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Internet and Food Production: Panel Data Evidence from North African Countries

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Abstract

Although a considerable body of research has examined the relationship between information and communication technology and the food production process, less attention has been paid to whether internet utilization impacts food production in north African countries. This research sought to investigate the short and long-run relationship between internet utilization and food production in north Africa. Yearly data sets from 4 countries (Algeria, Tunisia, Egypt, and Morocco) were used, covering the period 1990-2021. Given that the tested series are of mixed integrated levels of I (0) and I (I), the study employed a panel autoregressive distributed lag (ARDL) approach. The results show that internet usage and access to electricity favorably influence the food production index in both the long and short run. In the short run, food imports do not exhibit any significant effect on food production. Whereas, in the long-run nexus, a considerable negative impact from food imports to food production is evident. The study concludes that internet usage represents a vital driver of food production and should be further strengthened by making all north African food producers aware of its importance in promoting food productivity. On the other hand, these results serve as a reminder for north African countries to gradually reduce food imports, support domestic food production and move toward food self-sufficiency.

Keywords: Food production; Internet; food imports; access to electricity

1 Introduction

The food industry is one of the largest manufacturing sectors and a key contributor to the economy (FAO, 2022). As food is produced, stored, prepared, packaged, and delivered, it takes a huge amount of resources (i.e., material, labor, electricity, and water) and generates huge amounts of food waste, and generates vast amounts of food waste (Garcia-Garcia et al., 2019; Krishnan et al., 2020), which makes the food sector very inefficient (Jagtap et al., 2021)

North African nations have improved food production and decreased food insecurity over the last several decades. Yields have grown as a result of improved fertilizer and chemical management, improved supply networks, and improvements in machine technology. But several circumstances, including the conflict in Ukraine and its impact on supply chains, COVID-19, and a devastating drought that was the worst in 30 years, have put the Maghreb area in the crosshairs of new and serious food security challenges (FAO, 2022). As a consequence, the challenges of Resource-efficient of food production must be resolved to solve the food security problem.

Food insecurity can also result from reliance on imported food rather than domestically produced food (Kummu et al., 2020). According to Africa Agriculture Status Report (2022), 20% of the food eaten in Africa at the present is imported. The International Food Policy Research Institute estimates that this importation might cost as much as 150 billion US dollars (USD) by 2030, costing between 30 and 50 billion USD annually. Most of this imported food could be produced locally, providing youth and smallholder farmers with much-needed employment and profit. The concern is, how will Africa meet its food demands in the future years?

Africa's food industry, which is now one of the continent's top development objectives, is a major economic problem. The dilemma provided by the food industry has to be addressed by African food producers and consumers. Food losses in sub-Saharan Africa are estimated by the Food and Agriculture Organization of the United Nations (FAO) to total $4 billion yearly (FAO, 2022). Most food loss in Africa occurs between harvest and the point of sale; relatively little is lost by customers after the sale. Lack of cold chain facilities, particularly for perishables, unreliable and inadequate storage facilities, logistics, and a lack of food processing expertise among smallholder farming groups are some of the main causes of food loss in Africa. Several researchers have suggested that resource-efficiency of food production via internet usage can help in tackling these issues (Jagtap et al., 2021)

The literature on information technology and food production in developing countries has argued in favor of how the internet can increase information in food markets and possibly improve market efficiency (Aker, 2010; Aker & Fafchamps, 2015; Ali Chandio et al., 2022; Anadozie et al., 2022; Nakasone & Torero, 2016; Tadesse & Bahiigwa, 2015; Visaria et al., 2015), According to Aker (2010), Aker & Fafchamps (2015), and Akerman et al. (2022) the internet minimizes consumer and producer price dispersion both geographically and across time (supply chain transparency). Transparency has several additional advantages for businesses, such as better inventory management, cost reductions, and shorter lead times. Businesses may reap these advantages by spotting and resolving supply chain inefficiencies, surpassing and adhering to food safety standards, and providing consumers with transparency. According to Anadozie et al. (2022) The exchange of information, social connection, agricultural skills, and knowledge bolstered by mobile phone usage leads to better opportunities for farmers. These opportunities would make life easier for farmers and increase the quality and quantity of food production. In the same vein, The research on ICT and agriculture is mostly focused on agricultural markets, and the majority of the interventions are based on mobile phone technology (Nakasone & Torero, 2016). The empirical study carried out by Ali Chandio et al. (2022) revealed that ICT has a long-term, statistically significant, and favorable effect on agricultural production.

Current studies appear to support the notion that internet utilization has increased dramatically and is now widespread, which has greatly benefited users (Talavera et al., 2017). Real-time generation and consumption of data and services were among the key advantages. The internet of things (IoT) now provides comparable advantages to the items around us. Additionally, it gives us the chance to broaden our perspectives and change our surroundings. Interconnectivity, heterogeneity, stability and scalability, and object-related operations are key IoT properties (Sethi & Sarangi, 2017). The food industry is one of the main areas where IoT is being used. Furthermore, with the fast expansion of the digital economy, it is well-recognized that Internet users get instant access to information; which decreases information-seeking costs and information asymmetry (Zheng et al., 2021).

