What explains Total Factor Productivity in agriculture: An empirical investigation using panel data analysis

Ahmet Ali Koç*, Öznur Özdamar**, Peyman Uysal***

DOI: 10.30682/nm2302f
JEL codes: N50, 013, Q10, Q18

Abstract

Considering population projections, which are estimated to be 10 billion people in the world by 2050, agricultural demand is expected to rise by about 50% compared to 2013 levels, even under a moderate economic development scenario. The number of people will increase in cities, and higher income levels per person will all have a significant impact on future food demand. There is only one way to raise food production without further depletion of natural resources, and that is to boost Total Factor Productivity (TFP). This study uses panel data analysis to investigate the factors that affect agricultural TFP in both developed and developing countries. Data is taken from the USDA/ERS (the United States Department of Agriculture/Economic Research Service), the World Bank, Penn World Table, and FAO over the period of 2002-2016 and consists of 32 developed and developing countries. According to our results, TFP in agriculture is increasing with the high level of human capital in developing countries. Moreover, the results of the study indicate that increases in gross fixed capital formation and the amount of arable land in both groups of countries contribute positively to TFP. However, TFP decreases while the agricultural employment rate increases for both developed and developing countries.

Keywords: *Agricultural Total Factor Productivity, Agricultural production, Food demand, Natural resources.*

1. Introduction

The agricultural sector is crucial to the economic development of nations and their subsequent industrialisation. However, challenges like hunger and poor nutrition remain prominent due to the rapid growth of the world's population (Oğuz and Yener, 2018). By 2050, the world's population is projected to reach 10 billion people, increasing agricultural demand by almost 50% above 2013 levels under a scenario of moderate economic development (Searchinger *et al.*, 2019). Food demand will undergo structural changes because of population expansion, urbanization, and rising per capita income above 2013 levels under a scenario of moderate economic development. Food demand will undergo structural changes because of population expansion, urbanization, and rising per capita income. Income development in low- and middle-income countries would accelerate the move away from

* Department of Economics, Akdeniz University, Antalya, Türkiye.
** Department of Economics, Bakırçay University, İzmir, Türkiye.
*** Department of Economics, Antalya Bilim University, Antalya, Türkiye.
Corresponding author: peyman.uysal@antalya.edu.tr

grains toward meat, fruits, and vegetables, requiring commensurate production changes and placing strain on natural resources (FAO, 2017). However, natural resource depletion, agricultural underinvestment, and technological gaps may make maintaining the current rate of output growth more difficult than in the past. Recent research indicates that natural resources are under stress. The global "ecological footprint" is about 21.2 billion hectares, whereas the global "bio capacity" is approximately 12.1 billion hectares as of 2018. Additionally, the ecological footprint per capita reached 2.77 global hectares in 2018, whereas the bio capacity of each person was only 1.6 global hectares. Thus, in per capita terms, the ecological deficit exceeds the earth's biosphere capacity by 1.73 times. This ratio was equal to one in 1971 and continued to rise afterwards, reaching 1.41 and 1.73 in 2002 and 2018, respectively (https://data.footprintnetwork.org, viewed on January, 2023).

According to the report of the Food and Agriculture Organization (FAO) published in 2017, population, both in absolute numbers and population dynamics such as regional trends, age group composition, and residential location (rural or urban), all play a major role in determining changes in demand for food and agricultural products. The urban population portion will double to two-thirds of the total by 2050, from 54 percent now. Even though agricultural expenditures and technical advancements have increased productivity, yield growth has stalled at unacceptably low levels. Indeed, worldwide yearly average growth in maize, rice, and wheat has been little more than 1% on average during the 1990s, a pace much lower than in the 1960s. Degradation of natural resources, loss of biodiversity, and the spread of transboundary pests and diseases of plants and animals, some of which are becoming resistant to antimicrobials, all act to stifle productivity gains (FAO, 2017).

Increased food production without further depletion of natural resources is achievable only via an increase in Total Factor Productivity (TFP). TFP refers to gains in agricultural output that occur because of overall process efficiency improvements rather than increased resource consumption. It assesses the change in output brought about by technological advancements, efficiency gains, management skills, and production structure rather than a direct rise in input consumption (European Commission, 2016).

Meeting increasing agricultural demand with existing farming methods is expected to result in greater competition for natural resources, higher greenhouse gas emissions, and more deforestation and land degradation. These developments create a slew of issues, including food security and agricultural sustainability. High-input, resource-intensive farming techniques are incapable of ensuring sustainable food and agricultural production since they have resulted in substantial deforestation, water shortages, soil degradation, and high levels of greenhouse gas emissions. Conserving and enhancing the natural resource base while boosting production requires innovative methods. Furthermore, certain issues, such as climate change, strain on natural resources, underinvestment in agriculture, and technological gaps, may make sustaining the current rate of output growth more challenging than in the past. Rapid technological advancements and innovation offer promise for sustainably meeting future food needs. This, however, can only be achieved via well-considered public policies, greater investment, and public-private partnerships that capitalise on possibilities to maintain current levels of productivity, sustainably improve yields, and alleviate poverty and food insecurity (FAO, 2017).

Increases in input consumption accounted for about 60% of the threefold increase in global agricultural production between 1961 and 2009, leaving 40% to improvements in TFP. On the other hand, TFP's share of output growth has increased over time, accounting for almost three-quarters of global agricultural output growth in the last decade (2001-09). The pace of growth of natural resource usage (land and water) has decreased somewhat over time, while the rate of intensification of inputs has slowed significantly. As a result, the source of agricultural production growth has moved significantly away from input intensification and toward TFP enhancement (Fuglie and Wang, 2013). Increased productivity, it is generally acknowledged, is the primary driver of economic development in the agriculture sector of the United States. Farm production in the United States was about 2.9 times that of 1948, increasing at an average annual rate of 1.53 percent throughout the period. At the same time, aggregate input consumption increased by 0.07 percent year on year. The increase in agricultural sector production was mostly due to an increase in Total Factor Productivity of 1.46 percent each year on average (USDA/ERS, 2020).

Even though agricultural research and development continues to be one of the most profitable investments, with returns ranging from 30% to 75%, it is mostly neglected in the majority of low-income countries. In underdeveloped nations, agricultural research is presently dominated by the public sector, which means that further expenditures will have to come from government funds. Increased private sector investment will require resolving intellectual property rights while still allowing smallholder farmers access to new technology (FAO, 2010).

Enhancing agricultural efficiency – producing more with the same inputs – is critical for food security. TFP is a measure that agricultural systems use to determine their effectiveness. It is a proxy for the efficiency with which agricultural land, labour, capital, and materials (agricultural inputs) are utilised to produce a country's crops and animals (agricultural output) – it is calculated as the ratio of total agricultural output to total production inputs. When more output is generated from a given set of resources, TFP increases, indicating that resources are utilised more effectively. TFP aids policymakers and investors in their understanding of agricultural systems by enabling cross-country and cross-regional comparisons (IFPRI, 2019).

Although numerous studies have measured TFP in agriculture and its drivers at various levels (regional, national, and cross-country) using cross-sectional, time-series, or panel data, they have not come across a comprehensive empirical study focusing on the determinants of TFP in agriculture in countries classified according to their level of development. The purpose of this research is to use panel data analysis to investigate the drivers of TFP in agriculture in developed and developing nations. We add to the relevant literature by giving empirical support for policy initiatives that promote sustainable agricultural production. The following sections make up the paper: The theoretical context is discussed in Section 2. Section 3 summarises the current state of knowledge about TFP and its determinants. The empirical model and data utilised are described in Section 4. Finally, Section 5 covers the discussion of the findings, and Section 6 concludes.

2. Theoretical background

Several recent studies have suggested that the agricultural economy is experiencing a deceleration in productivity growth, which could exacerbate supply-side constraints while population, income, and energy growth continue to increase demand for agricultural products (Fuglie, 2010). Growth in agricultural productivity is often seen as a major factor, which explains why the global food supply can keep up with expanding demand. Moreover, findings indicate that investments in food and agricultural research systems generate new knowledge and technologies that accelerate productivity improvements (Fuglie and Toole, 2014).

Total Factor Productivity (TFP) is the percentage of total output that is not attributable to the amount of inputs used in production. Whereas partial productivity does not accurately reflect whether productivity growth is due to increased input use, increased efficiency in input use, or increased technology, TFP measures the net growth of output per unit of total inputs (Saiki, 2014). The level of TFP, therefore, indicates how proficiently and intensely those inputs are utilized. However, the term "productivity" is grossly misused in the literature; it is used synonymously with labour productivity in the manufacturing sector and with yield productivity in agriculture. However, using yield as the sole indicator of productivity in agriculture creates a deceptive picture of the extent of productivity growth (Coelli, 1996).

