Artificial Intelligence and Employment: Evidence from Various Sectors of the Tunisian Economy

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Abstract

Purpose: The purpose of this paper is to revisit the relationship between artificial intelligence (AI) and employment for eleven sectors of Tunisian economy in the period 2010-2022.

Method: To study the variability that captures the impact of administrative barriers on investment in a particular sector of activity, we apply a Swamy random coefficients linear regression model, which considers cross-sectional heterogeneity issues.

Results: The empirical results show a global negative effect of AI on employment. Sectoral analysis detected a non-significant positive effect for the energy and agricultural and food industries.

Originality / relevance: This study finds its originality through the application of Swamy's method to consider the heterogeneity of the sectors of the Tunisian economy in the adherence to AI.

Keywords Artificial intelligence, Employment, Slope homogeneity test, Swamy model

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Intelligence artificielle et emploi : Cas de divers secteurs de l'économie tunisienne

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Résumé

Objectif : Le but de cet article est de revoir la relation entre intelligence artificielle (IA) et l'emploi pour onze secteurs de l'économie tunisienne durant la période entre 2010-2022.

Méthodologie : Afin d'étudier la variabilité qui capture l'impact des barrières administratives sur les investissements dans un secteur particulier d'activité, nous appliquons un modèle de régression linéaire de coefficients aléatoires de Swamy, qui tient compte des questions d'hétérogénéité transversale.

Résultats : Les résultats empiriques montrent un effet négatif global de l'IA sur l'emploi. Une analyse sectorielle a mis en évidence un effet positif non significatif pour les industries de l'énergie, de l'agriculture et de l'alimentation.

Originalité / pertinence : Cette étude trouve son originalité dans l'application de la méthode de Swamy pour prendre en compte l'hétérogénéité des secteurs de l'économie tunisienne dans l'adhésion à l'IA.

Mots clés : intelligence artificielle, Emploi, Test d'homogénéité, Modèle de Swamy.

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1. Introduction

Technological development, and in particular digitalization, has major implications for labor markets. Assessing its impact will be crucial for developing policies that promote efficient labor markets for the benefit of workers, employers and societies, as a whole. Rapid technological progress and innovation can menace employment: *technological change causes loss of jobs* (Keynes, 1937). AI can affect employment directly by displacing workers from the tasks they were previously performing; or indirectly by increasing the demand for labor in industries or jobs that arise or develop thanks to technological progress. In this substantial change caused by AI, the quality of human capital also plays a crucial role. In this sense, the ability of individuals to use the technological advances for the benefit of their work requires developing particular digital skills. Automation and advanced machine-learning techniques will be increasingly capable of carrying out high-skill and possibly non-routine tasks. Moving from the efficiency gains in online trading to the extensive use of artificially intelligent systems in our industrial production concerns the potential displacement of labor emergence.

On the other side, many businesses and individuals are optimistic that this AI-driven shift in the workplace will result in more jobs being created than lost. AI will have a positive impact on economies by creating jobs that require the skill set to implement new systems. It is likely that AI will soon replace jobs involving repetitive or basic problem-solving tasks, and even go beyond current human capabilities. However, it is essential to reduce regulatory barriers to market entry and entrepreneurship, increase the international integration of domestic firms, and modify labor taxes in order to promote AI and create more and better jobs. Reducing prior authorization for investment and market entry, easing administrative burdens, and streamlining the tax code would increase productivity growth, create new opportunities for small, creative, and young businesses, and promote formal job creation. Since onshore businesses primarily serve the domestic market, high import barriers limit their access to high-quality inputs and AI transfer.

AI systems will be making decisions instead of humans in industrial settings, customer service roles and within financial institutions. Organizations will benefit from an increase in productivity as a result of greater automation, which means that more revenue will be generated. Thus, this provides additional money to spend on supporting jobs in the services sector.