To the best of the authors' knowledge, although a considerable body of research has examined the relationship between information and communication technology and the food production process, less attention has been paid to the context of whether internet utilization has any impact on food production in north African countries. This research investigates the short and long-run relationship between internet utilization and food production in north Africa using the food production index as a proxy for food production and Individuals using the Internet (% of the population) as a proxy for internet utilization. To accomplish this goal, a panel (ARDL) autoregressive distributed lag model is used. The rest of this study is organized as follows. First, the theoretical background and hypothesis are presented in Section 2. Section 3 provides the data examination and methodology. Section 4 presents the empirical results and discussion. Section 5 concludes with some policy implications.

2 Theoretical background and hypothesis formulation

2.1 Linking internet usage to food production

Numerous scholars have correctly observed the role of the Internet as a new channel that enables its users to get previously inaccessible material. Unlike ordinary mobile phones, any device connected to the internet is not only a communication technology; it is a significant source of knowledge and a great tool for sharing information and experiences. The Internet may thus boost productivity by giving market information and knowledge on other technologies and industrial processes (Ankrah Twumasi et al., 2021; Bi et al., 2022; Di Vaio et al., 2020; Kaila & Tarp, 2019; LeBel, 2008; Ma et al., 2022; ZHENG et al., 2022).

Through a research paper, Kaila & and tarp (2019) have openly questioned: « can the internet improves agro-food production ». The general picture emerging from their panel data analysis is that Internet access is associated with a 6.8% increase in gro-food production, arguing that these results can be reflected in the more appropriate use of fertilizer; Farmers who have access to the Internet can utilize fertilizers more effectively than farmers in locations where the Internet is not accessible. Meaning that food producers have genuinely been able to utilize the internet "as a source of agricultural knowledge" to their advantage to learn about modern inputs. This finding is congruent with the work of Ma, Zheng, and Deng (2022), who have declared a positive association between internet usage and chemical fertilizer, and indicate that the Internet considerably increases behavior towards applying proper fertilizers where social networks positively serve the mediating role. Further, their findings demonstrated that the degree of influence varies owing to changes in the level of education. In addition, the internet now gives information in the form of texts, photos, and videos, allowing farmers to grasp the environmental harm caused by the excessive use of chemical fertilizers and incentivizing them to utilize organic fertilizers. Furthermore, external variables such as government regulation and subsidies, which may be received through the Internet, are critical to modifying farmers' behavior to the best (Li et al., 2022).

Another research assessing the impact of internet growth on food output and restrictions carried out by Bi et al., (2022) found that food production might be encouraged when internet penetration directly improves, as well as through improving technology utilization and boosting operation scale development via the internet. However, the good impact of this cycle may be hampered by rural population aging, since there are several challenges that the elderly confronts while utilizing information and communications technologies (ICT).

According to the research by Di Vaio et al. (2020), the use of internet-based technology, including artificial intelligence (AI), as a sustainable business model (SMB) in the agri-food industry, has the potential to increase food security. Through a qualitative methodology and a thorough examination of the literature, the authors assert that the value chain in the agri-food business will be enhanced by innovatively using the internet in agri-food production. The same piece of research notes that the COVID-19 pandemic highlights the urgent necessity for using internet-based technologies in the agri-food sector to create an effective value chain. This is because modern technologies such as artificial intelligence and the internet of things (IoT) provide the more substantial results required to produce pertinent information that might significantly affect economic models.

The Internet of Things (IoT) is a network of devices that collect and transmit data via the Internet. The food business is gradually becoming familiar with the Internet of Things. With the number of remarkable Internet of Things applications, food suppliers, processors, and retailers is seeing great opportunities for operational and financial enhancement in their food businesses. Recent studies have tended to show how IoT may be used in agriculture for surveillance, control, forecasting, and logistics (Bhingarde & Pujeri, 2023; Jawad et al., 2017; Kaur et al., 2023; Vilas-Boas et al., 2023). According to Jawad et al. (2017), IoT devices in agriculture may be utilized as an agricultural surveillance system by delivering quantitative data with high geographical and temporal resolution. Bi et al., (2022) support the notion that an effective food supply chain lowers product costs, enhances producer revenue, decreases environmental effects, and enables the transportation of fresher and safer goods. The work of Bhingarde & Pujeri (2023) demonstrates that Soil characteristics have an important role in determining soil fertility. Farmers can produce a lot on a little piece of land if they consider the soil characteristics. The Internet of Things (IoT) has made significant contributions to agricultural automation. Farmers can easily assess soil fertility with IoT. Kaur et al. (2023) indicate that farmers can now track soil humidity, crop quality, and many other parameters using different sensors due to the Internet of Things (IoT). As a result of eliminating human interaction via automation, Internet of Things (IoT) technology may make agriculture more efficient, productive, and cost-effective. The Internet of Things is a doorway to the idea of smart farming, which will undoubtedly alleviate issues such as hunger.