TFP is the most informative indicator of agricultural productivity. The total amount of land, labour, capital, and material resources used in agricultural production is compared to the to-

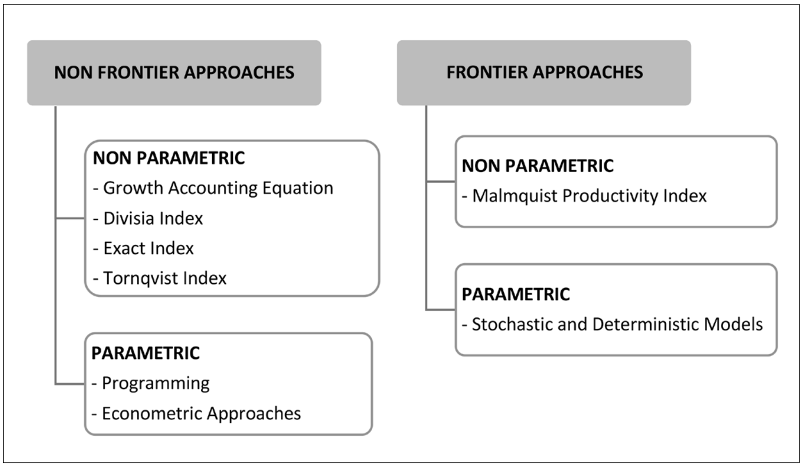

Figure 1 - Methodology classification for Total Factor Productivity measurement.

Source: Frija et al., 2015.

tal amount of crop and livestock output in TFP. An increase in Total Factor Productivity occurs when total output exceeds total inputs. TFP differs from other production indicators such as crop yield per acre or agricultural value added per worker in that it considers a larger range of inputs. TFP refers to the average productivity of all of these inputs employed in the production of all crops and animal commodities as a whole (USDA/ERS, 2021).

Measuring agricultural productivity and productivity growth over time provides information on natural resource effectiveness (Dhehibi *et al.*, 2014) and also an insight into the agricultural sector's competitiveness, contributing to the identification of critical government food security policies (Hayami and Ruttan, 1985; Ball, 1985). There are two distinct ways to quantify TFP growth: frontier and non-frontier approaches (Figure 1). Both techniques are further classified as parametric and non-parametric. The purpose of the frontier technique is to determine the best possible positions based on the estimation of a boundary function and given input amounts and prices. For example, a cost frontier denotes the lowest cost possible given input prices and output, but a production frontier denotes the maximum output possible given a set of inputs and technology (Frija *et al.*, 2015).

The methodology that the United States Department of Agriculture/Economic Research Service (USDA/ERS) uses to calculate TFP and TFP growth is taken from Fuglie (2012). The study defines TFP as the ratio of total output to total inputs. If X denotes total inputs and Y denotes total output, then TFP is as follows:

$$TFP = Y / X \tag{1}$$

Due to the variability of outputs produced and inputs utilized, it is usually difficult to offer meaningful definitions of real output or input. However, using index number theory, it is possible to construct meaningful definitions of output and input growth between any two time periods (Caves *et al.*, 1982). To do so, Fuglie (2012) calculates the rate of change in total output compared to the rate of change in total input to determine changes in TFP over time by changing Equation (1) to be expressed as logarithms as:

$$\frac{d\ln(TFP)}{dt} = \frac{d\ln(Y)}{dt} - \frac{d\ln(X)}{dt} \tag{2}$$

Equation (2) indicates plainly that the rate of change in Total Factor Productivity is equal to the difference between the rates of change in aggregate output and input. As agriculture is a process with multiple outputs and inputs, X and Y are vectors. When the underlying technology is depicted by a constant-returns-to-scale production function, producers maximise profits to the extent that the output elasticity of output with respect to an input equals the cost share of that input, and markets are in long-run competitive equilibrium while total revenue equals total cost. Equation (2), on the other hand, can be represented as:

$$\ln\left(\frac{TFP_t}{TFP_{t-1}}\right)=\sum_i R_i \ln\left(\frac{Y_{i,t}}{Y_{i,t-1}}\right)-\sum_j S_j \ln\left(\frac{X_{j,t}}{X_{j,t-1}}\right) \quad (3)$$

R_i is the revenue share of the i^{th} output, and S_j is the cost share of the j^{th} input in Equation (3). The total output growth rate is calculated by adding the growth rates of all output commodities weighted by their revenue share. Likewise, total input growth is calculated by adding the growth rates of all inputs and weighting them by their cost share. Thus, in Equation (3), TFP growth is defined as the value-share-weighted difference between total output and total input growth.

One distinction between growth accounting approaches is whether the revenue and cost share weights are constant throughout time or fluctuate. While the Paasche and Laspeyres indices employ constant weights, the Tornqvist-Thiel and other chained indices employ variable weights. Allowing for weight variation mitigates the risk of "index number bias." When producers swap between outputs and inputs based on their relative profitability or cost, index number bias occurs. In other words, the rates of growth of Y_i and X_j are dependent on changes in R_i and S_j. For instance, if labour wages increase in relation to the cost of capital, producers are likely to substitute more capital for labour, lowering labour growth and increasing capital growth.

In agriculture, as economic development progresses, the cost shares of agricultural capital and material inputs tend to increase, while the cost share of labour tends to decline. Cost shares are varied by decade if available to reduce the possibility of index number bias in TFP growth projections. Base year prices (or, more precisely, base year revenue shares) are fixed for outputs, as they are determined by the FAO's estimate of constant gross agricultural output. The 2004-2006 period is used as the base period for the output prices (https://www.ers.usda.gov, accessed in February, 2023).

The approach of Fuglie (2012) that USDA/ERS adopts enables a straightforward decomposition of the relative contributions of TFP and inputs to output growth. To be able to denote the annual growth rate of a variable, Equation 4 can be used.

$$g(Y)=g(TFP)+\sum_{j=1}^{J} S_j g(X_j) \quad (4)$$

As each $S_j g(X_j)$ term represents the increase in cost associated with increasing output by using more of the jth input, Equation (4) is a cost decomposition of output growth. Additionally, one can concentrate on a single input, say land (designated as X_1), and breakdown growth into the component owing to resource expansion and the yield of this resource as:

$$g(Y)=g(X_1)+g\left(\frac{Y}{X_1}\right) \quad (5)$$

This decomposition of Equation (5) is synonymous with extensification (land expansion) and intensification (land yield growth). Then, yield growth can be decomposed into the share due to TFP and the share owing to more intensive use of other inputs per unit of land with the help of Equation (6). This will represent a resource-based decomposition of growth since it is concerned with the quantity change of a physical resource (land) rather than its contribution to changes in the cost of production.

$$g(Y)=g(X_1)+g(TFP)+\sum_{j=2}^{J} S_j g\left(\frac{X_j}{X_1}\right) \quad (6)$$

Measuring productivity and technological change is crucial for two reasons. To begin, the measures can be used to make comparisons in specific, well-documented situations. That is, the productivity and technological accomplishments of one period or location can be compared to those of another. Second, measures of productivity and technological change can be used to assess the statistical relationship between productivity change and certain explanatory variables.

TFP increase, often referred to as "technical change," is both a required and sufficient condition for the agricultural sector's and economy's development. It is an essential requirement in that it helps agriculture avoid falling victim to Ricardo's law of decreasing returns, into which the sector has a tendency to fall. On the other hand, it is a necessary condition as it results in increased production over the long term with lower unit costs and prices (Desai and Namboodiri, 1997).

Technological advancement is determined outside the model (in other words, it is exogenous) according to the neoclassical growth models (Solow, 1957). Modern growth theories (Romer, 1986 and 1990) aspire to explain technological development and so supplement the old paradigm by elucidating how knowledge is generated (hence technological advancement is endogenous). Indeed, current growth models enable eternal growth through endogenous knowledge generation. Innovation is critical for technological advancement and is complimented by specialisation in that the latter boosts the former by increasing the sum total of knowledge. Combining ideas generates new ones, and this process is dynamically self-generating and self-feeding.