Between the negative and positive effects of AI on employment, this paper aims to study this issue in the case of sectors of the Tunisian economy to distinguish the most important ones. The remainder of this paper is structured as follows. Section 2 presents a theoretical and empirical literature review focusing on the relationship between AI and employment. Econometric methodology is presented in section 3. Results are discussed in section 4. Finally, section 5 presents the conclusions that we draw from this research.

2. Impact of AI: Literature review

Capital and labor are the classical factors of production that ensure growth in the economy. Growth improves as capital stock or labor increases, or when they are used more efficiently through innovations and technological change and their ability to enhance TFP.

Great technological progress has affected productivity but has not created completely new workforces. Today, we are in the presence of another transformative set of technologies called AI. We can consider this AI like past technological inventions; we can expect some growth but nothing transformational. Others suppose that AI has the potential to be a new factor of production as a capital-labor hybrid. On the one hand, AI can replicate labor activities at much greater scale and speed. On the other hand, AI can take the form of physical capital such as robots and intelligent machines; but contrary to conventional capital, it can actually improve over time, thanks to its self-learning capabilities (Prudy and Daugherty, 2017).

According to this notion, an important question appears concerning how much AI will affect businesses, consumers and the economy more generally. Employees want to know what AI means for their job and income, while businesses are wondering how they can capitalize on the opportunities that AI presents and where investment should be targeted.

Autor (2003) and Frey and Osborne (2013) emphasized its effects on employment due to the automation of some jobs and tasks, which is important for firms seeking to make their business run more efficiently and more rationally. Recently, some authors have shed light on the advantages of productivity gains associated with AI. However, AI technologies allow firms to develop the quality of products and adapt them to consumers and therefore increase their value.

According to Hirst (2014), AI can lead to unemployment of low-skilled work forces causing significant changes in unemployment rate, GDP, inflation and money. AI and Robotics will also be opening new pages in economics and business which are also bringing about new lifestyle and sociological side effects. Stiglitz (2014) studied the possible results and impacts of these effects. In this sense, many analysts are warning that advances in both Robotics and AI over the next few decades could lead to significant job losses or job polarization and hence widen income and wealth disparities (Korinek and Stiglitz, 2017; Méda, 2016).

Overall, existing studies suggest that employment effects specifically from the introduction of robots remained rather limited or - depending on the methodology used - were even positive in the aggregate (Acemoglu and Restrepo, 2017; Bessen, 2017b; Chiaccio et al., 2018; De Backer et al., 2018, Graetz and Michaels, 2015). Only when extending the analysis to developing countries did the introduction of robots produce significant negative effects on employment (Carbonero et al., 2018).

Concerning the recent studies, three primary arguments on the connection between AI and employment can be found by summarizing the literature:

The first effect of AI is the creation and filling of employment. The AI-driven intelligent manufacturing industry paradigm will help create a superior "human-machine cooperation" work environment. Because of the improved labor efficiency and advanced productive forces brought about by the improvement of the division of labor, the lowest class of people in an enlightened society benefits from the social state of shared prosperity. Technological advancements have both price and income effects through increasing production efficiency, lowering the final product's sales price, and promoting social consumption (Shen and Zhang, 2024). This encourages related businesses to increase their production scale, which raises the demand for labor (Sharma and Mishra, 2023). People frequently consider robots to be human competitors, yet this perspective merely reflects the materialistic perception of conventional equipment. It is not a zero-sum game for humans and machines to coexist. Tasks that shift from "cooperation for all" to "cooperation between man and machine" maximize total factor productivity and reduce production limitations, which leads to the creation of new collaborative tasks and additional jobs (Duan et al,. 2023). In addition, realized AI technology may increase the production efficiency between upstream and downstream businesses in the value chain and industrial chain, as well as the overall factor production efficiency in ways appropriate for its factor endowment structure. Its synergy will encourage the synchronous growth of the labor demand involving various skills, which will have a creative effect (Shen and Zhang, 2024). This increase in market efficiency will also drive the expansion of enterprises' production scale and encourage reproduction (Liu et al,. 2022). AI, a key component of the fourth industrial revolution, unavoidably alters the labor force's composition and human social standing (Chen, 2023). By automating repetitive jobs, AI and robotics boost labor productivity while also enhancing employee abilities and elevating the value of labor. Low-skilled jobs will therefore vanish in a machine-for-machine employment model, while new and as-yet-unrealized work categories will arise (Polak 2021). We may even contend that the training of expert robots and the increase in their relative pay are being facilitated by digital technology, artificial intelligence, and robot encounters (Yoon, 2023).

