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ARTICLE

Estimating Labor and Total Factor Productivity in the Jordanian Agricultural Sector

Ahmad Al-Majali

Department of Economics, Business and Finance, Mutah University, Mu'tah, Karak 61710, Jordan

ABSTRACT

This study investigates the Jordanian agricultural sector's labor productivity, technical efficiency, and total factor productivity from 1990 to 2023. It studies the interaction between agricultural output and the factors of production, including labor, capital, and land, while emphasizing the role of economic policy in maximizing output per unit of input. In terms of methodology, the study applied econometric models, including the growth accounting methodology and the vector error correction model (VECM) to analyze the long-run relationship and the data envelopment analysis (DEA) to measure technical efficiency. The results showed that labor productivity and total factor productivity (TFP) in the Jordanian agricultural sector went through three phases. The first was a noticeable decline in the 1990s, followed by an improvement during the period 2000–2011, and then a renewed slowdown after 2011, which was attributed to several factors, including a decline in agricultural investments, restrictions on foreign labor, and rising production costs. The VECM model results indicated a long-term relationship between agricultural output and each of capital, labor, and cultivated land, with labor showing greater importance than the other factors. On the other hand, the results of the DEA showed an improvement in technical efficiency up to 2011, followed by a decline due to the underutilization of economies of scale and weak resource use. The study recommends focusing on policies that support investment in agricultural technologies; It also recommends promoting local labor training and developing agricultural infrastructure to improve efficiency and achieve sustainable productivity growth.

*CORRESPONDING AUTHOR:
Ahmad Al-Majali, Department of Economics, Business and Finance, Mutah University, Mu'tah, Karak 61710, Jordan;
Email: majalia@mutah.edu.jo

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1. Introduction

Jordan's agricultural sector is vital to food safety and employment opportunities in rural and economically challenged areas. Despite its importance and commitment to implementing support policies, this sector faces numerous challenges, including low productivity, limited natural resources, and great reliance on informal and foreign labor. Analyzing labor productivity and the overall productivity of factors in the agricultural sector is important to increase production efficiency. This analysis will bring recommendations to help policymakers improve the economic policies of agricultural development and labor productivity.

The problem statement is that despite increased agricultural employment in Jordan, labor and total factor productivity (TFP) have not experienced sustained growth. Most existing studies have failed to quantitatively evaluate the technical efficiency and long-term relationships between agricultural output and key inputs in Jordan using advanced methodologies such as Data Envelopment Analysis (DEA) and Vector Error Correction Model (VECM). Furthermore, the impact of recent government policies, such as restrictions on foreign labor and the limited promotion of technological investment, remains underexplored regarding their effect on productivity and sector performance. Given this research gap, this study is based on the hypothesis that there is a long-term relationship between agricultural production in Jordan and key production factors, namely labor, capital, and agricultural areas. In addition, labor productivity significantly influences the effectiveness of the agricultural sector and is a decisive factor in its future growth. Economic policies, including regulations governing agricultural labor and incentives for technological investment, play an important role in shaping the overall productivity of factors in the Jordanian agricultural sector. The recent slowdown in productivity emphasizes the need for restructuring economic policies to ensure the sustainability of this industry.

This study aims to analyze labor productivity trends, measure technical efficiency, and assess the overall productivity of factors (TFP) in the Jordanian agricultural sector from 1990 to 2023. It also seeks to assess the relationship between agricultural value in Jordan and its key inputs, labor, and land space vector errors. This estimate will reduce the overall productivity of factors and assess agricultural efficiency over time through DEA, identification of the period of improvement, and a decrease in the effectiveness of the sectors. In addition, the study intends to provide political recommendations to increase agricultural productivity by adjusting labor policies, stimulating agricultural investment, and developing productive infrastructure.

This study's importance lies in its comprehensive analysis of agricultural productivity, which is essential for improving government economic policies, especially regarding rare natural resources and severe dependence on imports to meet food needs. The finding could serve as a scientific basis for developing policies that support increased agricultural production without expanding agricultural land or exhausting water resources.

The expected results of this study will guide policymakers in developing more effective strategies for managing agricultural labor, especially considering recent regulations on labor permits for foreign labor and their effects on productivity. Additionally, the findings can provide recommendations for supporting farmers in adopting modern agricultural technologies, thereby promoting economic sustainability and increasing the agricultural sector's contribution to GDP. This study is organized into five main sections, in addition to the introduction. The second section presents the theoretical framework, while the third section details the methodology, data sources, and economic analysis techniques employed. The fourth section analyzes the results, and the final section offers discussion and recommendations.

2. Literature Review and Previous Study

2.1. Literature Review

2.1.1. Labor Productivity

Productivity, measured in different ways, is an economic indicator of how efficiently production inputs are used, whether in different sectors or at a domestic level. It is considered a key tool for evaluating economic performance and optimizing production factors, especially labor, capital, soil, and technology. The combination of these inputs creates total productivity that is closely associated with macroeconomic policies that increase economic growth, competitiveness, and productivity [1].

As the main stage of partial productivity, labor productivity is one of the most widely used indicators to analyze labor market performance. It reflects the output created by every work and depends on factors such as skills and level of experience [2]. It is necessary to enable work to use modern methods and technologies to improve productivity. In addition, the working environment affects organization and coordination and creates an environment that supports creativity. The support infrastructure also plays a key role in production [3].

Increasing labor productivity means increased economic efficiency and greater production capacity without other human resources, thus reducing production costs and improving economic competitiveness [4]. As a result, increasing productivity is a national priority supported by governments through macroeconomic policies that support education and vocational education, improve the business environment and stimulate investments. These policies directly contribute to increasing the efficiency of work and their ability to effectively participate in economic growth [5].

Partial measures for productivity evaluate the efficiency of individual factors such as soil capital and productivity. These metrics provide insight into the performance of various industries and help identify the factors that control their growth. For example, a decrease in capital productivity in this sector may signal insufficient investments [6]. Agriculture increases the use of tractors, spray and irrigation machines and modern techniques of agricultural productivity, which increases labor productivity. Similarly, soil productivity often reflects the acceptance of advanced agricultural techniques that cause more limited soil. Overall, partial productivity analysis informs about economic policies aimed at improving resource use and increasing production efficiency in various sectors [7].

2.1.2. Total Factor Productivity (TFP)

In the combined contribution of partial productivity, they contribute to the TFP, a more comprehensive indicator of economic efficiency in converting all production inputs into outputs. This measure emphasizes the ability of the economy to optimize resources through innovation, better management, and advanced production methods [8]. The key factors affecting overall productivity, especially in agriculture, include technological progress, effective sources allocation, and adequate agricultural infrastructure. Improving overall productivity is the primary goal of government policies because it supports sustainable economic growth without the need for a significant increase in production inputs. This increases the ability of the economy to achieve a higher level of productivity in the agricultural sector and, at the same time, reduces costs, increases efficiency, and increases competitiveness [9].

2.1.3. Technical and Economic Efficiency

Economic efficiency is essential to measure productivity in all its forms. It refers to the ability of the economy to maximize production and, at the same time, use the smallest number of resources. Economic efficiency can be divided into several types [10]. Technical efficiency reflects the capacity of the production system to achieve the highest production level from available sources without waste and with optimum use. Allocation efficiency concerns the ability of the economy to distribute its resources in a way that maximizes economic and social benefits [11]. The effectiveness of the scale measures how well the economic entities achieve the optimum production level compared to their size, commonly known as savings of the extent. Some sectors may encounter decreasing returns on the scale if they extend to a certain point without achieving further operational efficiency, while others may experience increasing yields to the scale [12].

2.1.4. Role of Economic Policy in Enhancing Productivity

Government macroeconomic policies also influence economic effectiveness. Government's ability to strengthen the investment environment, promote research and development, and provide incentives for productive sectors [13]. Monetary and fiscal policies can directly affect productivity by facilitating access to available financing of productive enterprises and stimulating innovations through tax incentives for investment in research and development. In addition, business policies significantly increase productivity by opening markets to local products and encouraging the production industry to adopt higher quality standards [14].

Due to the limited availability of natural resources such as arable land and water in agriculture, it is necessary to increase the labor and productivity of capital. This improvement will increase the overall productivity of factors and economic efficiency [15]. Such progress is closely linked to the policy of the government's support, including the provision of training, creating a favorable working environment, and supporting investment in agricultural technologies that increase production efficiency and reduce resources [16].

2.2. Previous Study

Numerous studies have examined the growth of TFP and labor productivity in the agricultural sector. These studies focus on their determinants using various measurement methods and assess the impact of economic and technical factors on their development across different countries and sectors. Using panel data, Hsu et al. (2003) examined TFP growth in China's agricultural sector [17]. They computed the Malmquist productivity index and its components through DEA while employing Tobit regressions to identify key determinants of TFP growth. Their findings revealed that overall TFP growth was sluggish, as government tax policies and R&D investments did not significantly boost productivity, efficiency, or technical progress. where Tewari and Kant (2005) estimated an unconstrained translog cost function and used duality theory in production and cost to examine the production structure of South Africa's agriculture industry [18]. They evaluated several model limitations, including Hicks-neutral technological change, homotheticity, homogeneity, and unitary elasticity of substitution, but they were all deemed statistically unimportant. Land is the most readily replaced component, while fuel is the most difficult, according to their study's calculations of Allen Elasticity of Substitution (AES) and Morishima Elasticity of Substitution (MES). Despite growing returns to scale, the data revealed a negative increase in TFP since technological development had a detrimental impact on agriculture. Likewise, Tipi and Rehber (2006) measured technical efficiency and TFP growth in Turkey using the DEA model and the DEA-based Malmquist TFP index [19]. Their findings revealed an average technical efficiency score of 88.3% and a Malmquist TFP growth rate of 3.1% over the study period. In addition, Akpan et al. (2011) analyzed TFP among waterleaf farmers in Nigeria and utilized a Cobb-Douglas production function to assess output elasticity and production scale [20]. They also used Ordinary least squares (OLS) regression to estimate TFP. The results discovered decreasing returns to scale (DRS) for both crops, with farm size, hired labor, income, and access to credit significantly impacting TFP. Furthermore, to examine the impact of NAFTA on agricultural productivity in the United States, Canada, and Mexico, Yeboah et al. (2011) estimate the DEA model and the Malmquist Productivity Index [21]. Their analysis compared TFP, technical change, and efficiency change before and after NAFTA's implementation in 1994. The conclusions showed that TFP increased by 1.6% yearly among NAFTA countries, driven primarily by technical improvements. While TFP showed no significant change before NAFTA, it rose by 2.7% in the post-NAFTA period.