The general picture emerging from the previous studies' analysis, is that the use of the internet has several advantages for serving food production. First, the use of the internet of things (IoT) in the food industry has significantly reduced the likelihood of a food-borne disease outbreak. Sensors of various types are utilized to monitor critical manufacturing states, shipping times, and, most importantly, temperature. Real-time temperature monitoring sensors enable enterprises to precisely monitor food safety data points, guaranteeing efficient cold chain control. Second, the distribution chain may be effectively monitored all along the storage and transportation path at the sales locations or shops with the use of RFID (Radio Frequency Identification) transmitters and GPS devices. This also allows businesses to get more familiar with their consumers' tastes, better respond to market demands, and reduce surpluses. In addition, the internet can help food producers to address issues in faster ways, since most maintenance is preventative or reactive rather than predictive, using remote equipment monitoring allows them to identify problems before they arise, saving money and effort as well.

To sum up, these days, the Internet serves as a significant information resource and a tool for technology and education. The Internet offers knowledge and information in a variety of formats, including text, photos, and videos. These arrangements make it easier to inform food producers about the technical aspects of food production in a way that is more quickly comprehended. As a result, throughout the e-learning process, the food industry may increase both the quality and quantity of its output. On the other hand, food producers and consumers may quickly and easily look for the information they need on the Internet, which is a great platform for obtaining the needed information from various sources. Producers may develop better levels of contemporary production abilities as they gain more information, which encourages them to create and innovate more. In general, customers or buyers want transparency from the entities from whom they make purchases. Using traceability and transparency across the global supply chain can help food production flourish by gaining consumer loyalty and confidence. Internet utilization can make it easier for both businesses and consumers to complete the sale and purchase transaction in light of transparency and treatability. Figure 1 depicts how internet utilization affects food production.

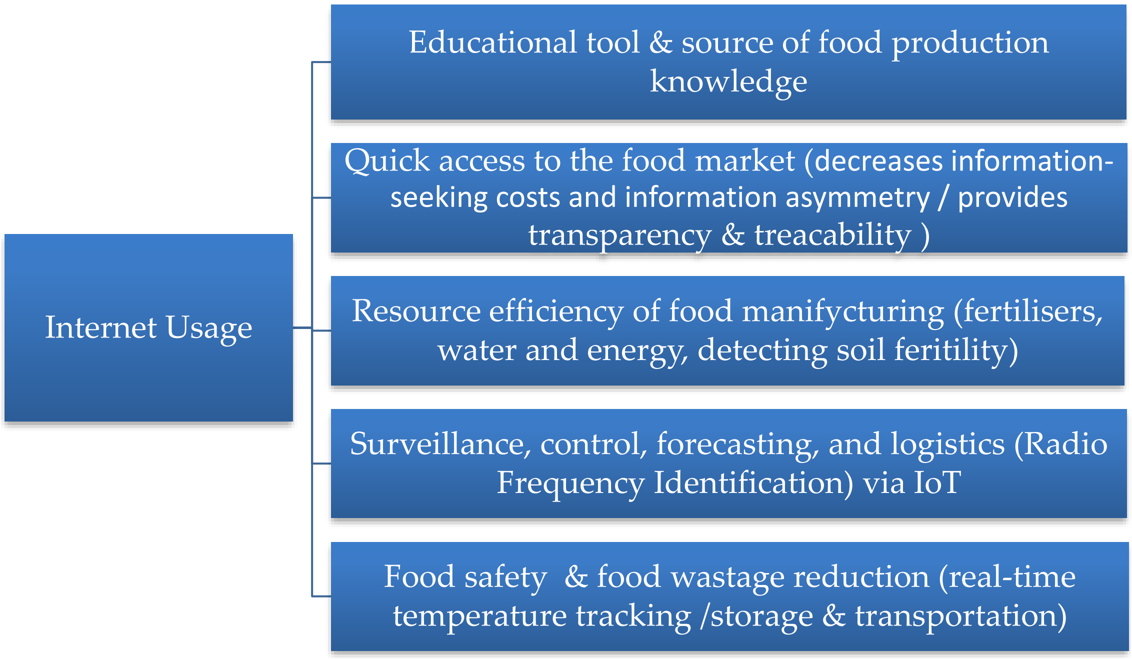


Figure 1 the effects of internet utilization on food production. Source: Author's elaboration

Based on the above discussion, this research suggests the following hypothesis:

H_{1}: Food production is significantly and positively influenced by the use of the internet in the north of Africa.

2.2 *The adverse effect of food import on food production*

Global food exchange has made it possible for many countries to ensure their food supply, overcome local growth constraints imposed by limited natural resources or underdeveloped farming practices, and lessen pressure on resources such as water on a global scale (Porkka et al., 2017). On the other hand, relying on food imports rather than domestic production can lead to food insecurity (Kummu et al., 2020). It ruins local food producers' livelihoods by undermining local food production and exposes low-income households to volatile global food prices.

It has been shown that food imports lower domestic food prices, suppress domestic food production, and dissuade farmers, which lowers food production in importing nations. Importing food at low prices endangers domestic food production and restricts the market for local agricultural goods, which can force many farmers to withdraw and switch to more lucrative activities (Maciej Serda et al., 2002; Odhiambo et al., 2004).

Numerous scholars have found evidence that Food imports skew labor markets, particularly in nations that rely heavily on agriculture for employment (Agustina, 2018). Due to the perception that agriculture in these places pays poorly, less labor will be dedicated to agricultural production, which is likely to reduce agricultural output. The labor is subsequently redirected to the non-agricultural sectors (high degree of rural-to-urban migration) since these endeavors are predicted to provide more revenue that can be utilized to purchase low-cost imported food.

