_t^*}{K_t} - \beta \frac{L_t^*}{L_t} \quad (9)$$

The framework of analyzing the effect of Digitalization on the TFP of NSE-listed firms

To analyze the effect of digitalization on the total factor productivity of NSE-listed firms. The research will adopt a similar approach as in the estimation of the output, which GMM estimation method.

$$TFP_{it} = \partial + TFP_{i,t-1} + \beta_1 Digitalization_{it} + \beta_2\ Size_{it} + \beta_3\ Age_{it} + \beta_4\ Management_{it} + \varepsilon_{it} \qquad (10)$$

Table 1: Definition and Measurement of Variables

Variables	Definitions	Measurement
Output	The total amount revenue generated by a firm	Measured annually in Kenyan Shillings
Capital	This is the total amount of the capital stock of the firm per year	Measured in Kenyan Shillings
Labour	This represents the total labour force employed by the firm per year	Number of employees in the firms
Total Factor Productivity	Total output not explained by key inputs such as capital and labor per year	Calculated as residual in production function analysis
Digitalization	This refers to the level of technology employed by the firm per year	Measured in Kenyan shillings from the digital tech spending
Size	It is the total value of firm assets	Measured in Kenyan Shillings per year
Age	The total years since the firm's establishment	Measured in years
Management	Quality and effectiveness of leadership within a firm	Total number of board members or directors

The study utilized annual panel data of NSE-listed covering the period from 2018 to 2023. Data was sourced from annual financial reports from the selected firms in NSE.

RESULTS AND DISCUSSSION

Descriptive Statistics

The fundamental statistics analysis was computed and compiled namely, Mean, Standard Deviation, Minimum and Maximum Values of the various research variables. The results of the computed variables are shown in Table 2.

Table 2: Statistical Summary

Variable	Number of Observations	Mean	Standard Deviation	Min	Max
Output (Kenyan Shillings in Billions)	48	46	29	17	159
Capital (Kenyan Shillings in Billions)	48	80	40	30	236
Labour (Number. of Employees)	48	3355	2,538	945	12,221
Digitalization (%)	48	98	3	87	99
Size (Kenyan Shillings in Billions)	48	531	349	49	2170
Age(years)	48	70	35	1	127
Management (Number of directors)	48	13	5	8	26

Table 1 shows the statistical summary of 48 observations from 7 firms over 6 years reveals significant variability across key metrics. The average firm output was KSh 46 billion (SD = KSh 29 billion), ranging from KSh 17 billion to KSh 159 billion, with KCB Bank generating the maximum output. Capital averaged KSh 80 billion (SD = KSh 40 billion), spanning from KSh 30 billion to KSh 236 billion. Labor employment showed wide variation with a mean of 3,355 employees (SD = 2,538), ranging from 945 to 12,221 employees. Digitalization levels were consistently high across firms, averaging 98% (SD = 3%), with a minimum of 87% and maximum of 99%. Firm size, measured by total assets, averaged KSh 531 billion (SD = KSh 349 billion), ranging from KSh 49 billion to KSh 2.17 trillion. The firms' ages varied considerably, averaging 70 years (SD = 35 years), from newly established (1 year) to well-established institutions (127 years). Management structure, measured by number of directors, averaged 13 directors (SD = 5), ranging from 8 to 26 directors.

Model Estimation

The dynamic panel data model was used as in Equation (9) to find the total factor productivity while the one-step difference GMM was adopted as in Equation (10) to determine the effect of digitalization on the total factor productivity in Kenyan listed firm.