Hamid and Ali (2012) investigate the determinants of TFP in Iran's agricultural sector utilizing growth accounting analysis [22]. Findings show a robust relationship among TFP and its determinants, with human capital contributing 30% and capital contributing 55% to TFP growth. Also, Khaledi and Shirazi (2013) studied the factors necessary to achieve 7% economic growth in the agricultural sector in Iran, using an economic growth approach to estimate the contributions of capital, labor, and total productivity to agricultural growth [23]. Their results showed that agricultural value added is influenced by labor, capital stock, and total productivity. Achieving the target requires growth of 1.9% in labor, 0.9% in capital, and 4.2% in total productivity. Karbasi (2013) also estimates TFP growth in Iran's agricultural sector using the Auto-Regressive Distributed Lag (ARDL) approach and a Cobb-Douglas production function that includes labor, capital, and energy as inputs [24]. The findings indicate elasticities of 1.04 (labor), 0.16 (capital), and 0.70 (energy) in agricultural production. The TFP growth rate contributes only 0.33% to the sector's overall economic growth rate of 4.43%. To examine TFP growth in Turkish agriculture, Ozden (2014) utilizes the DEA model and the DEA-based Malmquist TFP index [25]. The findings indicate an average TFP growth rate of –5.6%, primarily attributed to technological change rather than improvements in technical efficiency. The study highlights the need for technological advancements to reverse the decline in productivity and enhance Turkey's agricultural sector's performance. Additionally, Gautam and Yu (2015) provide a comparative analysis of agricultural TFP growth in China and India using different analytical models [26]. In China, a parametric output-based distance function with a translog stochastic frontier model is used, while in India, the DEA model and growth accounting are applied at the state level. The findings show that TFP growth exceeded 2% annually in China and ranged between 1–2% in India, driven mainly by technological advancements, though efficiency remained stagnant. Regional disparities exist, with rapid TFP growth in North and Northeast China and South and East India.

Frija et al. (2015) estimate TFP growth in Tunisia's agricultural sector using the Tornqvist TFP index to measure productivity and assess its key determinants [27]. The findings reveal high TFP fluctuations, primarily due to variability in agricultural output, which highlights the sector's dependency on climatic conditions. Structural factors, such as the share of cereal cultivation in total cropped areas and rural GDP growth, were found to negatively impact productivity gains. Abouzeid (2016) also estimated Malmquist productivity indices using the DEA model for 165 countries across eight regions from 1980 to 2007, classified into eight groups based on agricultural gross production value [15]. The analysis assesses TFP growth, considering resource allocation, modernization, technological change, and catch-up effects in agriculture. The Malmquist TFP index measures productivity changes by comparing distance functions between two data points. Using FAO data, the study also evaluates technical efficiency, technical efficiency change, and technical change at both regional and global levels to understand agricultural productivity dynamics worldwide [15]. Also, Dhehibi et al. (2016) estimated TFP in the Egyptian agricultural sector using the Tornqvist index methodology to estimate total productivity growth, technical efficiency, and technological change [28]. Their results showed that rural development variables negatively impacted agricultural productivity and that low-income levels led to reliance on low-productivity labor. Furthermore, they indicated that poor infrastructure impacted productivity gains.

Furthermore, Basit et al. (2016) estimated the total productivity growth in the Turkish agricultural sector using the Dependent Economics (DEA) model, the Malmquist productivity index, and a growth accounting approach [29]. The results showed that the total productivity of the agricultural sector in Turkey grew by 28.8% during this period, with an annual growth rate of 2%. The study emphasizes the importance of applying multiple estimation techniques to ensure effective results and provides insights into improved agricultural efficiency in Türkiye. Moreover, Jain et al. (2017) analyzed total productivity growth in the crop sector using the Tornqvist Sustainability Assessment Index (TSAI) [30]. Their results indicated that total productivity growth during the recovery phase (2004–2005 to 2011–2012) was 5.41%, with TPI contributing approximately 88% of price output growth. Their study concluded that agricultural productivity growth is likely sustainable, driven primarily by technological progress rather than intensive input use. The study of Khee et al. (2017) analyzed agricultural productivity in eight ASEAN countries, using a growth accounting approach and the Malmquist DEA index to estimate total productivity [31]. Their results indicated that ASEAN countries collectively achieved an average total productivity growth of 1.5% per year, with Malaysia leading in TPI growth, while Cambodia, Laos, Myanmar, and Vietnam (CLMV) lagged.

Madau et al. (2017) evaluated technical efficiency and TFP changes in dairy farms across 22 EU countries from 2004 to 2012, using DEA [32]. The analysis examines farm performance adaptations to the relaxation of the milk quota regime and assesses technical conditions before the quota abolition. The findings indicate limited potential for efficiency improvements using existing technical inputs and show a decline in TFP in the European dairy sector. This suggests that external factors, rather than efficiency improvements, will play a larger role in shaping future productivity and profitability in the EU dairy industry.

Derbas and Al-Qudah (2018) studied the impact of technology on the Jordanian agricultural sector using the Cobb-Douglas linear regression model [33]. Their results indicated that labor and capital have a positive, albeit statistically insignificant, impact on the agricultural sector. They also found that agricultural production operates under diminishing returns to scale (DRS), meaning that output growth lags behind increases in labor and capital. They also found that technology has a negligible impact, likely due to agricultural workers' low knowledge and skills. The study recommends promoting advanced agricultural technologies to enhance productivity and efficiency. Similarly, Wang et al. (2018) analyze TFP convergence in China's farm sector using multilateral TFP panel data [34]. The results indicate no evidence of σ convergence but strong evidence of β convergence, with estimated rates ranging from 0.016 to 0.039, depending on regional heterogeneity. Additionally, higher growth in education, R&D, capital/labor ratio, and intermediate goods/labor ratio positively influences TFP growth. Likewise, Le et al. (2019) evaluate agricultural productivity and environmental efficiency in nine East Asian countries using DEA, the Malmquist TFP index, and the Slacks-Based Measure (SBM) approach, considering undesirable outputs [35]. The findings reveal significant differences in productivity growth and environmental efficiency across countries. Overall, TFP declined due to decreases in technical efficiency. Taiwan, Japan, and Korea exhibited productivity growth and high environmental efficiency, while Thailand scored lowest. The study suggests that agricultural models from Taiwan, Japan, and Korea could be benchmarks for improving sustainability and efficiency in other East Asian countries.

Giang et al. (2019) examine TFP in Vietnam's agricultural sector using panel data [36]. The findings reveal that large firms (>300 employees) have significantly higher TFP (+38.8%), while small and very small firms exhibit negative TFP (−71.3% and −32.1%). Foreign ownership (3.8%) positively impacts TFP (+55.0%), whereas state ownership (30.7%) has a negative effect (−7.5%). Exports contribute marginally (+2.6%), reflecting limited export activity. Bank loans (73%) and Internet access (18.2%) positively influence TFP (+18.5% and +3.4%). The fixed effects model is preferred for TFP estimation. Similarly, Rey and Hazem (2020) examine macroeconomic and sectoral productivity and estimate capital stock using the permanent inventory method to infer TFP trends [37]. The findings indicate that economic growth was primarily driven by increased production factors, particularly labor, rather than labor productivity growth, which remained limited. Also, Ngo et al. (2024) examine TFP growth in China's agricultural sector using the index method based on a gross output model for crop and livestock industries [38]. By analyzing 26 key agricultural commodities, representing over 90% of total inputs and outputs, the findings reveal that China's agricultural TFP grew at an annual rate of 2.4% before 2009, comparable to OECD countries and double the global average. TFP growth contributed 40% of total output growth, with input expansion being the primary driver. However, productivity growth slowed after 2009 before gradually recovering in 2012, indicating emerging challenges in farm production and the need for further institutional reforms.

Lee (2020) examines agricultural production in South Korea, focusing on rice production using county-level data from statistical yearbooks [39]. Lee analyzes the role of land, labor, agricultural machinery, and chemical fertilizers in shaping agricultural productivity. The findings indicate that land and labor inputs explain over 95% of variations in rice production, with land being the dominant factor. Capital inputs, particularly agricultural machinery (power tillers, auto sprays, and tractors), played a role but accounted for only 3% of production variations. To analyze the impact of agricultural trade liberalization on TFP growth in Africa's agricultural sector, Sunge and Ngepah (2020) used panel data from 13 countries [40]. It employs the Malmquist-DEA approach to measure TFP growth for maize and rice and applies a dynamic fixed effects model with an autoregressive-distributed lag (ARDL) model. The findings indicate declining TFP growth for both crops, with domestic agricultural support boosting output but negatively affecting productivity. Aso will analyze agriculture's total productivity (TFP) growth for 79 countries over approximately 60 years. Bravo-Ortega (2021) will estimate productivity trends and identify key determinants [41]. Findings reveal significant cross-country variations, with leading nations achieving annual TFP growth rates between 2% and 3%. The study examines the influence of infrastructure, macroeconomic factors, and climate change on productivity growth, showing small within-country effects but substantial between-country differences.