Food import opponents make a variety of claims. First, food imports may have a negative impact on local production since they may result in lower pricing which discourages local producers. Lower pricing may limit the incentives to invest in production due to foreign competitiveness. Hence, the shortage in domestic food production will lead to more reliance on food imports. Second, the quality of food imports may be unexpected since it is determined by policymakers in surplus nations. Another important negative effect of food importing is that it may lessen the urgency of addressing food security issues by expanding food availability [Iseman and Singer, 1977; Ndegwa 1989] which forcedly leads to continuous food dependency.

In light of the above considerations, the following figure summarizes how can food imports affect domestic food production

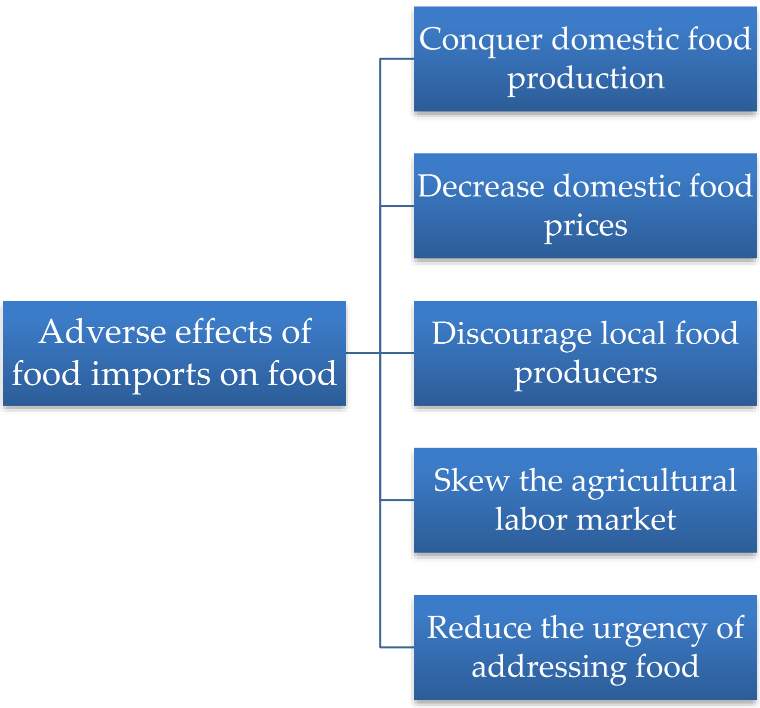


Figure 2 Impacts of food imports on domestic food production. Source: Author's elaboration.

Based on the prevailing literature, the current research brings forward the following hypothesis:

H$_2$: Food imports significantly and negatively influences food production.

2.3 The mediating role of electricity in the food production process

The reason behind including the electricity coverage variable in our model is twofold. First, this variable is considered a mediating variable that affects the relationship between the use of the internet and food production. It is considered a necessary component for the internet (our independent variable) to work. Access to ICTs is only made possible by electricity, and these technologies have the potential to raise agricultural output by enhancing communications and information exchange. Internet usage, for instance, may assist in arranging service providers for land cultivation, and it can be used to advertise new technology or give information on weather predictions that might assist in reducing hazards in agricultural output.

Second, Accessibility to electricity and food production (our dependent variable) are increasingly intimately associated (Candelise et al., 2021). Along the entire value chain in agri-food production, electricity is required for corps production, livestock, fishery, and forestry as well as for post-harvest processing (including manufacturing and preserving food such as cooling, cleaning canning, freezing, pasteurization, and packing, which all would increase resource efficiency and improve the overall food quality). It is also required for food storage and transformation, food transport and delivery, and food preparation (Borgstein et al., 2020).

Greater access to electricity, notably, may improve food quality via cooking and refrigeration, improving production, the efficiency of conversion, and storage of crops and agrifood products (Gupta, 2019). Electrification in rural regions may promote agricultural growth by boosting production (for example, by giving access to water pumping and irrigation) and the efficiency of crop transformation and storage. According to a Practical Action study, there are various ways, that access to power might raise agricultural output (Practical Action, 2012); Electricity may supply mechanical power that would otherwise be mostly given by human or animal energy for land preparation, planting, cultivation, irrigation, and harvesting. This gives farmers the advantage to be more productive and spend less time working. The irrigation potential is significantly influenced by the availability of water, and electricity may enhance water pumping. Last but not least, electricity enables more effective food processing. Food may be preserved (including smoking and forced air drying) and changed into forms with greater quality or additional value (including flour, de-husked rice, olive oil, and sugar). Based on the discussion above, figure 3 summarizes the mediating effects of electricity access on food production.