3. Literature review

Growth in TFP in agriculture and its determinants are the subject of various studies in the literature, as productivity and technical change measures at a relatively detailed level are beneficial for policy analysis. Earlier research has examined a variety of factors that contribute to productivity increases and technological change in agricultural output and other sectors of the economy. Suer (1995), for example, has conducted research from 1955 to 1981 on technical change and productivity in the food, beverage, and tobacco industries in the United Kingdom (UK). The author discovered that technical change in industries has been input biassed using a trans-log cost function. Färe *et al.* (1994) have calculated productivity growth for 17 OECD countries using a non-parametric programming model. They have found that Japan's productivity growth was the fastest in the sample, with more than half of the rise attributable to technical advances. Additionally, Färe *et al.* (1994) have shown that the long-run increase in Total Factor Productivity has been driven by technological development (TFP). Kim and Sachish (1986) have studied the period 1966-1983 and found that technological progress decreased labour input use and turned to be capital-intensive. McIntosh (1986) has used a two-factor vintage model to aggregate time series data from 1950 to 1978. The input-output coefficients of the model obtained indicate that technical progress and capital accumulation have been geared toward decreasing the amount of labour needed to produce a unit of output rather than increasing output. Bloch and Madden (1995) have used a model of technological change reflected in capital equipment to evaluate average labour productivity increases in a cross-section of Australian manufacturing sectors. The authors identified three drivers of productivity growth: the rate of advancement toward labour-saving technologies, the difference between wage and capital rental price changes, and the rate of expansion in industrial productive capacity. The authors have discovered that each of the drivers studied had a positive and statistically significant correlation with the rise in average labour productivity. Frisvold and Ingram (1995) have used an aggregate agricultural production function to perform research. According to their findings, land productivity has been the main driver of agricultural productivity increases.

The literature identifies human capital (labour quality and education levels), R&D, infrastructure (institutional factors), government programmes and policies (government expenditure), technology transfer and foreign R&D spillovers, health, structural change, resource redistribution, and trade openness as drivers of agricultural total productivity change.

In economic terms, human capital refers to the stock of knowledge and abilities carried by the working population. Capital in the form of a well-educated and talented workforce can easily integrate the latest innovations brought by foreign direct investment (Kariuki and Kabaru, 2022). Increased human capital does not only have the potential to increase productivity of the workers but also may have a moderating effect on the nexus of other determinants of TFP and productivity growth (Malikane and Chitambara, 2017). In fact, many studies in literature reveal the positive effect of human capital on TFP (Tsamadias *et al.*, 2019; Habib *et al.*, 2019; Liu and Lv, 2021; Rehman and Islam, 2023; Yu *et al.*, 2022).

Increase in human capital in a country will result with a qualified labour force and labour quality is essential for the growth of the economy (Barro, 2001). It has a direct effect on economic growth through improved labour productivity (Yadav, 2020; Wang *et al.*, 2021) and an indirect effect through increased productivity via spill over effect on TFP (Wang *et al*., 2021). A nation with a higher standard of living gains more from openness and foreign direct investment's favourable externalities. Consequently, improved worker quality is anticipated to result in greater productivity growth (Loko and Diouf, 2009; Ngo and Nguyen, 2020; Yu *et al.*, 2022). At this point, the level of education has great importance in achieving a high level of labour quality. It is a well-known fact that education is a kind of human capital investment through which people gain general problem-solving skills, similar to a farmer's physical capital investment. Scientists' education expedites the creation of new technologies. Additionally, education facilitates farmers' adoption of new technology. Farmers with a greater level of education are better prepared to assess the benefits of new technology, embrace it more rapidly, and effectively adapt it to their unique circumstances than farmers with a lower level of education (Frija *et al.*, 2015). By extending accessible resources and increasing the productivity of private capital, infrastructure helps to increase productive capacity (Munnell, 1992).

By restricting different kinds of capital and technology adoption, health has a direct impact on TFP growth (Misra, 2019; Yu *et al.*, 2022) through household income and wealth and indirectly through labour productivity savings and investment, and demography. When all other circumstances are equal, healthy employees produce more (Isaksson, 2007). Cole and Neumayer (2003) investigate the impact of poor health on TFP during the period 1965-1996 using data from 52 developed and developing countries. They argue that, although previous studies have examined the impact of poor health on production growth, this effect is probably underestimated since it is only indirect and occurs as a consequence of the effects of poor health on labour productivity and physical and human capital. The authors make a significant addition by examining the direct impact of ill health on aggregate output levels across nations. The study's findings indicate that health indicators include the proportion of the population that is malnourished (which mainly impacts the workforce), the prevalence of malaria and other related illnesses that reduce labour productivity and human capital, and life expectancy. Additionally, there are studies that integrate life expectancy into the production function in order to investigate the relationship between health and TFP. For example, Bloom *et al.* (2004) found that a one-year increase in the population's life expectancy leads to a 4% rise in production.

Increased productivity may be accomplished via the use of more sophisticated technology and/or more efficient management, whether technical, allocative, or scale-based. While some of the factors are within the control of the farm manager and are dependent on his or her management abilities, such as some efficiency improvements, others are external to the farm manager, such as the natural environment, technology development, investment in research and development, the advisory system and infrastructure, the availability of similar farms and value chains, and the applicability. Long-term productivity growth is primarily driven by innovation, which is fuelled by research spending. New technologies, including big data, whether open source or proprietary, plant breeding technologies, multi-actor business models, and precision farming, to name a few, have the potential to accelerate technological progress. Adoption of new technologies can easily be demonstrated by increasing the production frontier in frontier-based research (European Commission, 2016).

Agricultural research has concentrated on developing higher yielding crop types, optimising animal breeding procedures, developing more efficient fertilisers and pesticides, and improving farm management techniques. Agricultural research and development (agricultural R&D) is essential not only to increase agricultural production but also to prevent it from declining. For example, production gains associated with a specific plant variety are frequently lost over time as pests and diseases evolve to make the variety more vulnerable. Therefore, a significant part of agricultural research spending is spent on upkeep. Farmers gain from agricultural research in the short term since it results in lower costs and higher income. On the other side, agricultural research helps customers in the long term by reducing food costs. Additionally, agricultural research helps a nation maintain its competitiveness in global markets. Agricultural research can also contribute to the reduction of income and living standard inequality, as individuals with low-income benefit more from lower food prices than high-income individuals do and spend a greater proportion of their income on food than high-income individuals do (Frija *et al.*, 2015).

Considering the significant role of R&D in innovation and technological progress, many researchers concentrate on the connection between research and development and productivity. As demonstrated by the European Union's Horizon 2020 framework, this is also a key topic on the political agenda (Haider *et al.*, 2021). Following a decade of stagnant growth in the 1990s, worldwide agriculture R&D expenditure increased by an average of 3.1 percent per year on average between 2000 and 2009, increasing from US$25 billion to US$33.6 billion. Around half of the increase in expenditure is attributable to China and India. Argentina, Brazil, Iran, Nigeria, and the Russian Federation all increased their public agricultural research and development investment significantly, accounting for one-fifth of the global increase. However, R&D expenditure growth remains relatively small in many low- and middle-income nations (FAO, 2017). Coe and Helpman (1995) and Coe *et al*. (2009) empirically investigate the spillover effects of R&D expertise across nations by including institutional factors (such as ease of doing business, patent protection, and common vs. statute law). The idea is that productivity gains from R&D are not entirely dependent on local expertise but also on foreign R&D activity. They were able to demonstrate a positive connection between domestic research and development efforts and production in a sample of 22 highly developed nations, but also a parallel correlation for foreign research and development. Additionally, trade openness amplifies the impact of spillovers from overseas R&D, which is especially important in smaller countries.

A robust innovation system is essential for TFP expansion (Isaksson, 2007; Saleem *et al.*, 2019; Kijek and Matras-Bolibok, 2019; Liu *et al.*, 2020/2022). An innovation system may be described as a network of institutions (for example, universities, public and commercial research institutes, and policy research institutions), regulations, and procedures that influence how a nation obtains, produces, disseminates, and utilises information (Chen and Dahlman, 2004). An innovation system's main purpose is to foster research and development that results in new goods, technologies, and knowledge. R&D is often described in terms of two components: invention and enabling the understanding and replication of others' findings. The latter is linked with absorptive ability and aids in the transmission of technologies. While R&D is more likely to occur at the company or industry level, improved productivity will ultimately contribute to wider economic growth. R&D may originate from two sources: domestic (as described above) or foreign spillovers (Isaksson, 2007).

According to the data, R&D investments in food and agricultural research systems result in the development of new knowledge and technologies that boost agricultural output. Nonetheless, during the past few decades, these research systems have experienced substantial organisational and financial changes. Numerous traditional public sector activities, such as finance and research, are being taken over by the private sector. Three significant developments in the system that generates most of the new agricultural technology in the United States can be summarised as the slowdown of public agricultural research funding, the increase in private agricultural research spending, and the emergence of new institutional models for public and private agricultural research and technology development (Fuglie and Toole, 2014).