BiLiŞiK (2022) evaluates the performance of the agricultural sector in MIKTA countries (Mexico, Indonesia, South Korea, Turkey, and Australia) using DEA and the Malmquist Total Factor Productivity Method (MTFPM) to assess agricultural efficiency [42]. Inputs include agricultural land, rural population, and rural population percentage, while agriculture, forestry, and fishing value-added serve as the output. The analysis identifies super-efficiency scores and detects ineffective countries within MIKTA. The findings highlight agricultural growth risks due to climate change, economic shocks, and global disruptions, emphasizing the need for improved agricultural productivity in these economies.

Also, Zhou et al. (2023) evaluate Agricultural Green Total Factor Productivity (AGTFP) in China using an epsilon-based measurement data envelopment analysis (EBM-DEA) model for 31 provinces [43]. It applies social network analysis (SNA) to examine AGTFP network structures and uses the quadratic assignment procedure (QAP) to identify influencing factors. The findings reveal that AGTFP increased from 0.75 in 2002 to 0.90 in 2020, with regional disparities. The AGTFP network is complex and stable, with eastern and central provinces as key hubs. The network is divided into eight blocks, including net beneficial and spillover regions. Key influencing factors include transportation development gaps, technological progress gaps, and similarities in the structure of the agricultural industry. Policy recommendations include enhancing logistics efficiency, facilitating technology transfer, and promoting regional agricultural specialization to support sustainable agricultural development.

Sapolaite and Balezentis (2023) analyze agricultural TFP growth in EU countries using sector-level data from EU KLEMS, EUROSTAT, FAOSTAT, and USDA [44]. It examines TFP measurement, relevant data sources, and key growth drivers. The findings indicate that TFP increased in nearly all EU countries, playing a crucial role in agricultural labor productivity and value-added growth. However, differences among the databases in input-output levels and TFP growth rates are noted. The study highlights the importance of TFP in driving agricultural efficiency and economic performance across EU nations. Additionally, Сеитов and Seitov (2023) analyze TFP in Russia's agricultural sector to assess regional efficiency and growth disparities [45]. The findings reveal regional differentiation in TFP, with Pskov, Penza, Oryol, and Ryazan oblasts showing the highest growth, while Tyumen, Sakhalin, Primorsky, and Stavropol krais lag. Investment, technological progress, and rising TFP rates are key drivers of long-term agricultural growth. However, sustaining high TFP growth depends on effective innovation implementation. Moreover, Kuznietsova et al. (2023) examine TFP and multifactor productivity (MFP) in Ukraine's agricultural sector, using an index approach to analyze the relationship between TFP and resource costs [46]. The findings indicate that agricultural output has increased in absolute terms, but TFP has declined, reflecting reduced sector efficiency. Key factors contributing to this decline include increased labor input and changes in soil moisture conditions. The study systematizes methods for estimating MFP, explores the reasons for declining productivity, and identifies key factors influencing productivity growth in Ukraine's agricultural sector, emphasizing the need for strategic efficiency improvements.

Additionally, Yaman et al. (2024) analyze TFP in the agricultural sector across 81 provinces in Turkey from 2009 to 2019 using the Malmquist Index method [47].

The results indicate that agricultural productivity increased in 75 provinces and decreased in 6, with index values ranging between 1.186 and 0.952. Findings confirm that technological change is the key driver of productivity growth across all provinces. From a policy perspective, the study suggests developing and implementing advanced agricultural technologies, enhancing infrastructure, and promoting research. Additionally, it recommends revising the regional incentive system to reward performance and efficiency-based agricultural development. Finally, Ngo et al. (2024) propose a shadow price Fisher ideal TFP (SPFI) index as an alternative method to estimate TFP growth when price data is unavailable, using DEA [38]. A Monte Carlo experiment demonstrates that SPFI effectively estimates the true Fisher ideal TFP index (FI) with minimal errors. The empirical application to U.S. agriculture (1948–2017) confirms that SPFI outperforms the traditional Malmquist DEA, particularly for unbalanced panel or time series data where price information is missing. The study highlights SPFI's reliability as a superior method for TFP measurement in such cases.

3. Data and Methodology

3.1. Data

The study utilizes data from Jordan's agriculture sector covering the period from 1990 to 2023. to estimate total productivity (TFP) and technical efficiency. According to the available data, employment in the agricultural sector has witnessed a significant increase in absolute numbers, rising from 38.2 thousand laborers in 1990 to 101.6 thousand laborers in 2023, with an average annual growth rate of 4.9%. However, this increase in the number of laborers does not necessarily reflect a rise in Jordanian laborers in the sector. Additionally, the agricultural sector in Jordan has one of the highest proportions of informal labor compared to other economic sectors. Women laborers informally in the sector constitute 16%, while men account for 5%. Moreover, most agricultural laborers are seasonal, temporary, or family members, with seasonal laborers making up 8%, temporary laborers 50%, and non-Jordanian laborers 67%. The Jordanian agricultural sector remains unattractive to local labor due to the harsh conditions of laborers, the lack of social security, and the absence of job stability and security. **Figure 1** illustrates the number of laborers in the agricultural sector in Jordan, reflecting the trends and developments in employment within this sector.

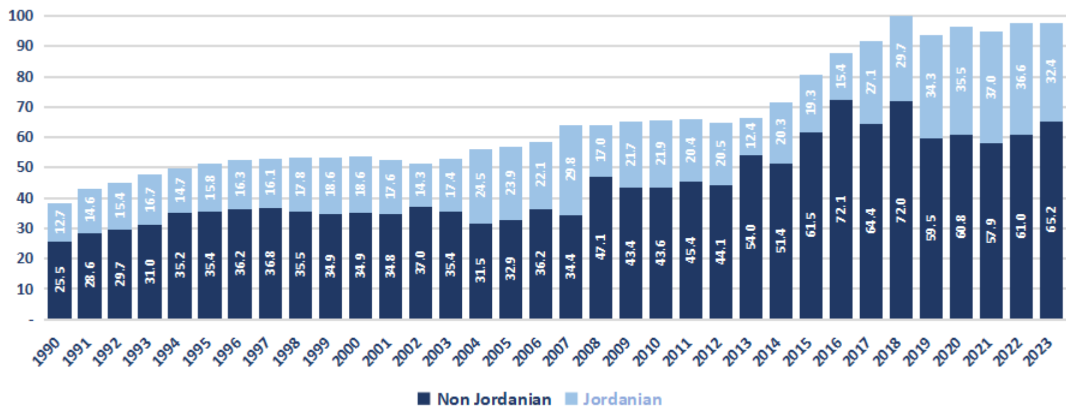

Figure 1. Labor Force in the Agricultural Sector in Jordan (Thousands).

Source: Department of Statistics, Labor Statistics.

Figure 2 indicates that the agricultural sector faces significant challenges in attracting local labor, as it primarily relies on non-Jordanian laborers, who constitute a substantial portion of the total labor force. The gap between local and foreign labor widened considerably between 2008 and 2016. However, this gap began to narrow after 2016 due to strict government regulations on agricultural labor permits, aimed at controlling the recruitment of foreign labor and limiting its migration to other sectors with high demand for local laborers. These measures included restructuring labor permits and imposing stricter conditions, which led to a decline in the number of foreign laborers in agriculture. However, this decline was not accompanied by a significant increase in local labor participation, highlighting the sector's continued struggle to attract Jordanian laborers. This ongoing challenge underscores the need for more effective incentive policies to ensure a sustainable agricultural labor force.

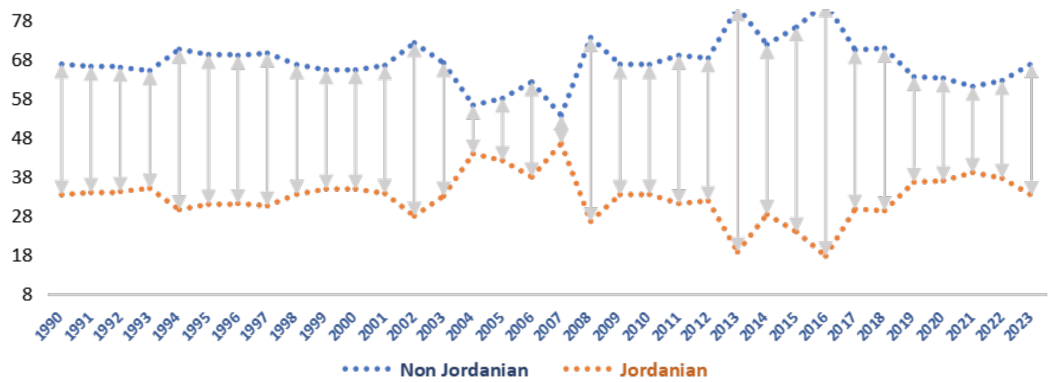

Figure 2. Labor Force in the Agricultural Sector in Jordan (%).

Source: Department of Statistics, Labor Statistics.

When comparing the share of labor in the agricultural sector to the total labor force in all sectors in Jordan, we find, as shown in **Figure 3**, that the percentage is declining, indicating that the agricultural sector in Jordan is not attractive to labor. The percentage of labor in agriculture decreased from 4.9% in 1990 to 1.7% in 2011 and remained at approximately the same level until 2023. The decline in agricultural labor can be attributed to several factors, most notably low wages, a lack of financial incentives compared to other professions, the seasonal nature of agricultural jobs, and harsh working conditions, which make the sector less competitive in the labor market. There is also no doubt that rural-to-urban migration has significantly reduced reliance on agriculture as a primary source of income, especially with the expansion of sectors such as trade, construction, and services, which have become more attractive to Jordanian workers. Although the agricultural labor force has remained relatively stable since 2011, this does not indicate an improvement in working conditions. Rather, it highlights the sector's continued inability to attract local labor without effective policies encouraging participation. Addressing this challenge requires new policies to improve the agricultural work environment, such as providing financial incentives, improving working conditions, and providing social security guarantees to attract more Jordanian workers to this vital sector.