Table 3: Dynamic Panel Data Estimation, One-Step Difference GMM

Variables	Coefficients	Standard Errors	P-value	F statistics
TFP(t-1)	0.488652	0.2521614	0.094	25.24
Size	-0.0030187	0.0012677	0.049	(0.00**)
Age	964	400	0.047	
Management	-538	468	0.288	
Digitalization	114	31	0.009	

Table 3 presents one-step difference GMM regression results showing the relationship between Total Factor Productivity (TFP) and various predictors. The model demonstrates high statistical significance (F-statistic = 25.24, p < 0.001), indicating the independent variables collectively explain substantial variance in TFP. Lagged TFP showed moderate significance (coefficient = 0.49, p = 0.09) at the 10% level, supporting Jovanovic's learning theory and aligning with Oliveira de Almeida et al.'s (2024) findings. Firm size demonstrated a positive, significant relationship with TFP (coefficient = 0.003, p = 0.049), consistent with Dvouletý & Blažková's (2021) research. Age also positively influenced TFP (coefficient = 968, p = 0.047), supporting Camino-Mogro's (2022) conclusions. Digitalization emerged as highly significant (coefficient = 114, p = 0.009), confirming Li et al.'s (2024) and Li & Tian's (2023) findings that digital transformation positively impacts productivity. Conversely, management showed a negative but statistically insignificant effect (coefficient = -538, p = 0.288), similar to Kyere et al.'s (2021) mixed findings regarding corporate governance and firm performance in British listed companies.

Model Diagnostic Tests

Table 4: Arellano Bond Tests

Test Name	Test statistics	P-value
Arellano Bond Tests AR (1)	55%	0.584
Arellano Bond Tests AR (2)	1.53%	0.125
F-statistics	55.14	0.001

Source Author's Computation

Table 4 presents results of Arellano Bond Tests. AR1, the test for the first order autocorrelation is not significant (P-value 0.584>0.05) indicating no problem with first-order autocorrelation. The study further conducted AR2 to ensure the necessary statistical conditions are satisfied. The expectation is that there is first order serial correlation in the residual series but not in the second-order correlation AR2, the test for second-order autocorrelation is not significant (p-value0.127>0.05), which suggests that the GMM estimator is valid and there is no issue with high-order autocorrelation.

Hansen Test

The adopted Hansen test for over-identifying restrictions to test for the valid of the instruments used in the system GMM of the estimated model. For example, if the p-value exceeds the statistical significance level picked by the researcher, then it confirms the validity of the instruments used in estimating the system GMM model.

Table 5: Hansen Test

Test Name	Test statistics	P-value
Hansen Test	16.43	0.06
F-statistics	55.14	0.001

Table 5 show the statistical results from Hansen test conducted with a test statistic of 16.43 and p-value of 0.06. The study does not reject the null hypothesis at 5% statistical significance level. Therefore, the instruments indicate potential instruments validity of the model. Lastly the F-test was used to test for the overall statistical significance of estimated coefficients. A p-value greater than the significance level chosen reveals that all regression coefficients are equivalent to zero. At in Table 4.5.2 above the p-value at 5% is 0.001. F-statistics (5, 7) is 55.14, which is highly significant p-value 0.001<0.05 suggesting a good fit for the model. Therefore, the null hypothesis is rejected which state that all regression do not explain the variations in TFP. The research study concludes that all regressors are statistically significant in explaining the variations in the TFP since all coefficients are not equal to zero.

CONCLUSION

The study concludes digitalization is a critical driver of Total Factor Productivity among firms listed in NSE. The findings emphatically support the hypothesis that digitalization serves as a catalyst for operational efficiency and fostering long-term competitive advantage. By streamlining operation processes, reducing transactions costs, and improving decision-making using data-driven insights, digitalization enables digitally-tech firms to optimize resource allocation and increase output levels relative to input. While digitalization enhances innovation and firm productivity, it equally presents potential trade-offs. One major concern is workforce displacement due to automation, where digital tools and AI is threatening to take up the traditional labor-intensive roles of employees. This shift raises alarm about the future job security, reskilling needs, and social inequalities. Further, the hefty initial costs of digital adoption may potentially cause financial constraints for some firms, particularly smaller firms.