A strong relationship exists between investment in research and innovation and increases in agricultural productivity (Fuglie and Heisey, 2007; Qi and Yang, 2021). There is, however, a significant time lag between the stage of research on a new technology and the point at which it is adopted and starts to affect production. The authors assert that monitoring research spending in food and agriculture is a critical indication of future agricultural productivity development trends. Agricultural research expenditures have a delayed impact on production due to the length of the research programmes and the time required for farmers to adjust to and learn about new technology. The earlier farmers and consumers benefit from research, the higher the rate of return on that investment. Thus, the agricultural extension system's goal is to reduce the period between technology development and deployment. Agents of extension are responsible for educating farmers about crops, animals, and management techniques, as well as demonstrating innovative ways. Furthermore, they advise farmers directly on particular production and management problems. In contrast to studies, it is reasonable to assume that expansion instantly increases output (Frija *et al.*, 2015).

Studies in literature reveal a strong positive connection exists between agricultural production and infrastructure (Gopinath and Roe, 1997; Khanna and Sharma, 2021). The most apparent example of how public investment in infrastructure may boost agricultural production is via public transportation and irrigation infrastructure. For example, an improved highway infrastructure may promote the integration of farmers' markets and decrease the cost of acquiring inputs and transporting products to market (Frija *et al.*, 2015). Also, improvements to the telecommunications and electricity infrastructure may enable the usage of particular machines and transportation (Hultén and Mölleryd, 2003) or better access to telecommunication networks is anticipated to increase the flow of information, which could result in efficient market clearing and increased competitiveness (Jensen, 2007).

Government efforts boost productivity by optimising resource allocation and output distribution through price control. Government engagement in agriculture is most common through agricultural programs. However, there are many more examples, such as where tax policy may be used to encourage private sector investment in technology development and adoption by farmers. Increased intellectual property protection may increase private business incentives to do agricultural research. Regulatory requirements have an effect on the pace of market entry for new fertilisers and agricultural chemicals (Frija *et al.*, 2015). Although research on the impact of government farm subsidies on agricultural production has been limited, a few studies have found a significant positive relationship (Huffman and Evenson, 1993). Direct government incentives, for example, may expedite the adoption of new technologies by encouraging the substitution of increased capital inputs for labour (Makki *et al.*, 1999).

Additionally, there are studies that demonstrate that TFP is significantly affected by the economy's structure and that institutions play a key role in the formation of the structure (Chanda and Dalgaard, 2005; Akhremenko *et al.*, 2019; Li and Tanna, 2019). For example, Chanda and Dalgaard (2005) argue that the connection between institutions and TFP occurs because the former affects the agricultural and non-agricultural composition of the economy. According to the authors, when an economy's institutions are weak, it results in a lack of money for investment and, therefore, capital accumulation. This affects the mix of production since capital-intensive non-agricultural industries may pay more, luring labour away from agriculture.

There is uncertainty about the connection between government spending as a proportion of GDP and productivity growth. Numerous studies indicate that government spending increases productivity growth through the generation of beneficial externalities because of a variety of factors, including the development of legal and administrative institutions, the development of economic infrastructures, and numerous interventions to address market failures (Ghali, 1998). Indeed, it is generally recognized that some level of government expenditure, especially on public goods, is necessary to promote productivity growth.

Excessive government spending, on the other hand, may stall productivity growth owing to government inefficiencies, the burden of taxes, and distortions created by government interference in free markets (Barro, 1991; Dar and Khalkhali, 2002). Thus, it is uncertain whether the size of the government has a net positive or negative impact on productivity growth or if the relationship is monotonic. However, the bulk of empirical research shows conclusively that a big and expanding government does not result in better productivity growth or economic success (Loko and Diouf, 2009).

Another driver of TFP growth is technology transfer through international research and development spillovers. According to Isaksson (2007), a limited number of technologically sophisticated nations generate knowledge. Because the bulk of nations do not produce cutting-edge technology, it must be imported. According to the author, there are many ways for information to transcend national borders. For instance, goods often integrate technology. As a result, importers with a moderate degree of expertise may be accessed. Trade, in general, helps to build international connections and may act as a conduit for information. Foreign research and development spillovers may also involve technological transfers in the form of research (new technologies and money) performed in a foreign nation. Trade and international research and development spillovers, as information carriers, should undoubtedly be regarded as having indirect impacts on TFP as their efficacy improves.

According to several research studies, favourable agricultural terms of trade are a key requirement for boosting technology adoption and mobilising higher levels of investment in agriculture transformation (Dantwala, 1976; De Janvry and Subbarao, 1986). According to another perspective, when prices are used as a policy instrument to accomplish a desired resource allocation, non-price elements (mainly technology, infrastructure, research, and extension) are more essential for sustaining agricultural development in countries. Sectoral terms of trade are important for policymakers to understand. Income redistribution across sectors and socioeconomic levels occurs because of changes in inter-sectoral terms of trade. Income redistribution has an impact on one's ability to save and on one's incentives to invest, produce, and sell. The term "terms of trade" refers to the relationship between export and import unit values. Agricultural exports and irrigation have been proven in the literature to have the greatest impact on decreasing technical inefficiency (Jemaa and Dhif, 2005). Exports of agricultural products expose producers in a country to worldwide competition, which promotes the development of efficient production methods. Agricultural imports, according to Frija *et al.* (2015), are symptomatic of a problematic agriculture sector. Increased terms of trade decrease inefficiency, resulting in a rise in Total Factor Productivity (TFP). This implies that any increase in the value of export units (or, conversely, any decrease in the value of import units) increases TFP.

Additional factors that may accelerate TFP growth include sustainable management of agricultural production resources (e.g., agriculture's share of water use), the proportion of primary cropland harvested relative to total cropland harvested, equitable territorial development (GDP *per capita* in rural areas), and the percentage of irrigated land relative to total agricultural land (Frija *et al.*, 2015).

4. Methodology

4.1. *Econometric model*

The aim of the study is to investigate the determinants of agricultural Total Factor Productivity with a cross-country analysis. We estimate the following panel-data model:

$$ATFP_{it} = \beta_0 + \beta_1 AL_{it} + \beta_2 AE_{it} + \beta_3 GFC_{it} + \\ + \beta_4 RD_{it} + \beta_5 \Delta HC_{it} + \vartheta_i + \lambda_t + e_{it}$$

In this model, subscripts *i* and *t* denote respectively the country and the year. represents the agricultural total productivity index (base year 2005=100) which is computed by the United States Department of Agriculture, Economic Research (USDA/ERS), using data collected by FAO and ILO. AL_{it} is the arable land measured by hectares per person. Agricultural employment AE_{it} refers to the employment in agriculture as the percentage of total employment. GFC_{it} represents the gross fixed capital formation as the share of the gross value added in agriculture. Other covariates controlled in the model are the human capital index[1] (*HC*) and the research and development expenditures (RD_{it}) as the share of

[1] The human capital index is calculated using Barro *et al.* (2013) average years of schooling and an expected rate of return on education based on Mincer equation estimates globally (Psacharopoulos, 1994).

GDP. Moreover, a full set of country dummies (ϑ_i), a full set of year dummies (λ_t), and an error term (e_{it}), capturing all other omitted factors, with $E(e_{it})$ is equal to 0 for all i and t.

We do not prefer to estimate the regression using the pooled-OLS estimator, which will be biassed and inconsistent since it ignores individual heterogeneity and assumes that each individual has a unique influence. Moreover, unobserved cultural and institutional factors, which are unobservable, country-specific, and time-invariant, can influence both the Total Factor Productivity of countries and the possible determinants. The fixed effect estimator can remove this source of bias, and on the other hand, it is reliable due to the assumption that each individual has a distinct influence. Therefore, we apply the fixed effect (FE) estimation method with robust standard errors (White, 1980) along with the Driscoll-Kraay standard errors and panel corrected standard errors (PCSE) (Beck and Katz, 1995). Our Hausman test results are also in favor of fixed effect estimation rather than random effects. Fixed effect with Driscoll-Kraay standard errors is considered a more precise technique, while Driscoll-Kraay standard errors are well calibrated when cross-sectional dependence exists. A fixed effect with robust standard errors produces a covariance matrix that is robust to certain violations of the regression model, such as heteroskedasticity or autocorrelation, but they do not consider cross-sectional correlation.

Beck and Katz (1995) show that their large T asymptotic-based standard errors (PCSE), which correct for contemporaneous correlation between the subjects, perform well in small panels. However, the finite sample properties of their estimator, panel corrected standard errors, function poorly when the panel's cross-sectional dimension N is larger than the time dimension T. Therefore, Driscoll and Kraay's approach eliminates this problem when the cross-sectional dimension N gets large (Hoechle, 2007).