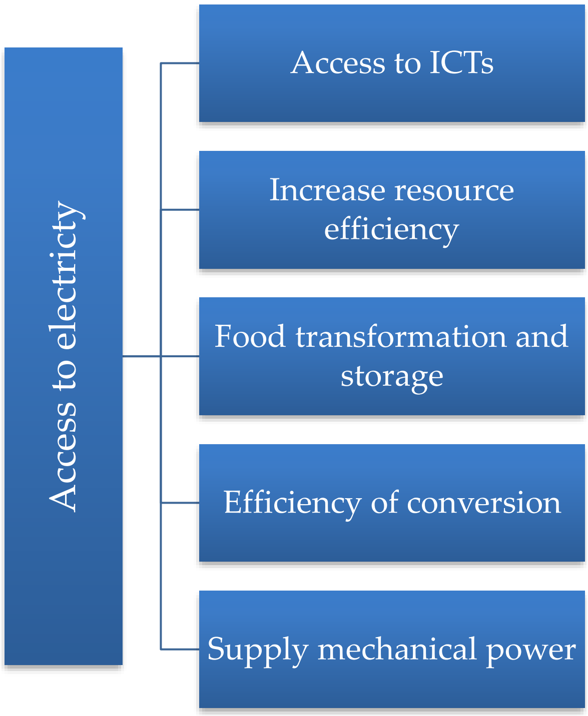


Figure 3 Effects of electricity access on food production. Source: Authors' elaboration.

Given previous considerations, we propose the following hypothesis:

H_3: Electricity access significantly and positively influences food production

3 Data examination and methodology

3.1 Data

The empirical section employs annual time series data during the period (2000 - 2020) from four North African countries, namely; Algeria, Egypt, Tunisia, and Morocco. The whole sequence of data for the identified macroeconomic indicators was selected and gathered from the World Development Indicator (WDI). The variables of interest include the food production index as a proxy for food security, the percentage of individuals using the Internet as a measure of internet utilization, and the Access to electricity to explain the strength of the relationship between the use of the Internet and innovation. Finally, the model employed the food import variable to clarify how food imports affect the countries' domestic food production.

The study 'model is presented in the following equation:

$$\boldsymbol{FPI_{it} = \alpha\_0 + \alpha\_(1)\, NET + \alpha\_2\, ELECT + \alpha\_3\, FOODIMP + \varepsilon\_it} \qquad \textit{(I)}$$

Where:

FPI: Food production index (2014-2016 = 100). According to the Food and Agriculture Organization of the United Nations (FAO): The food production index includes food crops that are deemed edible and that contain nutrients. Coffee and tea are omitted because, while edible, they have little nutritious value.

NET: Individuals using the Internet (% of the population). This variable covers Individuals who have utilized the Internet in the previous three months (from any place). The Internet may be accessed by a computer, a mobile phone, or a personal digital assistant, among other devices.

ELECT: Access to electricity (% of the population); As a proportion of the population, how many people have access to electricity?

FOODIMP: Food imports (% of merchandise imports). According to the Standard International Trade Classification (SITC), this indicator compromise; food and live animals, beverages and tobacco, animal and vegetable oils and fats, oil seeds, oil nuts, and oil kernels.

3.2 Unit root tests and model selection

Selecting the appropriate econometric model is a crucial step of panel data analysis, since incorrect model specification or the use of a wrong approach, often results in biased and erroneous estimations. The unit root test findings, which determine the stationarity of the variable, are used to select the appropriate model to run panel data calculations. Non-stationary time series cannot be analyzed using the same methods as stationary time series. The process becomes straightforward if all of the variables of interest are stationary. In this scenario, unbiased estimates can be obtained using ordinary least squares (OLS) or vector autoregressive (VAR) models. However, OLS or VAR models may not be effective for analyzing the connection if all of the variables of interest are non-stationary (Shrestha & Bhatta, 2018). An additional issue may occur when variables are of mixed order, i.e., some are stationary, and others are non-stationary. The ARDL method can tackle this issue as it does not necessitate all variables to be of the same order of integration I (1).

Taking the stated models above into consideration, we have also to prove that the variables are not integrated into order 2. Otherwise, the bound test would be erroneous in the presence of variables I (2) given that the two sets of critical values estimated by (Pesaran, M. H., Shin, 1999) are based upon the assumption that the variables are I (0) or I (1).

To figure out, we apply the two most frequent unit root tests for panel data, respectively, Im, Pesaran, and Shin test (Im et al. 2003), and the Breitung test (Breitung, 2000).

Im et al. (2003) adopt a heterogeneous unit root under the alternative hypothesis; however, Breitung (2000) presents a pooling panel unit root test that does not need bias correction factors, which is accomplished by suitable (based on the case considered) variable transformations. Additionally, and due to its pooled design, the Breitung test is an assessment against the homogeneous alternative.

Both unit-root test findings are shown in Table 1 and demonstrate that the food production index, internet usage, and access to electricity are not stationary at level, but integrated for order 1 (stationary at the first difference). At the same time, both tests reveal that the food imports variable is stationary at level, which leads us to conclude that the tested series are of mixed integrated level. Relating these results to the work of Pesaran and M. H., Shin (1999), and M.Pesaran and B.Pesaran (1997), We believe that an autoregressive distributed lag (ARDL) model is required to calculate the relationships between the studied variables. The ARDL model is an ordinary least squares (OLS) based approach that can be applied to both non-stationary and mixed-order of integration time series (Shrestha & Bhatta, 2018). This model has enough lags to represent the data generation process in a general-to-specific modeling technique.