Regarding agricultural land areas in Jordan, **Figure 4** illustrates that agricultural land is limited and faces several challenges, the most significant of which include urban expansion, changes in land use patterns, and the lack of large-scale government programs for land reclamation, which reduce the available land for agriculture. On the other hand, Jordan relies heavily on intensifying production within existing agricultural areas rather than horizontal expansion due to the scarcity of natural resources, particularly water, which is a crucial factor in determining the extent of cultivated land each year.

Regarding investment in the agricultural sector, modern farming is known to rely on technology and machinery to enhance productivity. According to available data, as illustrated in **Figure 5**, the Gross Fixed Capital Formation (GFCF) in the agricultural sector, which reflects expenditures on improving agricultural infrastructure, purchasing equipment and machinery, land reclamation, and developing irrigation systems, has a direct impact on boosting productivity and increasing the sector's efficiency.

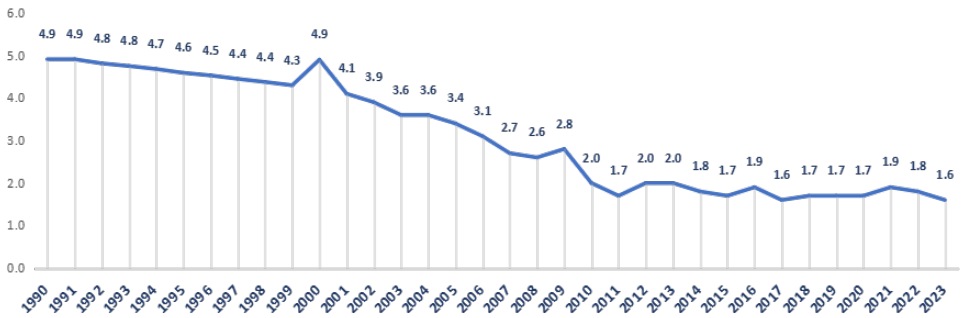

Figure 3. Laborers in Agriculture (% of Total Employment) (%).

Source: Department of Statistics, Labor Statistics.

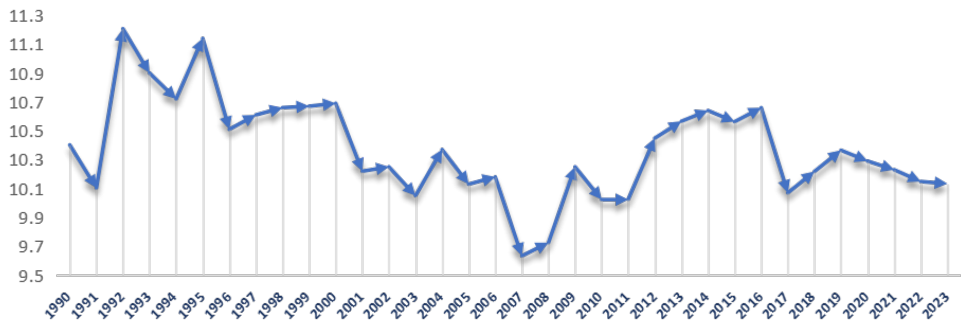

Figure 4. Agricultural Land (Square Meters) (Million).

Source: World Bank Database.

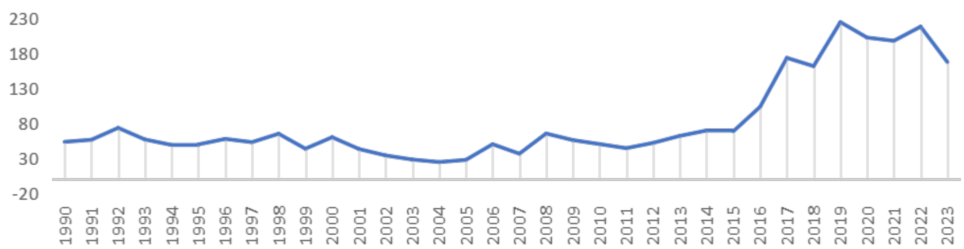

Figure 5. Gross fixed Capital Formation (Agriculture, Forestry, and Fishing).

Source: FAOSTAT (www.fao.org/faostat).

Investment in the sector showed only a slight increase until 2015, primarily due to the absence of large-scale government programs, lack of financial support and funding, and the impact of economic and political crises. However, after 2015, a notable rise in investment was observed, reflecting a shift towards promoting smart agriculture, particularly in response to the decline in the number of foreign laborers, who are typically more productive.

Despite this, Jordan's agricultural sector remains largely unattractive to private investment, which poses a significant challenge. Investors face multiple obstacles, including limited natural resources, high production costs, fluctuating agricultural markets, and weak supporting infrastructure. Therefore, stimulating agricultural investment requires supportive government policies, such as providing soft loans, improving agricultural marketing systems, and advancing agricultural technology to ensure sustainable production and enhance economic returns. Given these challenges, focusing on increasing spending on modern agricultural technologies, such as smart farming and water-efficient irrigation techniques, can significantly improve sector efficiency and productivity without expanding cultivated land.

Regarding the value-added contribution of the agricultural sector to Jordan's GDP, **Figure 6** illustrates significant fluctuations over time, influenced by various factors, including climate variability, agricultural policies, production costs, and the level of government support for the sector. Instead of exhibiting continuous growth, the sector's contribution has been highly volatile due to structural challenges, such as weak investments, water scarcity, and land use patterns.

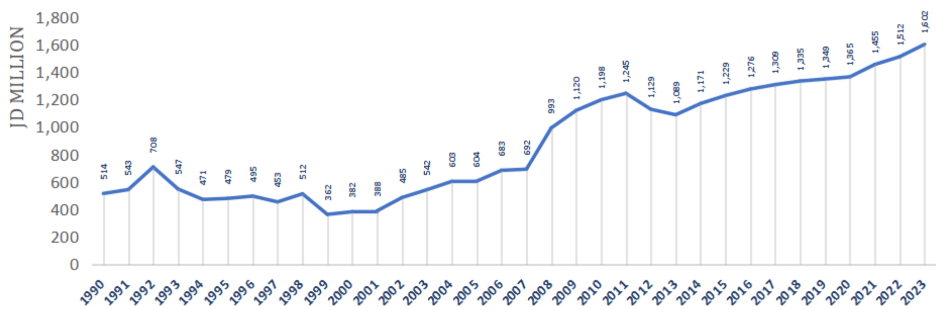

Figure 6. Added Value of the Agricultural Sector in the Jordanian GDP (JD Million).

Source: Department of Statistics, National Accounts Statistics.

Despite agriculture's crucial role in ensuring food security and providing employment opportunities, its share of GDP remains relatively limited compared to other sectors such as services and industry. Certain periods show increased agricultural value-added, often coinciding with government support programs or growth in agricultural exports. Conversely, periods of decline are typically associated with rising production costs, adverse weather conditions affecting crop yields, and fluctuations in domestic and international demand for Jordanian agricultural products.

3.2. Methodology

Based on the reviewed theoretical concepts, **Figure 7** presents the conceptual framework of this study. It illustrates how economic policies directly and indirectly influence agricultural productivity through their impact on labor, capital, and land production inputs. The model reflects how these relationships are captured using labor productivity, TFP, and technical efficiency (DEA) as key performance measures in the Jordanian agricultural sector.

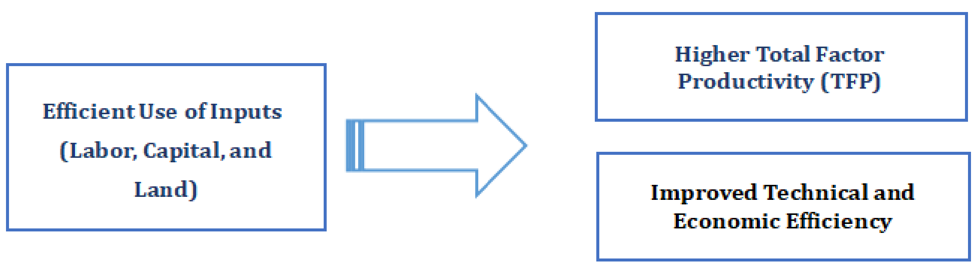

Figure 7. Relationship Between Input Efficiency, TFP, and Overall Efficiency.