4.2. *Data*

The summary statistics of variables reported in Table 1. These variables were obtained from the USDA/ERS (the United States Department of Agriculture/Economic Research Service), the World Bank, Penn World Table, and FAO over the period of 2002-2016. The data set consists of 32 developed and developing countries.[2] Our empirical work relies on balanced panel data, thus, from the dataset, we have removed countries with missing observations. In Table 1, we report the summary statistics of the variables employed in the empirical work.

Overall, we observe an average agricultural productivity index of 107.2. TFP is defined as "an indicator of how efficiently agricultural land, labour, capital, and materials (agricultural inputs) are used to produce a country's crops and livestock (agricultural output)". The minimum value is 80.97 in the dataset for agricultural total productivity, which belongs to Romania in 2007. On the other hand, 155.68 is the maximum value that agricultural total productivity reached in Portugal in 2015. As we expect, the average value of research and development expenditures (% of GDP) is quite low at only 1.54 percent. In 2016, Israel spent the most on research and development. Similar to Israel, South Korea also dedicates around 4 percent of its GDP to research and development. The minimum value for the research and development expenditure in the dataset is 0.03 spent by Trinidad and Tobago in 2008. Furthermore, the average human capital index is 3.07. It is measured based on the years of schooling and return to education. Developing and developed countries have similar human capital indices ranging from 1.81 to 3.76. Israel is the country with the highest value of the human capital index, while India has the lowest. Regarding other variables, arable land and gross fixed capital formation, Canada has the highest amount of arable land per person, while India,

[2] Data covers Argentina, Bulgaria, China, India, Mexico, Panama, Romania, and Turkey as the developing countries, and Austria, Belgium, Canada, the Czech Republic, Denmark, Finland, France, Germany, Hungary, Ireland, Israel, Italy, Japan, Kuwait, Lithuania, Poland, Portugal, the Republic of Korea, Slovakia, Spain, Trinidad and Tobago, the United Kingdom, and the United States as the developed countries.

Table 1 - Summary statistics.

Variables	*Data Source*	*Obs.*	*Mean*	*S.d*	*Min.*	*Max.*
Agricultural Total Factor Productivity (ATFP); 2005=100	USDA/ERS	480	107.25	12.33	80.98	155.68
Research and Development Exp. (RD); % of GDP	The World Bank	480	1.54	1.09	0.03	4.51
Human Capital Index (HC)	Pen World Table	480	3.07	0.48	1.81	3.77
Gross Fixed Capital Formation (GFCF); % Gross Value Added in Agriculture	FAO	480	2.92	2.01	0.06	11.12
Arable Land (AL); Hectare Per Person	The World Bank	480	0.28	0.25	0.06	1.30
Agricultural Employment Rate (AE); % of Total Employment	The World Bank	465	9.30	11.81	0.13	58.60

Lithuania, and Argentina are the leading countries for gross fixed capital formation (https://data.worldbank.org accessed in January 2022).

However, one issue in our analysis could be selection bias, where the availability of data and the selection of the sample countries explored in the study may not be random. Nevertheless, in order to avoid the problem of attrition and losing information, we prefer to use a balanced dataset, including 32 (9 developing and 23 developed) countries (Wooldridge, 2010).

As we mentioned in the previous section, the empirical results are obtained using the fixed effects (FE) regression with robust standard errors, the fixed effects regression with Driscoll Kraay standard errors (FE-DK), and the linear regression with panel corrected standard errors (PCSE). Due to the short time span, we have not checked the stationary nature of the variables using unit-root tests. However, we have done the necessary tests for the problems of heteroskedasticity, autocorrelation, and contemporaneous correlation. Based on those test results, to account for heteroskedasticity, autocorrelation, and contemporaneous correlation, we have employed FE-DK standard errors. Moreover, as a robustness check, we have obtained panel-corrected standard error (PCSE) estimates for the linear cross-sectional time series models, assuming that the disturbances are heteroskedastic and contemporaneously correlated across panels. To investigate whether countries are cross-sectionally dependent or contemporaneously correlated, we have employed the Pesaran (2004) CD test. Based on the test result, we could not reject the dependence across countries ($p = 0.24$) and reveal the cross-sectional

Table 2 - Pre-analysis tests.

Tests	*Test Statistics*	*Significance p-value*
Modified Wald Test for Heteroskedasticity	1.16	0.24
Peseran Test for Cross-Sectional Dependence	1640.52	0.00
Baltagi-Wu Autocorrelation Test	1.25	-

dependency. In addition, the Baltagi-Wu autocorrelation test and the modified Wald test for heteroskedasticity reveal the existence of these two problems. Therefore, we analyse the fixed-effects regression with DK standard errors (Driscoll and Kraay, 1998; Drukker, 2003).

5. Results and discussion

The motivation of this paper is the paucity of macro level studies that analyse the determinants of *agricultural Total Factor Productivity* in developed and developing countries. According to the World Bank's "World Development Indicators Country Classification," high-income countries are considered developed, while upper-middle and lower-middle income countries are considered developing. Our dataset does not contain low-income countries due to the unavailability of data for these countries. Table 3 shows the FE estimation results with robust standard errors. Moreover, we report FE-DK and PCSE estimates in Table 4 and Table 5, respectively.

Regarding the coefficients of covariates, estimates using three different methods show consistency. The coefficient of the human capital index is positively significant in increasing the agricultural Total Factor Productivity only in developing countries. In other words, Total Factor Productivity in agriculture is increased with high level of human capital in the developing countries. The negative but insignificant coefficients of human capital variable for developed countries in all estimations can exist due to the already existing high levels of human capital in developed countries. In developed countries, levels of human capital may have reached to a threshold and may have made the potential contribution to productivity gains already. In addition, institutional infrastructure of a country is also important to be able to benefit from human capital. For instance, in their study which aims to examine foreign direct investments on TFP taking into consideration the moderating effect of human capital on FDI-TFP growth nexus, Li and Tanna (2019) reveal that improving institutions is relatively more important than human capital development for developing countries to realise productivity gains. As developing countries focus on establishing new required institutions and empowering the existing ones to be able to achieve economic growth and development, human capital's positive impact on Total Factor Productivity in developing countries may be higher when compared to developed countries.

Human capital's positive impact on TFP is revealed by many studies in the literature regardless of whether the considered countries are developing or developed. For instance, Schultz (1975) shows that the human capital, associated with formal schooling increases the productivity of farmers. Moreover, Norton and Davis (1981) and Jamison and Lau (1982) review many studies investigating the relationship between human capital and agricultural Total Factor Productivity. The findings of these studies all point to the importance of human capital in the efficiency and productivity of farmers and family businesses in the agricultural sector. Also, from the fact that the transition from agricultural economy to an industrial one is brought about by an increase in human capital according to endogenous development theory (Tamura, 2002), human capital increase in countries (particularly in developing countries where the increase is faster as their human capital levels are much lower when compared to the levels in developed countries) may promote technological change and create an increase in the usage of machinery in agriculture by increasing the farmers' abilities to adapt themselves to technological developments in agricultural production and by increasing efficiency. The increase in human capital can have the potential to substitute excessive labour usage in agriculture while increasing Total Factor Productivity that can allow a more efficient resource allocation. As a result, human capital increase has the potential to lower the need for excessive agricultural employment and for a developing country which is still on the way to complete its transition to an industrial economy from an agricultural economy, one can expect that human capital increase will bring together the substitution effect of machinery use for agricultural employment. The farmers who are not educated enough to adapt themselves to technological changes may decrease the efficiency in agricultural production, hence may create a detrimental effect on Total Factor Productivity. Considering the significant difference between the developed and developing countries in the level of education represented by higher rates of basic literacy or advanced understanding of technical issues, human capital would not be significant any more in increasing the Total Factor Productivity for the farmers in the developed countries. However, it can still be an important determinant for the productivity of farmers in developing countries.

Surprisingly, research and development (RD) expenditures as a share of GDP are not a significant determinant in changing the level of Total Factor Productivity. This can be related to the covariate used in the model that represents general RD expenditures rather than the RD expenditures allocated specifically to the agricultural sector. Due to the lack of this data, we have used the general RD expenditures in all sectors, which may not directly represent the RD spending solely done in the agricultural sector. Another explanation can be that the productivity-boosting effects of R&D expenditures may need time to be captured (Salim *et al.*, 2020). The conclusion that R&D has a negligible impact on TFP in the short term is consistent with both empirical evidence and theoretical logic. For example, Huffman and Everson (2006) provide empirical evidence that the influence of R&D requires a longer period of time to manifest, which is not covered within one year. This is also consistent with the theoretical premise that boosting productivity through R&D expenditure requires time. Furthermore, recent studies in the agriculture of the United States of America (USA) have proven that it takes between 14 and 50 years for R&D to influence agricultural TFP growth (Salim *et al.*, 2020). For instance, Rahman and Salim (2013) have used a 14-year lag in their studies to capture the impact of R&D on Total Factor Productivity. In literature, the empirical findings of some studies imply that agricultural TFP and R&D have long-run equilibrium linkages. Also R&D expenditures and agricultural productivity are often thought of as having long lags (Chebil *et al.*, 2015). For example, Huffman and Evenson (2006) have used a 35-year lag of the variable reflecting R&D expenditure to account for the effects of R&D on TFP increase. Although our data does not cover a very short time span, the time needed to make innovations by the researchers can be longer.