Second, AI affects employment in two ways: negatively and positively. Machines started to compete with workers as soon as they were introduced as a mode of production. Artificial intelligence is a contemporary new technology that is basically intelligent human labor that simplifies complex labor. Similar to early industrialization's disruptive general-purpose technologies, automation technologies like artificial intelligence (AI) raise both hopes and concerns about machine replacement (Shen and Zhang, 2024). The organic composition of capital and the relative surplus population both rise as a result of technological advancement. In relation to its quantity, the new capital created through capital accumulation eventually absorbs fewer and fewer labor. Severe "technological unemployment" will ensue as old capital, which is regularly recreated in accordance with the new composition, starts to progressively exclude the workers it once employed. Increased productivity leads to more free time, particularly in sectors that have benefited greatly from AI, such healthcare, transportation, and industrial environment control (Shen and Zhang, 2024). However, while implementing AI on a wide scale in recent years, certain developed nations have encountered the challenge of decreasing labor income and the sluggish rise of overall labor productivity (Autor, 2019). Automation has a high chance of replacing lost and disabled personnel (Ramos et al,. 2022 ; Jetha et al,. 2023). The fact that some complex, cognitive, and creative jobs that are currently regarded as irreplaceable in the traditional view will also be replaced by AI as a result of the deep development of digital technologies like deep learning and big data analysis shows that automation technology is more than just a replacement for low-skilled labor (Novella et al,. 2023). The manufacturing job market is notably affected by AI and robots, and the disruptive impact of these technologies will result in a serious unemployment issue for jobs associated to this area (Zhou and Chen 2022 ; Sun and Liu 2023). Most economies around the world are currently dealing with the deep integration of the digital wave into their national economies. AI and digitalization are having an impact on all types of labor, including high-level tasks (Gardberg et al,. 2020). As with the industrial revolution, knowledge workers will surely suffer greatly from the rapid growth and distribution of technology, and the strength of AI models is increasing exponentially rather than linearly (Liu and Peng, 2023). Specifically, higher-level employees like researchers, data analysts, and product managers are more at risk from the advancement and development of AI-generated content in recent years than are physical laborers. Unprecedented levels of tension and uneasiness are being experienced by white collar professionals (Wang et al,. 2023).

Third, AI's impact on employment is unpredictable, and its effects on human labor do not fit neatly into either the "utopian" or "dystopian" scenarios; rather, they result in a hybrid of both (Kolade and Owoseni, 2022). At the corporate level, the effects of robotics on job creation and the rise of new jobs brought forth by technological advancement coexist (Ni and Obashi, 2021). Adopting an appropriate AI operation mode can reverse the nondirectional allocation of robots in the labor sector, encourage their reallocation in the manufacturing and service industries, and correct for the market's, businesses', and individuals' misallocation of resources to labor-intensive tasks. According to Tschang and Almirall (2021), and Reljic et al,. (2021), the extent of the influence on employment across the entire society is questionable. For instance, according to Oschinski and Wyonch (2017), only 1.7% of all positions in Canada are readily replaced by AI technology, and they have not yet discovered any proof that automation technology would result in widespread unemployment in the near future. For Wang et al,. (2022), industrial robots have a primarily negative short-term impact on labor demand but a primarily positive long-term impact on employment through job creation. The pessimism behind the notion that AI will significantly reduce the number of employment and quality of language workers is unfounded, according to Kirov and Malamin (2022). As such technology advances, some jobs may be lost, but many more will eventually be created.