Table 1 Stationarity tests

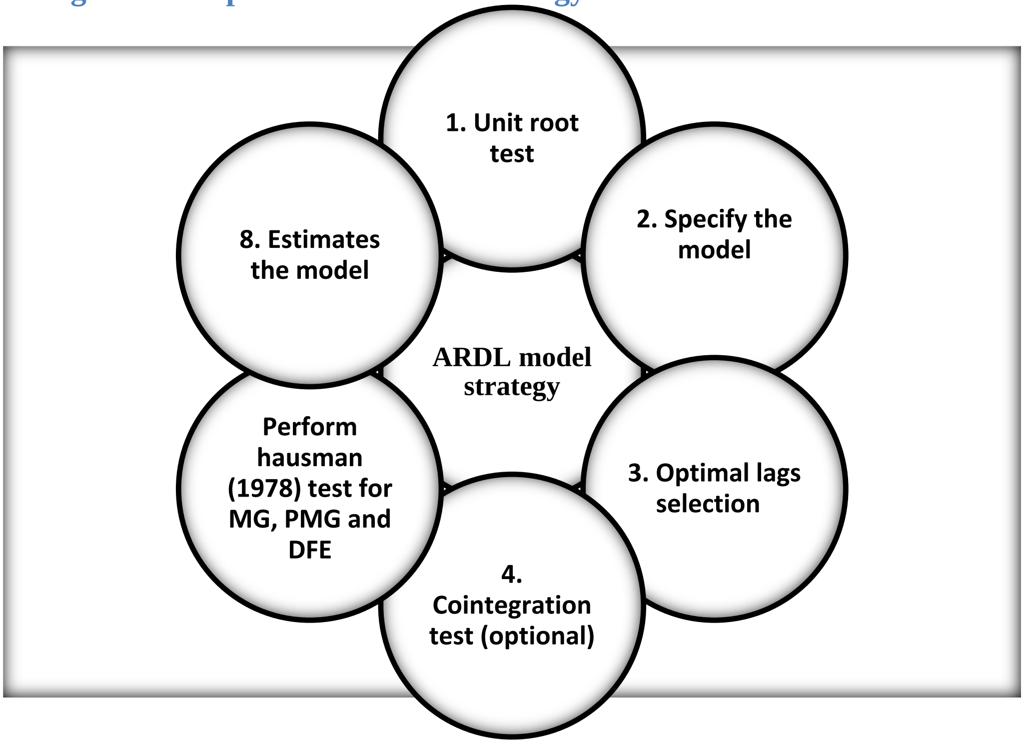
Unit root tests				
Variables	***Level data***		***First difference data***	
	IPS	Breitung	IPS	Breitung
FPI	0.1673(0.5664)	- 2.3091 (0.9895)	-5.8289(0.0000) ***	-3.5341 (0.0002) ***
NET	7.7747 (1.0000)	6.3959 (1.0000)	-2.4232(0.0077) ***	-2.3706 (0.0089) ***
ELECT	-1.0986(0.1360)	1.4780 (0.9303)	-5.8742(0.0000) ***	-1.6570 (0.0488) **
FOODIMP	-2.1388 (0.0162) **	-2.2095(0.0136) **	-----------	-----------
Corresponding P-values are in brackets where: *** p<0.01, ** p<0.05, * p<0.1				

Source: author's computation

3.3 Model specification and methodology

Based on the model's preliminary unit root test, the study is strictly on heterogeneous dynamic panel data modeling. Drawing on the work of (Pesaran, M. H., Shin, 1999) we propose the following empirical strategy demonstrated in figure 4:

Figure 4 The panel data ARDL strategy



Source: Pesaran, M. H., Shin (1999)

In this study, we are mostly interested in the re-parameterized ARDL (p, q, q……., q) error correction model, specified as:

$$\Delta y_{it} = \theta_i \left[y_{i,t-1} - \lambda'_i X_{it}\right] + \sum_{j=1}^{p-1} \xi_{y^2} \Delta y_{i,t-j} + \sum_{j=1}^{q-1} \xi_{ij} \beta'_{ij} \Delta X_{i,t-j} + \varphi_i + e_{it} \quad \textit{(3)}$$

Notes:

- θ_i = - (1- δ_i), group-specific speed of adjustment coefficient (expected that $\theta_i < 0$).
- λ'_i = vector of log-run relationship.
- ECT =$\left[y_{i,t-1} - \lambda'_i X_{it}\right]$, the error correlation term
- $\xi_{ij}\beta'_{ij}$, the short-run dynamic coefficients

The model specification:

$$\Delta FPI_{it} = \theta_i \left[FPI_{i,t-1} - \lambda'_i X_{it}\right] + \sum_{j=1}^{p-1} \xi_{y^2} \Delta FPI_{i,t-j} + \sum_{j=1}^{q-1} \xi_{ij} \beta'_{ij} \Delta X_{i,t-j} + \varphi_i + e_{it} \quad \textit{(4)}$$

The Panel ARDL approach is characterized by massive benefits that it emphasizes and provides the possibility of calculating multiple variables with varying stationary, which is the case of our unit root test outputs. Notably, the ARDL estimators enable one to estimate both short-term and long-term linkages and the coefficient of error correction. A straightforward linear transformation may be used to convert ARDL into a dynamic error correction model (ECM). Likewise, the ECM overcomes issues like spurious correlations caused by non-stationary time series data by integrating the short-run dynamics with the long-run equilibrium without losing long-run information.