In addition, not only the amount of R&D expenditures but also the intensity of R&D is important to be able to increase productivity. For instance, in their study that examines the determinants of ATFP in China, Huang *et al.* (2019) found out that the intensity of R&D does not specifically contribute to productivity increase in agriculture and the beneficial effect of R&D can be seen only after R&D intensity rises above a particular threshold.

Also, the diffusion of innovations and adaptations of new technologies to applications may need more time to have a significant effect on agricultural productivity. This point of view can be an explanation for the differences between developing and the developed countries in terms of estimation results. For R&D expenditures to have visible and positive effects on Total Factor Productivity, longer periods of time may be required. However, not only the innovations created by R&D expenditures, but also the diffusion of these innovations have great importance in enhancing productivity growth. In developing countries, where the human capital and gross capital formation are respectively lower than the developed countries, the diffusion and widespread use of inventions also may require longer periods of time. R&D expenditures yield much more contribution to productivity growth in developed countries where the levels of human capital and gross capital formation are already high.

Other studies, primarily country-case studies, that examine the effect of agricultural research and development spending on Total Factor Productivity generally show a positive effect of RD spending (e.g., Suphannachart and Warr, 2012; Cardarelli and Lusinyan, 2015). More spending on agricultural research and development would enhance farmers' productivity. Sequentially, the growth in agricultural productivity can perform as the engine of economic growth and cause the reduction of poverty or inequality by raising the incomes of producers.

Considering the coefficients of arable land in Table 3-5, we have consistent estimates since land scale is one of important source of ATFP. This result is showing consistency with recent studies in the literature (Dhehibi *et al.*, 2014; Sheng *et al.*, 2020; Azizi, 2020; Liu *et al.*, 2020/2022). According to entire findings, as the arable land per person increases in countries, we observe an increase in the Total Factor Productivity both in the developed and developing countries. But for the Total Factor Productivity, the related literature puts more emphasis on how well the land is used than on how much arable land is available. Comparing with extensification (the number of new lands) or the intensification (the increased use of inputs such as land), Coomes *et al.* (2019) declare that the efficient use of land or other inputs (such as capital or labour) is more useful for boosting the agricultural yield and productivity. The positive coefficient of the arable land variable shows that arable land in the developed or developing countries still contribute to the Total Factor Productivity efficiently. However environmental problems, such as freshwater stress or decreasing quality of lands due to the climate change, may prevent the efficient use of lands in the future and thereby would not positively affect the Total Factor Productivity in the estimates covering next years.

Regarding the negative coefficients of agricultural employment, we can state that the related estimates show its detrimental effect on Total Factor Productivity. In other words, increasing amount of labour employed in agriculture decreases agricultural Total Factor Productivity. For instance, according to the results of the study of Oğuz and Yener (2018) in which they conduct a productivity analysis of dairy cattle farms in Konya province in Turkey, dairy farms considered in the research either need to decrease their reliance on total active capital, and in particular, labour force without increasing any other inputs in order to be able to increase productivity. This can be because of the inefficient use of labour or the superior contribution of capital or technological inputs in the era of new-generation agricultural production. Even though labour is an important input for traditional production in the agricultural sector, recent developments reveal the importance of capital, including machinery operating with advanced technology. As Acemoglu and Restrepo (2019) emphasize, the development and the often use of new technologies enable capital to substitute labour. In other words, capital replaces labour for many tasks, and the performance of labour is reduced due to the displacement effect. Moreover, the shift from an agricultural economy to an industrial one can significantly improve agricultural TFP, and this can also be used to explain our finding that agricultural employment has a major negative impact on agricultural TFP. Since an increase in industrial output is likely to lure people away from agriculture and towards manufacturing, reducing agricultural employment has the potential to create incentives for capital investment and technological improvement, allowing farmers to increase their output per capita (Nin-Pratt *et al.*, 2010). New institutions are introduced by the transition processes, which improve institutional infrastructure and are anticipated to increase agricultural output. The inefficient use of labour can be the reason for the decreasing effect of agricultural employment on Total Factor Productivity, but this effect may also be mitigated by the fact that capital and technology are now playing a larger role in agricultural production. Despite the fact that labour has always been essential to agriculture's output, contemporary conditions emphasise the significant role that capital, particularly machines that make use of cutting-edge technologies, plays

Table 3 - Determinants of Total Factor Productivity in agriculture (fixed effect estimates with white robust standard errors).

Variables	*(1)* *FE-All Countries*	*(2)* *FE-Developed*	*(3)* *FE-Developing*
HC	10.4212 (18.2902)	-2.1260 (19.1464)	162.7997** (57.9000)
RD	2.3011 (3.4218)	1.5076 (4.2007)	9.8238 (10.6122)
GFC	2.2210** (0.8541)	1.6723* (0.9428)	4.0998*** (1.1945)
AE	-1.3346*** (0.4730)	-0.8171 (1.9349)	-1.1499* (0.5758)
AL	36.2052** (14.3195)	43.1984** (17.8658)	47.5784* (23.0598)
Constant	59.7067 (53.8954)	91.2633 (60.2142)	-330.7695* (143.5986)
Observations	465	344	121
R-squared	0.5972	0.5426	0.7779
Number of Countries	32	23	9

*White robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

Table 4 - Determinants of Total Factor Productivity in agriculture (panel corrected standard errors estimates).

Variables	*(1) PCSE All Countries*	*(2) PCSE Developed*	*(3) PCSE Developing*
HC	10.0204 (9.6554)	-1.6920 (11.9694)	159.6886** (72.4438)
RD	1.9142 (2.0384)	1.2195 (2.1954)	8.3107 (5.0643)
GFC	1.6811*** (0.5678)	0.8673 (0.8387)	3.9531*** (0.9048)
AE	-1.2747*** (0.2406)	-0.8038 (0.7896)	-1.1834*** (0.2853)
AL	31.4200** (12.9699)	34.6919** (16.6121)	50.1331*** (9.5585)
Constant	23.5676 (30.7200)	91.0883** (40.8790)	-421.8683** (196.3443)
Observations	465	344	121
R-squared	0.6733	0.6663	0.7819
Number of Countries	32	23	9

*Panel corrected standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

Table 5 - Determinants of Total Factor Productivity in agriculture (fixed effect estimates with Driscoll Kraay standard errors).

Variables	*(1) FE-DK All Countries*	*(2) FE-DK Developed*	*(3) FE-DK Developing*
HC	10.4212 (7.8395)	-2.1260 (11.2403)	162.7997*** (44.9862)
RD	2.3011 (1.7734)	1.5076 (1.7836)	9.8238 (5.7532)
GFC	2.2210*** (0.7094)	1.6723 (1.1827)	4.0998*** (1.0426)
AE	-1.3346*** (0.1857)	-0.8171*** (0.2724)	-1.1499*** (0.3358)
AL	36.2052*** (7.8065)	43.1984*** (7.0956)	47.5784** (17.9232)
Constant	14.8904 (30.3103)	0.0000 (0.0000)	-429.7901*** (136.0797)
Observations	465	344	121
R-squared	0.7213	0.6717	0.8559
Number of countries	32	23	9

*Driscoll-Kraay standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

in the industry. Acemoglu and Restrepo (2019) emphasise that the proliferation and widespread adoption of new technology allow capital to substitute for labour. Therefore, the performance of labour is diminished as a result of the displacement effect, since capital is substituted for labour in many contexts. The same result is indicated in the study of Xu *et al.* (2022). According to the authors, the widespread use of machinery in agriculture has resulted in a dramatic increase in the efficiency of agricultural production by displacing a major portion of the labour input of traditional agriculture, particularly in developing countries in which the increase in machinery use is respectively faster when compared to developed countries. Thus, in the context of agricultural mechanisation, an excessive amount of labour input in agricultural production impacts the overall allocation efficiency between different input elements, which is not favourable to the improvement of agricultural efficiency and thus has a negative influence on agricultural Total Factor Productivity.