3.2.1. Laborer Productivity in Agriculture

The Growth Accounting Method is one of the most widely used approaches for computing productivity. It assumes that aggregating real output (y) in the economy follows a Cobb-Douglas production function [48, 49] (α, B, δ Output Elasticities of Capital):

$$Y_t = A_t k_t^{\alpha} L_t^{B} X_t^{\delta} \tag{1}$$

where k represents capital (GFCF in Agriculture, Forestry, and Fishing is used as a proxy for the stock of fixed capital due to the lack of consistent and reliable data on the dynamics of the fixed capital stock in Jordan's agricultural sector); this approach is commonly adopted in empirical research and with practices in other studies focusing on agricultural productivity, ensuring the robustness of the estimated Total Factor Productivity

(TFP) values under data constraints. Moreover, fixed capital productivity is the ratio between output and fixed capital stock. When direct data on capital stock is unavailable, using GFCF becomes a practical alternative supported by Pavelescu (2022), who proposes an econometric model to project capital stock from investment flows [50]: L represents labor, X indicates Agricultural land, t points to year, A represents technology; an increase in A leads to higher output without the need for additional capital, labor, or land, and α, B, δ Output Elasticities of Capital, Labor, and Land. This is simply a measure of production efficiency. Since an increase in A enhances the productivity of other factors, it is referred to as TFP, the most used term. To determine output per individual in the economy, instead of aggregate output, we focus on output per laborer, which is also known as productivity growth, as expressed as follows:

$$\frac{Y_t}{L_t} = A_t k_t^{\alpha} L_t^{\beta-1} X_t^{\rho} \tag{2}$$

Rearranging Equation (2) yields

$$y_t = A_t \left(\frac{K_t}{L_t}\right)^{\alpha} \left(\frac{x_t}{L_t}\right)^{\rho} L_t^{(\alpha+B+\delta-1)} \tag{3}$$

The Neoclassical Growth Theory assumes that this equation illustrates four potential ways to increase productivity: technological advancement and improved efficiency in the use of input by the economy, represented by increases in A, increases in capital per labor, increases in land per labor, and, finally, increases in the number of laborers. Assuming constant returns to scale (CRS), as posited by most growth theories, where α+β+ρ−1 = 0, Equation (3) then becomes:

$$\frac{Y_t}{L_t} = A_t \left(\frac{K_t}{L_t}\right)^{\alpha} \left(\frac{x_t}{L_t}\right)^{\rho} \tag{4}$$

Given a certain level of technology, the proportions of capital, land, and labor mix determine a laborer's productivity.

3.2.2. Agricultural Total Factor Productivity TFP

However, economic growth over time, referring to the fundamental Equation (1) and assuming CRS, leads to

$$Y_t = A_t k_t^{\alpha} L_t^{1-\alpha-\rho} x_t^{\rho} \tag{5}$$

By differentiating Equation (5) with respect to time, we obtain

$$\frac{\mathrm{d}Y_t}{\mathrm{d}t} = \frac{\mathrm{d}A_t k_t^{\alpha} L_t^{1-\alpha-\rho} X_t^{\rho}}{\mathrm{d}t} \tag{6}$$

$$\begin{gathered}\frac{\mathrm{d}Y_t}{\mathrm{d}t} = k_t^{\alpha} L_t^{1-\alpha-\rho} x_t^{\rho} \frac{\mathrm{d}A_t}{\mathrm{d}t} + \\ A_t L_t^{1-\alpha-\rho} x_t^{\rho} \frac{\mathrm{d}K_t^{\alpha}}{\mathrm{d}t} + A_t k_t^{\alpha} x_t^{\rho} \\ \frac{\mathrm{d}L_t^{1-\alpha-\rho}}{\mathrm{d}t} + A_t k_t^{\alpha} L_t^{1-\alpha-\rho} x_t^{\rho} \frac{\mathrm{d}X_t^{\rho}}{\mathrm{d}t}\end{gathered} \tag{7}$$

By applying the chain rule to calculate the changes in capital (K), land (X), and labor (L), we can derive

$$\frac{\mathrm{d}K_t^{\alpha}}{\mathrm{d}t} = \frac{\mathrm{d}K_t^{\alpha}}{\mathrm{d}K_t}\frac{\mathrm{d}K_t}{\mathrm{d}t} = \alpha K_t^{\alpha-1}\frac{\mathrm{d}K_t}{dt} \tag{8}$$

$$\begin{gathered}\frac{\mathrm{d}L_t^{1-\alpha-\rho}}{\mathrm{d}t} = \frac{\mathrm{d}L_t^{1-\alpha-\rho}}{\mathrm{d}L_t}\frac{\mathrm{d}L_t}{\mathrm{d}t} = \\ (1-\alpha-\rho)\, L_t^{-\alpha-\rho}\frac{\mathrm{d}L_t}{\mathrm{d}t}\end{gathered} \tag{9}$$

$$\frac{\mathrm{d}X_t^{\rho}}{\mathrm{d}t} = \frac{\mathrm{d}X_t^{\rho}}{\mathrm{d}X_t}\frac{\mathrm{d}X_t}{\mathrm{d}t} = \rho X_t^{\rho-1}\frac{\mathrm{d}X_t}{\mathrm{d}t} \tag{10}$$

Applying the chain rule to Equation (7) leads to

$$\begin{gathered}\frac{\mathrm{d}Y_t}{\mathrm{d}t} = k_t^{\alpha} L_t^{1-\alpha-\rho} x_t^{\rho} \frac{\mathrm{d}A_t}{\mathrm{d}t} + \\ A_t L_t^{1-\alpha-\rho} x_t^{\rho} \alpha K_t^{\alpha-1} \frac{\mathrm{d}K_t}{\mathrm{d}t} + \\ A_t k_t^{\alpha} x_t^{\rho} (1-\alpha-\rho)\, L_t^{-\alpha-\rho} \frac{\mathrm{d}L_t}{\mathrm{d}t} + \\ A_t k_t^{\alpha} L_t^{1-\alpha-\rho} x_t^{\rho} \rho X_t^{\rho-1} \frac{\mathrm{d}X_t}{\mathrm{d}t}\end{gathered} \tag{11}$$

By dividing both sides of Equation (11) by Y_t to calculate the output growth, we have

$$\begin{gathered}\frac{1}{Y_t}\frac{\mathrm{d}Y_t}{\mathrm{d}t} = \left(\frac{k_t^{\alpha} L_t^{1-\alpha-\rho} x_t^{\rho}}{A_t k_t^{\alpha} L_t^{1-\alpha-\rho} x_t^{\rho}}\right)\frac{\mathrm{d}A_t}{\mathrm{d}t} + \\ \left(\frac{A_t L_t^{1-\alpha-\rho} x_t^{\rho} \alpha K_t^{\alpha-1}}{A_t k_t^{\alpha} L_t^{1-\alpha-\rho} x_t^{\rho}}\right)\frac{\mathrm{d}K_t}{\mathrm{d}t} + \\ \left(\frac{A_t k_t^{\alpha} x_t^{\rho} (1-\alpha-\rho) L_t^{-\alpha-\rho}}{A_t k_t^{\alpha} L_t^{1-\alpha-\rho} x_t^{\rho}}\right)\frac{\mathrm{d}L_t}{\mathrm{d}t} + \\ \left(\frac{A_t k_t^{\alpha} L_t^{1-\alpha-\rho} x_t^{\rho} \rho X_t^{\rho-1}}{A_t k_t^{\alpha} L_t^{1-\alpha-\rho} x_t^{\rho}}\right)\frac{\mathrm{d}X_t}{\mathrm{d}t}\end{gathered} \tag{12}$$

By rearranging Equation (12) again, we can obtain

$$\begin{gathered}\frac{1}{Y_t}\frac{\mathrm{d}Y_t}{\mathrm{d}t} = \frac{1}{A_t}\frac{\mathrm{d}A_t}{\mathrm{d}t} + \alpha\frac{1}{K_t}\frac{\mathrm{d}K_t}{\mathrm{d}t} + \\ (1-\alpha-\rho)\frac{1}{L_t}\frac{\mathrm{d}L_t}{\mathrm{d}t} + \rho\frac{1}{X_t}\frac{\mathrm{d}X_t}{\mathrm{d}t}\end{gathered} \tag{13}$$

which can also be written as:

$$G_t^Y = G_t^A + \alpha G_t^K + (1-\alpha-\rho)\, G_t^L + \rho G_t^X \tag{14}$$

which explains that the output growth rate equals the technological growth rate plus a weighted average of capital growth, land growth, and labor growth, where the weight is determined by the coefficient α and ρ. By rearranging Equation (14), we can calculate the TFP growth rate using

$$G_t^A = G_t^Y - \alpha G_t^K - (1-\alpha-\rho)\, G_t^L - \rho G_t^X \tag{15}$$

To get total productivity, we take

$$TFP = e^{G_t^A} \tag{16}$$

To find α and ρ, take the natural logarithm on both sides to Equation (5)

$$\begin{aligned} lnY_t = lnA_t + \alpha lnk_t + (1-\alpha-\rho)\, lnL_t \\ +\rho lnx_t + \in_t \end{aligned} \tag{17}$$

Given that the stationarity test results (**Appendix A Table A1**) indicate that all variables are integrated of order one (I(1)) and that there exists cointegration among them (**Appendix A Table A2**), we can specify the model in a VECM, which captures both the long-run equilibrium and short-run dynamics.

The VECM representation is given as

$$\Delta Zt = \Pi Z_{t-1} + \sum\nolimits_{i=1}^{p-1} \Gamma_i \Delta Z_{t-1} + \in_t \tag{18}$$

where Zt = [lnY_t, lnk_t, lnL_t, lnx_t] is the vector of endogenous variables, ΔZ_t represents first differences, ΠZ_{t-1} captures the long-run equilibrium relationship, Γ_i represents short-run dynamics, and ϵ_t is the error term. Since cointegration exists, the matrix Π has a reduced rank (r < n), meaning:

$$\Pi = \alpha\beta' \tag{19}$$

where ($\beta' Z_{t-1}$) represents the long-run equilibrium relationship. (α) is the speed of the adjustment matrix, indicating how quickly deviations from equilibrium are corrected. The estimated VECM for lnYt can be written as:

$$\begin{aligned} \Delta lnYt = \gamma + \beta_1(lnY_{t-1} - \alpha lnk_{t-1} - \\ (1-\alpha-\rho)lnL_{t-1} - \rho lnx_{t-1}) \\ + \sum_{i=1}^{p-1} \Gamma_i \Delta Z_{t-i} + \in_t \end{aligned} \tag{20}$$

where $(lnY_{t-1} - \alpha lnk_{t-1} - (1-\alpha-\rho)lnL_{t-1} - \rho lnx_{t-1})$ represents the cointegrating equation, ensuring long-term equilibrium. (β1) is the error correction coefficient, indicating how the speed of adjustments occurs. The summation captures short-run dynamics.