Test the null hypothesis of homogeneity through a Hausman-type test, based on the comparison among the mean group (MG), the pooled mean group (PMG), and (DFE) dynamic fixed effects estimators, which is demonstrated in table 2.

Table 2 Hausman test assumptions (Mg, Pmg, Dfe)

MG vs PMG	MG vs DFE	DFE vs PMG
H_0: proposes that the estimates of MG and PMG are not considerably different. PMG More Effective H_1: indicates that estimates of MG and DFE are different. We reject the null hypothesis and chose MG as the ideal model if the "prob-value < 0.05" For all cases, the null hypothesis will not be discarded if the "prob-value > 0.05" determines PMG as the ideal model.	H0: proposes that the estimates of MG and DFE are not considerably different. DFE More Effective H1: indicates that estimates of MG and DFE are different. We reject the null hypothesis and chose MG as the ideal model if the "prob-value < 0.05" For all cases, the null hypothesis will not be discarded if the "prob-value > 0.05" and determines DFE as the ideal model	H_0: proposes that the estimates of DFE and PMG are not considerably different. PMG More Effective. H_1: indicates that estimates of DFE and PMG are different. We reject the null hypothesis and chose DFE as the ideal model if the "prob-value < 0.05" For all cases, the null hypothesis will not be discarded if the "prob-value > 0.05" determines PMG as the most favorable model.

Source: Pesaran, M. H., Shin (1999)

4 Empirical results and discussion

4.1 *Correlation and multicollinearity testing*

To strengthen the results' viability, Food security (FPI), the use of the internet (NET), Access to electricity (ELECT), and Food imports (% of merchandise imports), were all correlated in pairs. The table below displays the significance level, and Pearson coefficient value for each variable in the data set.

Table 3 Pairwise correlations & the variance inflation factor test

Variables	FPI	NET	ELECT	FOODIMP	VIF
FPI	1.000				------------
NET	0.831* (0.000)	1.000			1.35
ELECT	0.351* (0.001)	0.281* (0.010)	1.000		1.34
FOODIMP	-0.258* (0.022)	-0.320* (0.017)	0.237* (0.034)	1.000	1.23
**** p<0.01, ** p<0.05, * p<0.1*					Mean VIF: 1.31

Source: author’s computation

The pairwise correlations’ output reflects a negative correlation between food imports and the food production index which is significant at a 1% significance level. In contrast, a positive correlation exists between internet usage, access to electricity, and FPI.

The variance inflation factor (VIF) determines the existence and magnitude of correlations between independent variables. When the VIF is larger than 5, it indicates a critical degree of multicollinearity where the p-values and coefficients are doubtful (Daoud, 2017). As indicated in table 2, there are no severe correlations between independent variables of our model as long as values (VIF), are not higher than 5.

4.2 Findings and discussion

Table 4 ARDL regression output, lags (1 0 0 0), PMG, MG, and DFE.

	Mean Group Estimation (MG)		*Pooled Mean Group Regression (PMG)*		*Dynamic Fixed Effects Regression (DFE)*	
Variables	ECT	SR	ECT	SR	ECT	SR
ECT		-0.722*(0.370)		**-0.499** (0.24)**		-0.416*** (0.109)
D.Elect		-1.308 (4.687)		4.397* (2.656)		0.539* (0.292)
D.Net		-0.341 (0.237)		0.460* (0.237)		
D.FoodIMP		-1.189 (0.725)		-1.071 (0.703)		-0.111 (0.465)
Elect	0.376 (10.32)		0.583** (0.241)		-0.204(0.553)	
Net	0.401 (0.262)		0.466*** (0.08)		0.716*** (0.15)	
FoodIMP	0.171 (1.071)		-0.451 (0.760) **		-1.463 (0.987)	
Constant		-867.4 (579.0)		14.86*** (4.47)		46.64* (24.14)
Observations	74	74	74	74	.	.
*Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*						
Hausman mg/pmg: Prob>chi2 = 0.9594 *Hausman dfe/pmg: Prob>chi2 = 0.8280*						

Source: author’s computation

Estimation findings of MG, PMG, and DFE models are listed in table 3. These models' outputs provide the short-term and long-term impacts of internet utilization, food imports, and access to electricity on food production. The calculated outcome orientation depends more on PMG, where the Hausman test confirms its significance and reliability over the MG and DFE estimators.

The Error Correction Term related to the pooled mean group regression in table 3 displays a value of is -0.499, which is negative and less than 1. The negative sign demonstrates the propensity stabilities of short-run towards long-run equilibrium. In addition, the results indicate that the ECM is significant at 5% at the level of confidence which affirms the existence of long-term cointegration between the study variables. The ECM's coefficient value (-0.49), suggests a convergence of 49% each year from short-run equilibrium to long-run equilibrium.

The PMG long-run nexus findings reveal that the coefficient of internet usage is 0.446 and highly significant at a 1% level, implying food production can be enhanced to 44.6% by increasing by 1% in internet usage. This result is congruent with the work of many others, where there was an agreement that the use of the internet in the food industry and agriculture boost productivity by providing market information, and knowledge on other technologies and industrial processes (Ankrah Twumasi et al., 2021; Anser et al., 2021; Bi et al., 2022; Di Vaio et al., 2020; Kaila & Tarp, 2019; LeBel, 2008; Ma et al., 2022; ZHENG et al., 2022).