POLICY RECOMMENDATION

To build dynamic and advanced digital tech systems that would amplify firm productivity, policymakers, stakeholders and firms must implement strategic interventions. These policy recommendations were proposed and categorized into the short-term, medium-term and long-term strategies to provide a structured roadmap for fostering digitalization-driven productivity growth. First, on the short-term intervention basically the immediate action within the first 2 years, the policymakers should prioritize building a robust digital infrastructure such as broadband connectivity, cyber-security frameworks, digital transaction frameworks and roll-out of AI-driven digital training to ensure seamless digital tools accessibility. Secondly, medium-term intervention spanning for 3-5 years, strengthening of digital policy and regulation. By developing forward-oriented policies on data protection laws, public private digital initiatives, and intellectual property to create an enabling environment for firms to innovate and expand their digital capabilities without potential risks. Lastly, on the long-term intervention for over 6 years, building an AI-driven workforce is inevitable. In the current evolving digital age being reshaped by AI, corroborating efforts to up-skill the workforce and accelerate firm operations by AI-powered digital literacy training, cloud computing simulation and cyber security programs is essential. This will objectively ensure that firms utilize AI related digital tools, blockchain technology and big data analytics to optimally realize high productivity gains. Similarly, up to date digital literacy and advanced technology courses, such a coding, data analytics, cyber security and machine learning should be integrated into all into all firm operations.

REFERENCES

Anderton, Robert, Paul Reimers, and Vasco Botelho. "Digitalisation and productivity: gamechanger or sideshow?" (2023).

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The review of economic studies*, *58*(2), 277-297.

Bartelsman, Eric J., and Mark Doms(2000). "Understanding productivity: Lessons from longitudinal microdata." Journal of Economic literature 38.3): 569-594.

Blundell, R., Bond, S., & Windmeijer, F. (2001). Estimation in dynamic panel data models: improving on the performance of the standard GMM estimator. *Nonstationary panels, panel cointegration, and dynamic panels*, 53-91

Bond, S. R. (2002). Dynamic panel data models: a guide to micro data methods and practice. *Portuguese Economic Journal*, *1*, 141-162.

Camino-Mogro, S. (2022). TFP determinants in the manufacturing sector: the case of Ecuadorian firms. *Applied Economic Analysis*, *30*(89), 92-113.

Communications Authority of Kenya (2022). Kenya launches trials for 5G technology. : https://www.ca.go.ke/kenya-launches-trails-for-5g-technology/

Dvouletý, O., & Blažková, I. (2021). Exploring firm-level and sectoral variation in total factor productivity (TFP). *International Journal of Entrepreneurial Behavior & Research*, *27*(6), 1526-1547.

Gaglio, C., Kraemer-Mbula, E., & Lorenz, E. (2022). The effects of digital transformation on innovation and productivity: Firm-level evidence of South African manufacturing micro and small enterprises. *Technological Forecasting and Social Change*, 182, 121785. https://www.sciencedirect.com/science/article/pii/S0040162522003092

Gal, P., Nicoletti, G., Renault, T., Sorbe, S., & Timiliotis, C. (2019). Digitalisation and productivity: In search of the holy grail–Firm-level empirical evidence from EU countries.

George, A. S., & George, A. H. (2024). Riding the wave: an exploration of emerging technologies reshaping modern industry. Partners Universal International Innovation Journal, 2(1), 15-38.

Kenya National Bureau of Statistics Economic Survey (KNBS)- https://www.knbs.or.ke/economic-survey-2023/

Kyere, Martin, and Marcel Ausloos. "Corporate governance and firms financial performance in the United Kingdom." *International Journal of Finance & Economics* 26.2 (2021): 1871-1885.

Li, P., Liu, J., Lu, X., Xie, Y., & Wang, Z. (2024). Digitalization as a Factor of Production in China and the Impact on Total Factor Productivity (TFP). *Systems*, *12*(5), 164.

Li, S., & Tian, Y. (2023). How does digital transformation affect total factor productivity: Firm-level evidence from China? Sustainability, 15(12), 9575.

Oliveira de Almeida, E., Cateia, J. V., Barbosa, W., & Ataides de Freitas, C. (2024). Trade liberalization and total factor productivity in Brazil: A vecm modeling. *PloS one*, *19*(11), e0312599.

Piper, A. T. (2014). *The benefits, challenges, and insights of a dynamic panel assessment of life satisfaction.*

Romer, P. M. (1986). Increasing returns and long-run growth. *Journal of Political Economy*, 94(5), 1002-1037.

Skilton, M., & Hovsepian, F. (2018). The 4th industrial revolution. Springer Nature.