Adebayo et al. (2023) have focused on closing the gap between the enormous potential of AI and its successful application in developing nations. They investigate how AI is currently being adopted in developing nations, examining the possible advantages, difficulties, and moral dilemmas. To address infrastructure constraints and skill gaps, the findings highlight the significance of capacity building, public-private partnerships, and customized policy frameworks. To help policymakers, practitioners, and academics navigate this rapidly changing technological landscape, the research adds to a more nuanced understanding of the opportunities and challenges surrounding the implementation of AI in developing nations. Always with the impact of AI on developing countries, From 2012 to 2022, Charles and Nicholas (2024) have examined how AI investment affects employment and economic growth in the BRICS nations, accounting for the moderating effect of both general governance and particular governance metrics like political, institutional, and economic governance, among others. The findings of the study suggest a long-run equilibrium relationship among the variables analyzed in both the employment and growth models. The causality results for the main variables of interest differ in the employment-growth models.

Focusing on low-income countries, Khan et al., (2024) explore the importance of AI by presenting the feasibility of catch-up in these countries. Findings show that there is no one-size-fits-all approach to achieving AI catch-up. Authors make policy recommendations that advocate for the swift integration of AI into critical low-income countries domains such as health, education, energy, and governance. According to this study, these countries must address challenges related to digital infrastructure, human capital and institutional robustness.

3. Econometric methodology

The empirical analysis in this paper is carried out in three steps. First, we present the econometric model through the hypotheses used to reach the equation to be estimated. Second, as a prerequisite to our random coefficients model, we carry out tests for cross-section heterogeneity (slope homogeneity). Third, based on the results from preliminary analysis, we estimate the retained model using the appropriate method.

3.1. Presentation of the Model

To arrive at the econometric model adopted in this study, we start from the simple static problem of the producer behavior which consists in maximizing his profit under the technological constraint of Cobb-Douglas type:

$$Q_{it} = A_{it}^{a} K_{it}^{b} L_{it}^{d} \tag{1}$$

Where we note Q the real output, K the stock of capital and L the used work. b and d represent, respectively, the elasticities of production in relation to capital and labor.

$$b = \frac{Q'}{Q} L = \frac{\frac{\partial Q}{\partial L}}{Q} L \qquad d = \frac{Q'}{Q} K = \frac{\frac{\partial Q}{\partial K}}{Q} K \tag{2}$$

a measures the potential for change in efficiency for each factor. i represents the sector and t the time.

The maximization of firms' profits is conditioned on the one hand by equal levels of marginal labor productivity with wages w and by equal levels of the marginal product of capital with cost c on the other. Using first order conditions, Milner and Wright (1998) express the output by labor factor as follows:

$$Q_{it} = A_{it}^{a} \left(\frac{bL_{it}}{d}\frac{w}{c}\right)^{b} L_{it}^{d} = A_{it}^{a} \left(\frac{b}{d}\right)^{b} \left(\frac{w}{c}\right)^{b} L_{it}^{b+d} \tag{3}$$

The arrangement of this equation and the proposal of vector of variables explaining the employment give an equation object of estimation defined as:

$$L_{it} = \phi_0 + \phi_1 GII_{it} + \phi_3 H_{it} + \mu_{it} \tag{4}$$

Where H represents a vector of variables that can explain employment in the different sectors of the Tunisian economy. The variables used in the econometric analysis were collected by matching four sources. The definition and measuring method are presented in table 1. The descriptive statistics of these variables are presented in Table 2.