3.2.3. Agricultural Production Efficiency Measurement

To estimate agricultural production efficiency in Jordan, the study utilized the data envelope analysis (DEA) model, which will be used to assess the efficiency. This methodology aims to provide valuable insights into improving the utilization of human and material resources, thereby enhancing the agricultural sector's performance and achieving sustainable growth.

The DEA model is a mathematical, non-parametric technique used to measure the efficiency of decision-making units (DMUs) that convert multiple inputs into multiple outputs. This approach was first developed by Farrell (1957) to assess the productive efficiency of firms or DMUs [1]. It was later enhanced by Charnes et al. (1978) through the introduction of the CCR model and further expanded by Banker et al. (1984) with the BCC model [2], allowing for more flexibility in terms of returns to scale [3].

(1) DEA Model Used in the Study

Since this study focuses on efficiency analysis over a time series rather than distinct units, the DEA model will be applied to different years. The relative efficiency of each year will be measured based on the following inputs and outputs:

a. **Outputs:**
   - **Agricultural sector value-added in Jordan (Y)**: A measure of the productivity of the agricultural sector and its contribution to the economy.
   - **Agricultural exports (AX)**: An indicator of the sector's success in reaching external markets and increasing export revenues.

b. **Inputs:**
   - **Capital invested in the agricultural sector (K)**: Reflecting the financial investment in the sector.
   - **Number of agricultural laborers (L)**: Representing the labor force contributing to agricultural productivity.
   - **Agricultural land used (x)**: Measuring the cultivated area utilized for agricultural production.

(2) DEA Model Formulation

The efficiency score for each year is determined using the following model:

$$\max \sum_{k=1}^{s} v_k Y_{ki} \tag{21}$$

Subject to:

$$\sum_{j=1}^{m} u_j X_{ji} = 1 \quad (22)$$

$$\sum_{k=1}^{s} v_k Y_{ki} - \sum_{j=1}^{m} u_j X_{ji} \leq 0, \forall i \quad (23)$$

$$v_k, u_j \geq 0, \forall k, j \quad (24)$$

Where Y_{ki} is the quantity of output k produced in year i, X_{ji} is the quantity of input j used in year i, v_k is the weight assigned to output k, and u_j is the weight assigned to input j.

(3) Application of the DEA Model

- The **output-oriented DEA model** will be applied to assess the sector's ability to increase production and exports using available resources.
- The **CCR model** (assuming CRS) will be compared with the **BCC model** (allowing for Variable Returns to Scale, VRS) to determine whether sector size influences productivity efficiency.
- Efficiency trends will be analyzed over time to identify periods of improvement or decline in resource utilization.

This methodology enables a relative performance evaluation of Jordan's agricultural sector over time, offering evidence-based recommendations for enhancing productivity and optimizing resource utilization.

4. Results

This section introduces the results of estimating Jordanian labor productivity in the agricultural sector. It also estimates TFP using the Growth Accounting Method and VECM examines the long-term relationship between agricultural inputs and output and assesses the technical efficiency in Jordan's agricultural sector using DEA.

4.1. Agriculture Labor Productivity

The average marginal labor output (APL) indicator was used to analyze labor productivity trends. As shown in **Figure 8**, the results indicate that labor productivity in Jordan has undergone three periods. The first period (1990–1999) witnessed a decline in agricultural labor productivity in Jordan, which can be attributed to several factors, including a decline in agricultural investments, a heavy reliance on unskilled labor, and a lack of modern production technologies. In addition, the economic challenges Jordan faced during this period, particularly the 1989 economic crisis, had a widespread impact on all sectors, including agriculture, leading to a decline in individual labor productivity. The second period (2000–2011) witnessed a significant improvement in agricultural labor productivity, peaking in 2011. The overall economic boom can explain this growth, increased demand for agricultural products, improved agricultural exports, and enhanced labor efficiency.

However, in the third period (2012–2023), labor productivity entered a slowdown, despite government efforts to regulate the agricultural labor market, particularly by reducing reliance on foreign labor. Contrary to expectations, these measures did not lead to increased productivity but contributed to a decline in overall productivity. This can be attributed to the higher productivity levels of foreign labor than local laborers due to their expertise and the lack of sufficient local replacements. Additionally, rising production costs, declining investment, and environmental and climatic pressures further contributed to the continued slowdown in productivity.

In line with the trend of average productivity, the marginal product of labor (MPL) in Jordan's agricultural sector (**Figure 9**) exhibited fluctuations over time, reaching its peak in 2011 before slowing down afterward. This pattern indicates that the additional productivity of each laborer declined during periods of low investment in agricultural technologies or increased reliance on unskilled labor, while it improved during periods characterized by higher aggregate demand and increased sector investments. After 2011, despite government measures to regulate labor, marginal productivity was negatively affected due to the declining efficiency of the local labor force and the failure to replace productive foreign labor with suitable alternatives. This highlights the importance of enhancing skills and advancing technology in agriculture to ensure greater returns from employment in this sector.

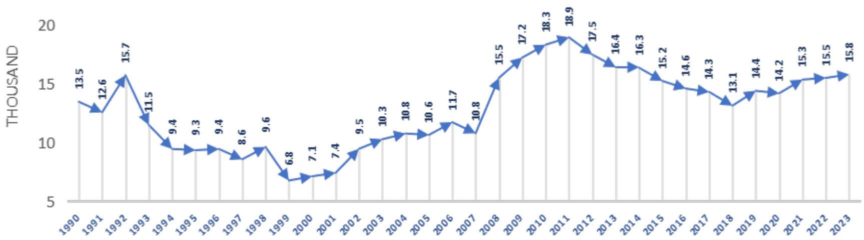

Figure 8. Average Production Per Labor (APL) in the Jordanian Agricultural Sector.

Source: Prepared by the Researcher based on Data from the Department of Statistics.

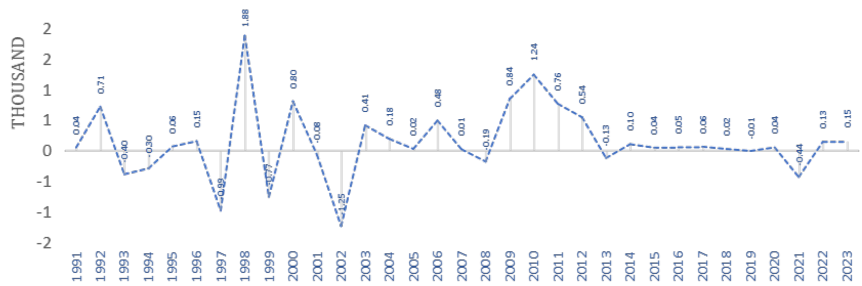

Figure 9. Marginal Production of Labor (MPL) in the Jordanian Agricultural Sector.

Source: Prepared by the Researcher based on Data from the Department of Statistics.

4.2. Agricultural Total Factor Productivity TFP

Before presenting the estimation results of the VECM, it was necessary to test data stationarity to determine the degree of integration. This was done using the Augmented Dickey-Fuller (ADF) unit root test, as shown in **Appendix A Table A1**. The results indicate that all variables used in the analysis were non-stationary at level (I(0)) but became stationary at the first difference (I(1)), suggesting the potential existence of a long-term equilibrium relationship among these variables. Additionally, the Johansen Cointegration Test was applied, as detailed in **Appendix A Table A2**, revealing two cointegrating relationships at a 5% significance level. This indicates the presence of a long-term equilibrium relationship between agricultural output (Y) and other production inputs, namely capital (K), labor (L), and agricultural land area (X). Based on these findings, the VECM model was adopted to measure the relationship between these variables. **Table 1** presents the results of the long-run equilibrium equation along with error correction terms for the key variables.

Table 1. Vector Error Correction Model Estimation.

Variable	Parameter	Standard Errors	t-Statistics
LOG(Y(−1))	1.00000	-	-
LOG(K(−1))	−0.273676	(0.04277)	[−6.3987]
LOG(L(−1))	−0.513739	(0.16967)	[−3.02792]
LOG(X(−1))	−0.212585	(0.15094)	[−2.21015]
C	−11.27998	-	-
	Error Correction:		
D(LOG(Y))	−0.804864	(0.25585)	[−3.14583]

The estimation indicates that the long-term relationship between agricultural production and production inputs can be given as follows:

$$lnY_t = -11.28 + 0.274lnk_t + 0.514lnL_t + 0.112lnx_t \tag{25}$$

An increase in capital by 1% in the long run leads to a 0.27% increase in the agricultural value-added. Meanwhile, a 1% increase in labor results in a 0.51% increase in agricultural value-added over the long term. Similarly, a 1% expansion in arable land leads to a 0.11% increase in agricultural value-added in the long run. Also, the estimated value of the elasticity of the output related to the fixed capital is lower than that of the output related to the labor substitution by the fixed capital. This situation was remarked even by Solow when he built his neoclassical growth model in 1956 [4].

The analysis shows that labor elasticity is significantly higher than capital elasticity, which can be attributed to inefficient capital utilization or weak productive investments in the sector. In contrast, increasing agricultural labor leads to a substantial improvement in output. Regarding the Error Correction Terms (ECTs), the results indicate that agricultural production returns to equilibrium at a rate of 80.5% annually following any deviation from the long-term relationship. This implies that if a shock causes agricultural production to deviate from its equilibrium path, approximately 80.5% of this imbalance is corrected within one year, demonstrating a rapid adjustment process in this sector compared to others, which may require longer periods for correction.

(1) Reliability of the VECM Estimations

To ensure the reliability of the VECM estimations, several diagnostic tests were conducted to confirm the absence of statistical issues that could affect the accuracy and validity of the results.