6. Conclusion

This study aims to determine the primary factors of agricultural TFP for both developing and developed countries using a panel dataset containing 32 countries for the period of 2002-2016. Regarding biassed and inconsistent results of the pooled-OLS estimation due to ignorance of heterogeneity across individuals, the fixed effect estimator is found to be reliable as it accounts for individual heterogeneity. Thus, for the panel data analysis, the fixed effect (FE) estimation method is used instead of the pooled-OLS framework to account for the time-invariant characteristics that are specific to countries. As a further robustness check, and to account for potential econometric concerns such as autocorrelation, heteroscedasticity, and cross-sectional correlation, we reported the FE results with Driscoll-Kraay (DK) standard errors and panel corrected standard errors (PCSE).

Based on the estimates, the level of human capital is found to have a positive impact on TFP only in developing countries. The results also indicate that gross fixed capital formation and arable land per capita significantly increase TFP, while increased agricultural employment has a detrimental effect on TFP. However, the impact of research and development expenditures is not found to be significant, contrary to our expectations and the findings of the previous empirical studies. This result may be because of using total RD expenditures rather than agricultural RD expenditures in regressions due to the lack of data.

The coefficients of gross fixed capital formation are found to be positive and statistically significant in all estimation procedures, indicating that increases in gross fixed capital stocks for all countries will increase agricultural Total Factor Productivity. As a result, governments should implement policies to boost gross fixed capital formation. One way to do this is to stimulate the private sector to make investments in agriculture by ensuring economic stability, providing necessary infrastructure, and launching policies that promote efficient resource allocation to boost investment levels.

These findings have significant policy implications to motivate a sustainable increase in agricultural production for developed and developing countries. First, as emphasised in the study of Maudos *et al.* (1999), investment in human capital and improving the education and health status of individuals are necessary for TFP growth. Public investment in agriculture is not complete without attention to the development of human capital (Zepeda, 2001). Thus, governments should develop policies to increase human capital in all sectors, including the agricultural sector. Gains in productivity and efficiency can be obtained with enhanced levels of training and education.

Based on the findings of this study, an optimal level of agricultural employment should be targeted and the labour force in agriculture should have higher human capital levels. The policy recommendation that may be made at this point is that the governments (especially the governments of developing countries) should facilitate the transition process for agricultural workers by providing them education and training programmes to lower illiteracy rates, facilitate work force redistribution (Mulungu and Ng'ombe, 2017), modernise teaching practises by updating and expanding the agricultural and farming education system, as well as investing in education aimed at the farming community (Salim *et al.*, 2020), and make the adaptation process for workers shorter. In addition, governments should empower the newly established institutions during the transition.

In terms of innovations and R&D activities, the most important thing for developing countries to do in order to catch up to the developed ones is to take advantage of the technology that already exists. Thus, although developed countries lead the way in innovation, developing ones take in new ideas and practises. Hence, the advance technology created in developed countries should be modified to be productive in developing countries (Isaksson, 2007). One policy recommendation for the governments of developing countries at this point is to provide support to farmers to modify the advanced technologies to the specific needs and conditions of the countries.

This study not only gives a clear map of agricultural productivity increase and its drivers in both developed and developing countries, but it also provides the relevant research on agricultural productivity analysis considering the socio-economic factors that have effect on agricultural Total Factor Productivity. But in terms of sustainability, future research on the topic should include not only socio-economic factors but variables concerning efficient allocation of environmental resources and the consequences of climate change in terms of green Total Factor Productivity in agriculture.

References

Acemoglu D., Restrepo P., 2019. Automation and new tasks: How technology displaces and reinstates labour. *Journal of Economic Perspectives*, 33(2): 3-30.

African Union, NEPAD, 2006. *Comprehensive Africa Agriculture Development Programme: Integrating livestock, forestry and fisheries subsectors into the CAADP*. *New Partnership for Africa's Development (NEPAD)*. Companion document. Rome: FAO. http://pubs.iclarm.net/resource_centre/NEPAD.pdf (accessed: May 2021).

Akhremenko A., Petrov A., Yureskul E., 2019. Institutions, productivity change, and growth. In: Smirnov S., Ozyildirim A., Picchetti P. (eds.), *Business Cycles in BRICS*. Cham: Springer, pp. 29-54.

Azizi J., 2020. Natural resources revenues, agriculture development and urbanization in African countries. *New Medit*, 19(4): 15-33.

Ball E., 1985. Output, input, and productivity measurement in US agriculture: 1948-1979. *American Journal of Agricultural Economics*, 67: 475-486.

Barro R.J., 1991. Economic growth in a cross section of countries. *The Quarterly Journal of Economics*, 106(2): 407-443.

Barro R.J., 2001. Education and economic growth. The contribution of human and social capital to sustained economic growth and well-being. In: Helliwell J.F. (ed.), *The Contribution of Human and Social Capital to Sustained Economic Growth and Well-Being*. Paris: OECD, pp. 13-41.

Barro R.J., Caselli F., Lee, J.W., 2013. Symposium on human capital and economic development: An introduction. *Journal of Development Economics*, 104: 181-183.

Beck N., Katz J.N., 1995. What to do (and not to do) with time-series cross-section data. *American Political Science Review*, 89(3): 634-647.

Bloch H., Madden G., 1995. Productivity growth in Australian manufacturing: a vintage capital model. *International Journal of Manpower*, 16(1): 22-31.

Bloom D.E., Canning D., Sevilla J., 2004. The effect of health on economic growth: a production function approach. *World development*, 32(1): 1-13.

Cardarelli M.R., Lusinyan M.L., 2015. *US Total factor productivity slowdown: Evidence from the US States*. IMF Working paper, no. 116. Washington, DC: International Monetary Fund.

Caves D.W., Christensen L.R., Diewert W.E., 1982. The economic theory of index numbers and the measurement of input, output, and productivity. *Econometrica*, 50(6): 1393-1414.

Chanda A., Dalgaard C.J., 2005. *Dual economies and international Total Factor Productivity differences*. Department of Economics, Working paper no. 11. Louisiana State University.

Chebil A., Frija A., Alyani R., 2015. *Measurement of Total Factor Productivity and its determinants: case of wheat sector in Tunisia*. ERF Working Paper no. 943, presented at the 21st Annual Conference on Democracy and Economic Development, Gammarth, Tunisia. Dokki, Giza: The Economic Research Forum.

Chen D.H.C., Dahlman C.J., 2004. *Knowledge and development: A cross-section approach*. Policy Research Working paper no. 3366. Washington DC: World Bank.

Coe D.T., Helpman E., 1995. International R&D spillovers. *European economic review*, 39(5): 859-887.

Coe D.T., Helpman E., Hoffmaister A.W., 2009. International R&D spillovers and institutions. *European Economic Review*, 53(7): 723-741.

Coelli T.J., 1996. Measurement of total factor productivity growth and biases in technological change in Western Australian agriculture. *Journal of applied econometrics*, 11(1): 77-91.

Cole M.A., Neumayer E., 2003. The pitfalls of convergence analysis: is the income gap really widening?. *Applied Economics Letters*, 10(6): 355-357.

Coomes O.T., Barham B.L., MacDonald G.K., Ramankutty N., Chavas J.P., 2019. Leveraging total factor productivity growth for sustainable and resilient farming. *Nature Sustainability*, 2(1): 22-28.

Dantwala M.L., 1976. Agricultural policy in India since independence. *Indian Journal of Agricultural Economics*, 31: 31-53.

Dar A.A., Khalkhali S.A., 2002. Government size, factor accumulation, and economic growth: evidence from OECD countries. *Journal of Policy Modeling*, 24: 679-692.

De Janvry A., Subbarao K., 1986. *Agricultural price policy and income distribution in India*. Delhi: Oxford University Press.

Desai B.M., Namboodiri N.V., 1997. Determinants of total factor productivity in Indian agriculture. *Economic and Political Weekly*, 32(52): 165-171.

Dhehibi B., Telleria R., Aw-Hassan A., 2013. *Impacts of Public, Private, and R&D; Investments on Total Factor Productivity Growth in Tunisian Agriculture*. Paper submitted to the 4th International Conference of African Association of Agricultural Economists – Commercializing Agriculture in Africa: Social, Economic and Environmental Impacts, September 22-25, Hammamet-Tunisia. https://ageconsearch.umn.edu/record/160584/ (accessed: April 2021).

Dhehibi B., Telleria R., Aw-Hassan A., 2014. Total factor productivity in Tunisian agriculture: measurement and determinants. *New Medit*, 13(1): 4-14.

Driscoll J.C., Kraay A.C., 1998. Consistent covariance matrix estimation with spatially dependent panel data. *Review of economics and statistics*, 80(4): 549-560.