Concerning the AI indicator, we choose the global innovation index (GII). Created in 2007 by Cornell University, INSEAD and the World Intellectual Property Organization (WIPO). GII goes further than the indicators traditionally used to measure innovation in a country (R&D spending, number of scientific publications, etc.) and thus focuses more on the interaction between the various agents of the innovation system (enterprises, public sector, higher education and society). The GII index, which can score between 0 (for the worst performances) and 100 (for the best performances), is calculated on the basis of two sub-indicators: inputs (institutions, human resources and research, infrastructures, market sophistication and business environment sophistication) and the outputs (knowledge and technology, creativity) of the innovation system. It is based on a total of 82 basic indicators and is published annually. According to the 2024 GII ranking and for the 14th consecutive year, Switzerland is the most innovative economy followed by Sweden, the United States, Singapore and the United Kingdom. Tunisia is ranked 81st, with Mali, Niger and Angola in last places.

Tunisia's trade in intermediate goods has remained relatively modest despite recent improvements, indicating that the country is not a part of the major global production networks. This may be partially explained by the high degree of protection found in the services industry, which includes important industries like logistics, transportation, and telecommunications. Significant barriers to service trade and inefficient service delivery may cause the nation to fall outside of important international value chains. For instance, in certain industries, decisions about production relocation may be limited by obstacles to establishment (such as the equity limits enforced in many sectors of Tunisia) and movement of persons (such as the requirements for Tunisian nationality for employment in professional services).

3.2. Slope homogeneity tests

Another important point in the random coefficients approach is testing for cross-sectional heterogeneity. To account for the sector specific characteristics, this approach does not allow capturing the heterogeneity, if the slope homogeneity is assumed without any empirical evidences (Breitung 2005; Menyah *et al*. 2014). The null hypothesis of slope homogeneity and the alternative hypothesis of heterogeneity can be described as follows:

$$H_0 : \beta_1 = \beta_2 = ... = \beta_n = \overline{\beta} \tag{5}$$

The statistics allowing the choice between a model with homogeneous slopes or with heterogeneous slopes is defined by:

$$H = \sum_{i=1}^{n} \frac{(\hat{\beta}_i - \overline{\overline{\beta}})' X_i^{'} X_i (\hat{\beta}_i - \overline{\beta})}{s_{ii}} \tag{6}$$

With $\overline{\overline{\beta}} = \left[\sum_i \frac{X_i ' X_i}{s_{ii}} \right]^{-1} \sum_i \frac{X_i ' X_i}{s_{ii}} b_i$. This statistic follows a Chi-squared distribution with $k(n-1)$ degrees of freedom.

3.3. Choice of estimation method

Given that the objective of the econometric study is to estimate the sensitivity of sectoral employment to the development of AI, we need to use models that consider the heterogeneity of the coefficients between sectors of activity. Traditional panel data models assume that the coefficients for all explanatory variables are the same for all periods and all individuals of the sample. In other words, these models assume that the heterogeneity between individuals or periods is not captured by the explanatory variables but is earlier represented either by the constant of the models (individual effects, temporal effects or individual-temporal effects) or by the error term (random effects). This is why this model family is not compatible with the objective of our study. According to conventional models, the heterogeneity of slopes between individuals is not possible. This implicitly implies that all industries in our sample have the same sensitivity to each explanatory variable and to the variable representing AI. Since our sample is made up of different branches of economic activity, it is not realistic to assume that all these sectors react in the same way to the AI development. Random coefficients models appear to be the most appropriate since they consider the heterogeneity of the coefficients of explanatory variables between sectors of activity. Random coefficients models allow modeling the coefficients associated with the different exogenous variables in the form of a stochastic process for each sector of activity.

These models are classified into two categories: Stationary Random Coefficient Models and Non-Stationary Random Coefficient Models. In this section, we present only the Swamy model, which is part of the stationary random coefficients' models (Swamy, 1970). This choice is driven by the fact that models with non-stationary random coefficients assume that the non-stationary random coefficients-whose averages and variances vary over time to represent the variation systematic structure over time are not compatible with our sample, which is characterized by a reduced time dimension (only 13 years).