- **Heteroskedasticity Test:** The results of the heteroskedasticity test (**Appendix A Table A5**) show that the Chi-square statistic (192.74) is not significant at the 5% level (p-value = 0.2446). This indicates no evidence to reject the null hypothesis (H_0) of homoscedastic errors, confirming that the model does not suffer from heteroskedasticity. This means that the parameter estimates are consistent and efficient.
- **Serial Correlation LM Test:** The LM test results (**Appendix A Table A6**) confirm that the model's residuals are not autocorrelated over time.
- **Normality Test:** The Chi-square test results (**Appendix A Table A7**) confirm that the residuals follow a normal distribution, supporting the reliability of the statistical estimations.
- **Dynamic Stability Test:** The results (**Appendix A Figure A1**) show that all roots fall within the unit circle, confirming that the model is dynamically stable and, thus, its long-term estimations are reliable.

Based on these findings, the model's estimations are robust and reliable for analyzing the relationship between agricultural production in Jordan and various production inputs. This enhances the credibility of the policy recommendations derived from these estimations.

(2) Total Factor Productivity (TFP) Estimations

Using the estimated parameters from the Cobb-Douglas production function, we substituted the values into Equations (15) and (16) to compute the TFP in Jordan's agricultural sector, as shown in **Figure 10**.

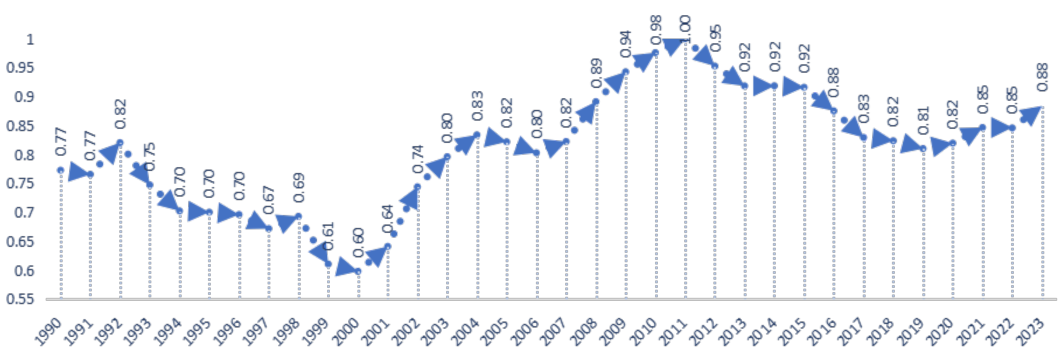

Figure 10. Total Factor Productivity (TFP).

The analysis reveals three distinct phases in TFP growth:

a. **First Phase (Before 2000): Low and Fluctuating TFP**

- The total productivity was low and volatile, indicating inefficiencies in resource utilization.
- Contributing factors included a lack of modern agricultural technologies, weak investments, and reliance on unskilled labor.

b. Second Phase (2000–2011): Significant TFP Growth

- TFP improved significantly, peaking in 2011, driven by enhanced agricultural policies, increased investments, and the adoption of modern farming techniques.
- The growth in aggregate demand for agricultural products, along with overall economic expansion, further supported productivity improvements.

c. Third Phase (Post-2012): TFP Slowdown

- TFP experienced a slowdown, influenced by declining agricultural investments, inefficient replacement of foreign labor, and increasing challenges related to water scarcity and rising production costs.
- Despite government efforts to regulate foreign labor, these measures did not lead to higher TFP. Instead, they resulted in declines during certain periods, underscoring the critical role of skilled labor and technology in enhancing production efficiency.

In conclusion, the results highlight a long-term equilibrium relationship between agricultural production and its key inputs. However, capital and land utilization inefficiencies indicate an urgent need for better production policies and investments in modern agricultural technologies to boost productivity. Furthermore, the TFP analysis reveals that improvements in agricultural productivity are closely linked to technology adoption, investment strategies, and labor market dynamics. As such, future policies should prioritize advancements in agricultural technology, enhancement of labor force skills, and efficient resource allocation to support sustained productivity growth in Jordan's agricultural sector.

4.3. Agricultural Production Efficiency

Table 1 presents the agricultural production efficiency analysis results in Jordan, using DEA. Three key indicators were estimated to measure efficiency:

- **Technical Efficiency under Constant Returns to Scale (CRS TE):** This measures how efficiently the agricultural sector converts inputs into outputs without assuming economies or diseconomies of scale.
- **Technical Efficiency under Variable Returns to Scale (VRS TE):** This accounts for the size of agricultural operations and its impact on efficiency.
- **Scale Efficiency (SE):** The ratio between CRS technical efficiency (TE) and VRS TE reflects how much the sector optimally benefits from its scale to achieve maximum efficiency.
- **Returns to Scale (RTS):** This indicates whether the agricultural sector operates under increasing returns to scale (IRS), DRS, or CRS.

During 1990–1999, technical efficiency under CRS recorded low values (ranging from 0.23 to 0.66), indicating poor utilization of available resources. Meanwhile, VRS TE was relatively high (0.62–0.98), suggesting that farmers achieved some efficiency when considering their specific production conditions. However, scale efficiency remained low (below 0.7 in most years), indicating that most agricultural operations were not at their optimal size for maximizing productivity. During this period, the sector operated under IRS, suggesting that expanding resource use could have enhanced production. However, this potential was not realized due to ineffective expansion strategies. The 2000–2011 period saw a significant improvement in production efficiency. Technical efficiency under CRS rose from 0.66 in 2003 to 1.00 in 2011, indicating an improved capacity to effectively transform input into agricultural output. VRS TE approached 1.00, suggesting that most farmers operated at high efficiency at the individual farm level. Achieving optimal scale efficiency (1.00) in 2011 indicates that the agricultural sector fully optimized its available resources, producing at the lowest possible cost. Throughout this period, the sector continued to experience IRS; however, by 2011, returns stabilized, reflecting gains from expansion and improvements in the agricultural investment environment.

After 2011, CRS TE declined to levels between 0.74 and 0.88, indicating a slowdown in resource optimization. Although VRS TE remained high (0.84–0.98), scale efficiency began to decline again, suggesting that the sector was losing its ability to fully capitalize on production scale. By 2015, returns to scale shifted from increasing (IRS) to decreasing (DRS), indicating that expanding resources no longer contributed significantly to production growth, leading to waste in certain resources. This decline aligns with government policies that reduced reliance on foreign labor, impacting local labor force efficiency. Additionally, rising production costs due to resource scarcity further constrained sector performance.

Figure 11 illustrates that scale efficiency in Jordan's agricultural sector has gone through three distinct phases: a decline in the 1990s, significant improvement until 2011, followed by a slowdown and decline thereafter. This trend aligns with the results of **Table 2**, indicating that achieving sustainability in scale efficiency requires investments in technology, improved labor policies, and the development of more efficient production strategies.

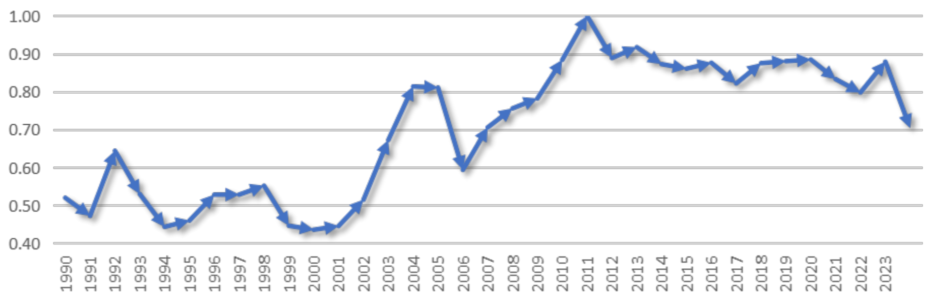

Figure 11. Scale Efficiency.

Table 2. Efficiency Summary.

Year	Crste	Vrste	Scale	Return to	Year	Crste	Vrste	Scale	Return to
1990	0.51	0.98	0.52	irs	2007	0.55	0.79	0.71	irs
1991	0.46	0.98	0.47	irs	2008	0.67	0.89	0.76	irs
1992	0.63	0.98	0.64	irs	2009	0.74	0.94	0.78	irs
1993	0.46	0.86	0.53	irs	2010	0.88	0.99	0.88	irs
1994	0.42	0.94	0.44	irs	2011	1.00	1.00	1.00	irs
1995	0.35	0.77	0.46	irs	2012	0.87	0.98	0.89	-
1996	0.36	0.67	0.53	irs	2013	0.90	0.98	0.92	irs
1997	0.36	0.67	0.53	irs	2014	0.80	0.91	0.87	-
1998	0.36	0.66	0.55	irs	2015	0.82	0.96	0.86	drs
1999	0.28	0.62	0.45	irs	2016	0.86	0.98	0.88	drs
2000	0.23	0.52	0.44	irs	2017	0.80	0.97	0.82	drs
2001	0.41	0.91	0.45	irs	2018	0.74	0.84	0.88	irs
2002	0.51	0.98	0.51	irs	2019	0.78	0.89	0.88	drs
2003	0.66	0.98	0.67	irs	2020	0.79	0.89	0.88	drs
2004	0.80	0.98	0.81	irs	2021	0.76	0.91	0.83	drs
2005	0.80	0.98	0.81	-	2022	0.77	0.96	0.80	drs
2006	0.47	0.79	0.59	irs	2023	0.80	0.91	0.88	drs

Note: crste = technical efficiency from CRS DEA, vrste = technical efficiency from VRS DEA, scale = scale efficiency = crste/vrste, irs: increasing return to scale, drs: decreasing return to scale.