While, food imports display a negative sign coefficient (-0.451), and a significant effect on food production at a 5% level in the long term. This suggests that food production improves at the rate of 45.1% by reducing food imports by 5%. This result is in line with the one carried out by Kummu et al. (2020) who supports the notion that relying on food imports rather than domestic production can lead to food insecurity. More precisely, Food imports decrease domestic food prices, inhibit domestic food production, and discourage producers, resulting in less food production in importing countries. Others suggest that Importing food at low prices impedes domestic food production and limits the market for local agricultural commodities, forcing many farmers to exit and shift to more profitable activities (Maciej Serda et al., 2002; Odhiambo et al., 2004).

Access to electricity has shown a positive significant effect on food production at a 1% significance level, which indicates that increasing 1% access to electricity, will increase the rate of food production by 58.3 %. As argued by Candelise et al. (2021), and Gupta (2019), greater access to electricity improves food quality via refrigeration and storage. Access to electricity boosts food production through the efficiency of conversion, and the supply of mechanical power. Electricity is required for corps production, as well as for post-harvest processing (Borgstein et al., 2020)

Furthermore, Table 3 also provides the findings of the short-run nexus. It demonstrates that food imports have a negative sign of the coefficient, but do not exhibit significance at any level. Therefore, we can argue that there is no short-run relationship between food imports and food production.

In addition, internet usage and access to electricity both reject the null hypothesis at the significant threshold of 10%. This suggests that food production improves by 46% to an increase of 10 % in internet usage, and 439.7 % due to an increase of 10% in access to electricity.

5 Conclusion

Several circumstances, including the conflict in Ukraine and its impact on supply chains, COVID-19, and a devastating drought that was the worst in 30 years, have put the Maghreb area in the crosshairs of new and severe food security challenges (FAO, 2022). As a consequence, the challenges of resource-efficient of food production must be resolved to solve the food security problem. Many researchers have suggested that resource-efficiency of food production via internet usage can help tackle these issues (Jagtap et al., 2021).

This research adds to the literature by investigating the effect of internet utilization, access to electricity, and food imports on food production in north Africa. Thereby highlighting the contribution of the internet in the food industry, along with the risk of food import dependency, which can endanger domestic food production and restrict the market for local food producers.

To meet the research's purpose, we mainly employed a panel ARDL model that considers other estimation issues like cross-sectional dependency and slope heterogeneity. The empirical section employs annual time series data from four North African countries, namely; Algeria, Egypt, Tunisia, and Morocco, during the period (2000 – 2020). The entire sequence of data for the identified macroeconomic indicators was selected and gathered from the World Development Indicator (WDI). The variables of interest include the food production index as a proxy for domestic food production, the percentage of individuals using the internet as a measure of internet utilization, and the access to electricity. Finally, the model employed the food imports variable to clarify how food imports affect local food production.

The pooled mean group estimator (PMG) results demonstrate that internet utilization and access to electricity are vital drivers for long-term domestic food production in north Africa. The PMG long-run nexus findings reveal that food production can be significantly enhanced to 44.6% by increasing 1% in internet usage, where the increase of 1% in access to electricity will increase the rate of food production by 58.3 %. In the short run, food production improves by 46% to an increase of 10 % in internet usage and 439.7 % due to an increase of 10% in access to electricity. This result could be attributed to the significant role that the internet plays in the food production processes (Anser et al., 2021; Kaila & Tarp, 2019). The internet can be used in the food industry as a source of information and communication, training, and a tool for technology adoption and education. Thus, increasing both the quality and quantity of food production capacity, expanding market possibilities, boosting revenue, and breaking the cycle of poverty while achieving food security.

The same applies to the extent of electricity coverage, as it is considered essential for the activation and use of the internet. In addition, electricity is required for corps production, livestock, fishery, and forestry as well as for post-harvest processing (including manufacturing and preserving food such as cooling, cleaning, canning, freezing, pasteurization, and packing, which all would increase resource efficiency and improve the overall food quality). It is also required for food storage and transformation, transport and delivery, and preparation (Borgstein et al., 2020).

However, our study yielded an adverse finding regarding food imports. The study confirms that food import has a significant negative impact on food production in the long term. This result is explained by the fact that Food imports bring high pressure on local producers. Imported food restricts the market for local food production, which can discourage local food producers and endanger domestic food production. Here, we raise a question that could be discussed in future research. What will happen if food-exporting countries stop exporting? Especially if we take the conflict between Russia and Ukraine that has yielded a blockade of both countries' food exports and caused foreign exchange volatility. This incident may serve as a reminder for the studied countries to support domestic food production and move toward food self-sufficiency. Governments should act now to wean their nations off their dependency on imports. To achieve this goal, this research proposes to stimulate domestic food production, the studied countries should direct the use of the internet to the food Industry by sensitizing domestic food producers to the importance of the internet as a modern driver of food production. In addition, Adopting the internet of things strategy as a gateway of smart farming to maximize resource efficiency of food production, hence food security.

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