This econometric model with random coefficients is estimated using the generalized least squares method. The expression of the estimator is written as:

$$\hat{\beta}(\theta) = \left[X'(V(\theta))^{-1} X \right]^{-1} X'(V(\theta))^{-1} Y = \sum_{i=1}^{n} \omega_i \hat{b}_i \tag{7}$$

With $V(\theta)$ is a symmetrical format matrix representing the variances co-variances matrix of the model's random terms vector.

4. Estimation results and economic implication

Before presenting the results of the selected model's econometric estimation, we focus on the data and the definition of the variables used.

4.1. Data description

Tables 1 and 2 present respectively the data (variables and sources) and the descriptive statistics.

Table 1: Data of selected variables

Variables	Symbols	Sources
The quantity of employment	L_{it}	*Tunisian institute of competitiveness and quantitative studies (TICQS)*
The gross fixed capital formation	$GFCF_{it}$	
The openness in terms of the sum of imports and exports	$OPEN_{it}$	*National institute of statistics (NIS)*
The foreign direct investment	FDI_{it}	*Foreign investment promotion agency (FIPA Tunisia)*
The AI indicator In terms of global innovation index	GII_t	*https://www.globalinnovationindex.org/analysis-indicator*

Table 2: Descriptive statistics

Variables		Mean	Std.dev.	Min	Max	Observations	
L	overall	140.557	153.5473	19.297	587.775	N=	143
	between		159.5701	20.70914	526.2644	n=	11
	within		11.15236	114.0336	202.0676	T=	13
GII	overall	33.64286	1.883755	27.9	36.5	N=	143
	between		0	33.64286	33.64286	n=	11
	within		1.883755	27.9	36.5	T=	13
FDI	overall	179.7912	286.9536	0	1317.1	N=	143
	between		280.3404	8.59	1000.316	n=	11
	within		99.78058	-24.1245	730.2097	T=	13
OPEN	overall	5987.904	7126.006	513.9	29690.5	N=	143
	between		7327.033	641.5571	25746.11	n=	11
	within		1154.504	2591.79	9932.29	T=	13
GFCF	overall	895.4338	1230.19	138.7	4783.1	N=	143
	between		1268.342	164.7286	4349.5	n=	11
	within		177.9788	172.5339	1495.091	T=	13

We use annual data over the period stretching from 2010 to 2022 for eleven sectors of the Tunisian economy. The data sources are national (TICQS, NIS and FIPA) when the information concerns the sectors, and international when it concerns the global innovation index.

4.2. Results and discussion

For the econometric study, we choose the random coefficients model, which is estimated with generalized least squares. The table below summarizes the results of the impact of artificial intelligence (GII), foreign direct investment (FDI), openness (OPEN) and investment (GFCF) on global employment and employment by sector.

Table 3: Econometric model estimation results

	Random-coefficients regression

	L(1)	L(2)
GII	-0.37**	-0.40**
FDI	0.05*	
OPEN	0.07	
GFCF		0.04
Cons	1.17***	1.25***

Slope homogeneity test results (1)

Chi-square	**Prob.**
291.73	0.0000

Slope homogeneity test results (2)

Chi-square	**Prob.**
119.88	0.0000

Symbols (1) and (2) refer to the two scenarios of estimated equations according to the selected exogenous variables.

Group-specific coefficients

	L(1)	L(2)
Agriculture and fisheries		
GII	-0.14	-0.57**
FDI	0.08*	
OPEN	-0.32***	
GFCF		-0.36**
Cons	1.25***	1.74***
Energy		
GII	0.07	-0.10
FDI	0.09**	
OPEN	0.12***	
GFCF		0.14
Cons	0.68**	0.90**
Agricultural and food industries		
GII	0.03	-0.08
FDI	0.12***	
OPEN	0.31***	
GFCF		0.40***
Cons	0.54***	0.64**
Ceramic, construction materials and Glasses		
GII	-0.73***	-0.91***
FDI	0.05	
OPEN	0.25**	
GFCF		-0.07
Cons	1.34***	1.76***
Mechanical & electrical industries		
GII	-0.61**	-0.26
FDI	0.02	
OPEN	0.65***	
GFCF		0.46***
Cons	0.87**	0.75**
Chemical industries		
GII	-0.54**	-0.32