5. Conclusions and Recommendations

The analysis of Jordan's agricultural sector productivity reveals a decline in the 1990s, followed by an increase from 2000 to 2011, and a subsequent slowdown after 2011. This trend indicates an initial boost in productivity driven by economic growth and rising demand for agricultural products, which was later hindered by restrictions on foreign labor and the failure to effectively replace it with a competent local Labor force. TFP followed a similar trajectory, showing significant growth between 2000 and 2011, fueled by increased agricultural investments and the adoption of modern technologies. However, productivity began to decline thereafter, primarily due to rising production costs, decreased labor efficiency from foreign labor restrictions, and a lack of innovative agricultural policies to sustain growth. Estimates from the VECM indicate that capital and agricultural land area increases did not significantly enhance agricultural output, highlighting inefficiencies in using these inputs. Strategies must be adopted to enhance productivity, address the sector's challenges, and increase the agricultural sector's value added to GDP. These should include supporting modern agricultural technologies, improving marketing and export systems, and developing financial policies that encourage investment in the sector. Furthermore, enhancing resource efficiency—especially in water usage—and implementing sustainable farming practices can significantly bolster the sector's sustainable contribution to the national economy.

The study recommends optimizing production scale, particularly considering DRS observed post-2015, through the following actions:

- Enhancing agricultural technologies and increasing reliance on mechanization.
- Reevaluating labor policies to balance reducing dependence on foreign labor and training the local labor force to boost productivity.
- Establishing specialized training programs for farmers and local agricultural laborers to enhance efficiency and address the skill gap with foreign labor.
- Encouraging investment in agricultural technology, assisting farmers in modernizing agricultural equipment, and providing investment incentives to attract capital into the agricultural sector.

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Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

The data supporting the findings of this study are available from official sources, including the Department of Statistics of Jordan, the World Bank, and FAOSTAT. These data are publicly accessible and were used in compliance with the respective terms of use. Any specific datasets or calculations generated during the current study are available from the author upon reasonable request.

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Conflicts of Interest

The author declares no conflict of interest.

Appendix A

Table A1. Unit Root Test Results Table (ADF).

Null Hypothesis: The Variable Has a Unit Root					
		At Level			
		LNY	LNL	LNK	LNX
With Constant	t-Statistic	−1.1898	−0.8120	−0.7829	−1.1700
	Prob.	***0.6631***	***0.8025***	***0.8109***	***0.6740***
		n0	n0	n0	n0
With Constant and Trend	t-Statistic	−6.0399	−1.8599	−1.7232	−4.6588
	Prob.	***0.0002***	***0.6523***	***0.7181***	***0.0039***
		*	n0	n0	*
Without Constant and Trend	t-Statistic	1.7719	3.8376	0.6308	1.4411
	Prob.	***0.9785***	***0.9999***	***0.8476***	***0.9595***
		n0	n0	n0	n0

Table A1. *Cont.*

Null Hypothesis: The Variable Has a Unit Root					
At First Difference					
		d(LNY)	d(LNL)	d(LNK)	d(LNAX)
With Constant	t-Statistic	−2.2552	−5.0821	−6.8914	−5.2812
	Prob.	***0.1931***	***0.0002***	***0.0000***	***0.0002***
		n0	*	*	*
With Constant and Trend	t-Statistic	−1.8844	−4.1249	−7.0468	−5.0829
	Prob.	***0.6336***	***0.0161***	***0.0000***	***0.0015***
		n0		*	*
Without Constant and Trend	t-Statistic	−5.3500	−4.0931	−6.8438	−4.9829
	Prob.	***0.0000***	***0.0002***	***0.0000***	***0.0000***
		*	*	*	*

Notes:
b: Lag Length based on SIC
c: Probability based on MacKinnon (1996) one-sided p-values.

Table A2. Unrestricted Cointegration Rank Test (Trace).

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.
None *	0.579581	59.92441	47.85613	0.0025
At most 1 *	0.482788	32.19633	29.79707	0.0260
At most 2	0.289138	11.09865	15.49471	0.2055
At most 3	0.005541	0.177808	3.841465	0.6733

Trace test indicates 2 cointegrating eqn(s) at the 0.05 level.
* denotes rejection of the hypothesis at the 0.05 level.
MacKinnon-Haug-Michelis (1999) p-values.

Table A3. Lag Order Selection Criteria.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	−6.221603	NA	2.23e−05	0.638850	0.822067	0.699581
1	97.40416	174.8685	9.41e−08	−4.837760	−3.921675*	−4.534104
2	122.8819	36.62424*	5.48e−08*	−5.430118*	−3.781165	−4.883537*

Table A4. Vector Error Correction Estimates.

Cointegration Restrictions:
B(1,2) + B(1,3)+ B(1,4) = 1
Convergence achieved after 1 iterations.
Restrictions identify all cointegrating vectors
Restrictions are not binding (LR test not available)

Cointegrating Eq:	CointEq1
LOG(Y(−1))	1.00000
LOG(K(−1))	−0.273676
	(0.04277)
	[−6.3987]
LOG(L(−1))	−0.513739
	(0.16967)
	[−3.02792]
LOG(X(−1))	−0.212585
	(0.15094)
	[−2.21015]
C	−11.27998

Table A4. *Cont.*

Error Correction:	D(LOG(Y))	D(LOG(K))	D(LOG(L))	D(LOG(X))
CointEq1	−0.804864 (0.25585) [−3.14583]	−2.008689 (0.43517) [−4.61583]	0.069795 (0.10215) [0.68327]	−0.036706 (0.07127) [−0.51505]
D(LOG(Y(−1)))	0.026660 (0.18546) [0.14375]	−1.036971 (0.31545) [−3.28730]	−0.019586 (0.07405) [−0.26451]	−0.007149 (0.05166) [−0.13839]
D(LOG(Y(−2)))	−0.257581 (0.21169) [−1.21681]	−0.405526 (0.36005) [−1.12629]	0.097279 (0.08452) [1.15101]	0.026084 (0.05896) [0.44236]
D(LOG(K(−1)))	−0.139739 (0.09989) [−1.39890]	−0.215329 (0.16990) [−1.26735]	0.088432 (0.03988) [2.21734]	−0.014918 (0.02782) [−0.53614]
D(LOG(K(−2)))	0.142888 (0.09051) [1.57872]	0.051245 (0.15395) [0.33288]	−0.035903 (0.03614) [−0.99356]	−0.009164 (0.02521) [−0.36348]
D(LOG(L(−1)))	−0.648508 (0.52784) [−1.22862]	1.438929 (0.89779) [1.60275]	0.326310 (0.21074) [1.54840]	−0.067367 (0.14703) [−0.45819]
D(LOG(L(−2)))	0.416005 (0.53020) [0.78462]	2.892890 (0.90181) [3.20787]	−0.086576 (0.21168) [−0.40899]	0.062846 (0.14769) [0.42554]
D(LOG(X(−1)))	−0.555268 (0.75647) [−0.73402]	2.613063 (1.28667) [2.03087]	−0.075030 (0.30202) [−0.24842]	−0.334072 (0.21071) [−1.58543]
D(LOG(X(−2)))	−0.472425 (0.76230) [−0.61974]	0.183815 (1.29659) [0.14177]	0.219440 (0.30435) [0.72101]	−0.213368 (0.21234) [−1.00485]
C	0.038847 (0.02442) [1.59065]	−0.041111 (0.04154) [−0.98967]	0.015333 (0.00975) [1.57252]	−0.002987 (0.00680) [−0.43906]

Table A5. VEC Residual Heteroskedasticity Tests (Levels and Squares).

Joint Test:		
Chi-sq	df	Prob.
192.7483	180	0.2446

Table A6. VEC Residual Serial Correlation LM Tests.

Null Hypothesis: No Serial Correlation at Lag h						
Lag	**LRE* Stat**	**df**	**Prob.**	**Rao F-stat**	**df**	**Prob.**
1	6.506228	16	0.9816	0.375801	(16, 46.5)	0.9821
2	8.278495	16	0.9401	0.486344	(16, 46.5)	0.9416
3	10.69825	16	0.8277	0.643315	(16, 46.5)	0.8314
Null Hypothesis: No Serial Correlation at Lags 1 to h						
Lag	**LRE* Stat**	**df**	**Prob.**	**Rao F-stat**	**df**	**Prob.**
1	6.506228	16	0.9816	0.375801	(16, 46.5)	0.9821
2	13.14606	32	0.9987	0.340686	(32, 42.2)	0.9989
3	21.44667	48	0.9997	0.308434	(48, 29.0)	0.9998

Table A7. VEC Residual Normality Tests.

Orthogonalization: Cholesky (Lutkepohl)				
Null Hypothesis: Residuals are multivariate normal				
Component	**Skewness**	**Chi-sq**	**df**	**Prob.***
1	−1.316998	8.961505	1	0.0028
2	0.382958	0.757726	1	0.3840
3	−0.343659	0.610190	1	0.4347
4	0.003065	4.85E−05	1	0.9944
Joint		10.32947	4	0.0352

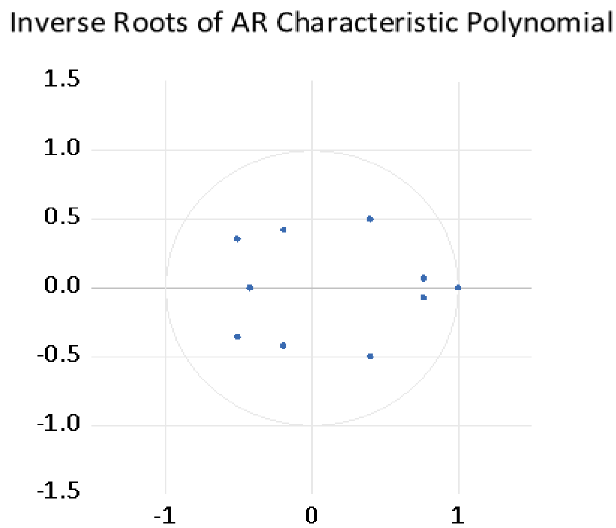

Figure A1. Stability Tests.

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