FDI	-0.006	
OPEN	0.07	
GFCF		-0.02
Cons	1.47***	1.25***
Textiles, clothing and leather		
GII	-0.51***	-0.11
FDI	0.05**	
OPEN	-0.42***	
GFCF		-0.09
Cons	1.80***	0.99***
Diverse manufacturing industries		
GII	-0.30	-0.08
FDI	0.06	
OPEN	-0.34***	
GFCF		-0.11
Cons	1.48***	1.13***
Telecommunications		
GII	-0.72**	-0.75**
FDI	0.03	
OPEN	-0.04	
GFCF		0.15
Cons	1.34***	1.44***
Banks and insurances		
GII	-0.37	-0.77***
FDI	0.09**	
OPEN	-0.04	
GFCF		-0.34**
Cons	1.26***	1.92***
Other services		
GII	-0.25	-0.42*
FDI	0.01	
OPEN	0.37*	
GFCF		0.10
Cons	0.81**	1.21***

*Note : * 10% significance, ** 5% significance, *** 1% significance.*

We note that the slope homogeneity test results presented in Table 3 confirm the inter-sectoral heterogeneity of the sensitivity of employment to the various explanatory variables of our equations. For both scenarios (1) and (2), the results show that the effect of the AI on global employment is negative and significant. This effect is of the order of 40%. This result can be explained firstly by the direct effects of robotics and automation on a certain type of jobs. Secondly, the measurement of AI by the global innovation index may account for this result because this index is based in its calculation on the degree of innovation which does not exactly reflect artificial intelligence. Further analysis following a division of employment between skilled and unskilled will undoubtedly lead to better results and interpretations based on the effect of compensation between the two types of employment.

The analysis by sector showed the same impact of AI on employment, except for the sectors of energy and the agricultural and food industries where the effects are negative but not significant. Sectoral results can be explained by the lack of detailed data on the selected sectors concerning especially the

degree to which each sector is integrated into the use of AI, which would allow a better quality of estimation and results.
The results obtained do not allow significant economic implications for the important sectors in AI investment. In order to achieve this objective, we are currently carrying out further work on areas that are still relevant to the issue of the AI impact and that deal with growth and productivity.

5. Summary and Conclusion

This paper revisited the relationship between employment and AI for eleven sectors of the Tunisian economy using a random coefficients approach which considers the heterogeneity of the coefficients between sectors of activity of the Tunisian economy for the period 2010-2022. We estimated two equations based respectively on three and two exogenous variables to explain the development of global and sectoral employment. Other variables (such as value added or output, wage compensation, etc.) which necessarily contribute to the explanation of employment were not considered because their effects are trivial.
The empirical results show that AI affects negatively global employment. Concerning the analysis by sector, the slope homogeneity test confirms the heterogeneity of the coefficients of explanatory variables between sectors of activity following the rejection of the null homogeneity hypothesis. This sectoral analysis shows that the positive impact is detected only for the sector of energy and the agricultural and food industries, which is not significant. Some interesting conclusions emerge from this empirical study. First, the most important negative effect concerns the sectors which are based on the use of AI, such as ceramic construction materials and glass, telecommunications and mechanical and electrical industries. Second, this negative impact is not significant for these sectors: agriculture and fisheries, diverse manufacturing industries, banks and insurances and other services.
This diversity has flow-on effects on employment. Therefore, policy makers should take measures to enhance the efficiency of their sectors so that they contribute to the reduction of unemployment, especially for higher education graduates. Several challenges remain for public authorities that should act to improve and optimize the entire innovation ecosystem by organizing public/private dialogues to promote innovative financing and orientation of the education system towards modern science and technology. Concerning administrative barriers, enhancing the legal and fiscal framework for capital investment is advised to enable investment companies in risk capital to effectively benefit from a variety of ways to participate in business capital and make foreign investments.

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