Drukker D.M., 2003. Testing for serial correlation in linear panel-data models. *The Stata Journal*, 3(2): 168-177.

European Commission, 2016. *Productivity in EU agriculture - slowly but steadily growing*. EU Agricultural Markets *Briefs*. https://agriculture.ec.europa.eu/system/files/2019-10/agri-market-brief-10_en_0.pdf (accessed: July 2021).

FAO, 2010. *How to Feed the World in 2050*. http://www.fao.org/fileadmin/templates/wsfs/docs/expert_paper/How_to_Feed_the_World_in_2050.pdf (accessed: July 2021).

FAO, 2017. *The future of food and agriculture: Trends and challenges*. https://www.fao.org/3/i6583e/i6583e.pdf (accessed: May 2021).

Färe R., Grosskopf S., Norris M., Zhang Z., 1994. Productivity growth, technical progress, and efficiency change in industrialized countries. *The American Economic Review*, 84(1): 66-83.

Frija A., Dhehibi B., Aw-Hassan A.A., 2015. Total factor productivity growth of the Tunisian agricultural sector: a review of historical trends and main determinants. *African Journal of Economic and Sustainable Development*, 4(4): 293-307.

Frisvold G., Ingram K., 1995. Sources of agricultural productivity growth and stagnation in sub-Saharan Africa. *Agricultural Economics*, 13(1): 51-61.

Fuglie K.O., 2010. Total factor productivity in the global agricultural economy: Evidence from FAO data. In: Alston J.M., Babcock B.A., Pardey P.G. (eds.), *The Shifting Patterns of Agricultural Production and Productivity Worldwide*, 2nd ed. Ames, Iowa: CARD Books, pp. 63-95. https://core.ac.uk/download/pdf/38908877.pdf#page=92 (accessed: March 2021).

Fuglie K.O., 2012. Productivity growth and technology capital in the global agricultural economy. In: Fuglie K.O., Wang S.L., Ball V.E. (eds.), *Productivity growth in agriculture: an international perspective*. Wallingford: CABI, pp. 335-368.

Fuglie K.O., Heisey P.W., 2007. *Economic returns to public agricultural research*. Economic Brief no. 10. USDA, Economic Research Service.

Fuglie K.O., Toole A.A., 2014. The evolving institutional structure of public and private agricultural research. *American Journal of Agricultural Economics*, 96(3): 862-883.

Fuglie K.O., Wang S.L., 2013. New evidence points to robust but uneven productivity growth in global agriculture. *Global Journal of Emerging Market Economies*, 5(1): 23-30.

Ghali K.H., 1998. Public investment and private capital formation in a vector error-correction model of growth. *Applied economics*, 30(6): 837-844.

Global Footprint Network (GFN), 2017. *Ecological Footprint and Biocapacity Country Trends*. https://data.footprintnetwork.org (accessed: July 2021).

Gopinath M., Roe T.L., 1997. Sources of sectoral growth in an economy wide context: the case of U.S. agriculture. *Journal of Productivity Analysis*, 8(3): 293-310.

Habib M., Abbas J., Noman R., 2019. Are human capital, intellectual property rights, and research and development expenditures really important for total factor productivity? An empirical analysis. *International Journal of Social Economics*, 46(6): 756-774.

Haider F., Kunst R., Wirl F., 2021. Total factor productivity, its components and drivers. *Empirica*, 48(2): 283-327.

Hayami Y., Ruttan V.W., 1985. *Agricultural Development*. Baltimore: Johns Hopkins University Press.

Hoechle D., 2007. Robust standard errors for panel regressions with cross-sectional dependence. *The Stata Journal*, 7(3): 281-312.

Huang J., Cai X., Huang S., Tian S., Lei H., 2019. Technological factors and total factor productivity in China: Evidence based on a panel threshold model. *China Economic Review*, 54: 271-285.

Huffman W.E., Evenson R.E., 1993. *Science for agriculture: a long term perspective*. Research paper no. 10997, Iowa State University, Department of Economics.

Huffman W.E., Evenson R.E. 2006. Do formula or competitive grant funds have greater impacts on state agricultural productivity? *American Journal of Agricultural Economics*, 88(4): 783-798.

Hultén S., Mölleryd B., 2003. Entrepreneurs, innovations and market processes in the evolution of the Swedish mobile telecommunications industry. In: Metcalfe J.S., Cantner U. (eds.), *Change, Transformation and Development*. Heidelberg: Physica, pp. 319-342.

IFPRI - International Food Policy Research Institute, 2019. Agricultural Total Factor Productivity (TFP), 1991-2015. In: *2019 Global Food Policy Report*. Washington, DC: IFPRI, pp. 132-136. https://www.ifpri.org/publication/agricultural-total-factor-productivity-tfp-1991-2015-2019-global-food-policy-report (accessed: July 2021).

Jamison D.T., Lau L.J., 1982. *Farmer Education and Farm Efficiency*. Baltimore: Johns Hopkins Press.

Jemaa M.M., Dhif, M.A., 2005. *Agricultural productivity and technological gap between MENA region and some European countries: A meta-frontier approach*. Economic Research Forum, 9/2005, 20 pp.

Jensen R., 2007. The digital provide: Information (technology), market performance, and welfare in the South Indian fisheries sector. *The Quarterly Journal of Economics*, 122(3): 879-924.

Kariuki C.W., Kabaru F.W., 2022. Human capital, governance, foreign direct investment and their relationship with TFP growth: Evidence from Sub-Saharan Africa. *The Journal of International Trade & Economic Development*, 31(5): 708-724.

Khanna R., Sharma C., 2021. Does infrastructure stimulate total factor productivity? A dynamic heterogeneous panel analysis for Indian manufacturing industries. *The Quarterly Review of Economics and Finance*, 79: 59-73.

Kijek T., Matras-Bolibok A., 2019. The relationship between TFP and innovation performance: Evidence from EU regions. *Equilibrium. Quarterly Journal of Economics and Economic Policy*, 14(4): 695-709.

Kim M., Sachish A., 1986. The structure of production, technical change and productivity in a port. *The Journal of Industrial Economics*, 35(2): 209-223.

Isaksson A., 2007. *Determinants of total factor productivity: a literature review*. Research and Statistics Branch, UNIDO.

Li C., Tanna S., 2019. The impact of foreign direct investment on productivity: New evidence for developing countries. *Economic Modelling*, 80: 453-466.

Li J., Chen J., Liu H., 2021. Sustainable agricultural total factor productivity and its spatial relationship with urbanization in China. *Sustainability*, 13(12): 6773.

Liu F., Lv N., 2021. The threshold effect test of human capital on the growth of agricultural green total factor productivity: Evidence from China. *The International Journal of Electrical Engineering & Education*. doi:10.1177/00207209211003206.

Liu J., Wang M., Yang L., Rahman S., Sriboonchitta S., 2020. Agricultural productivity growth and its determinants in south and southeast Asian countries. *Sustainability*, 12(12): 4981.

Liu S., Hou P., Gao Y., Tan Y., 2022. Innovation and green total factor productivity in China: a linear and nonlinear investigation. *Environmental Science and Pollution Research*, 29(9): 12810-12831.

Loko M.B., Diouf M.A., 2009. *Revisiting the Determinants of Productivity Growth-What's new?*. International Monetary Fund Working Paper no. 225.

Makki S.S., Tweeten L.G., Thraen C.S., 1999. Investing in research and education versus commodity programs: implications for agricultural productivity. *Journal of Productivity Analysis*, 12(1): 77-94.

Malikane C., Chitambara P., 2017. Foreign direct investment, productivity and the technology gap in African economies. *Journal of African Trade*, 4(1-2): 61-74.

Maudos J., Pastor J.M., Serrano L., 1999. Total factor productivity measurement and human capital in OECD countries. *Economics Letters*, 63(1): 39-44.

McIntosh J., 1986. Economic growth and technical change in Britain 1950-1978. *European Economic Review*, 30(1): 117-128.

Misra B.S., 2019. Determinants of total factor productivity in Indian states. *Indian Growth and Development Review*, 13(1): 259-282.

Mulungu K., Ng'ombe J.N., 2017. Sources of economic growth in Zambia, 1970-2013: A growth accounting approach. *Economies*, 5(2): 15.

Munnell A.H., 1992. Policy watch: infrastructure investment and economic growth. *Journal of Economic Perspectives*, 6(4): 189-198.

Ngo M.N., Nguyen L.D., 2020. Economic growth, total factor productivity, and institution quality in low-middle income countries in Asia. *The Journal of Asian Finance, Economics and Business*, (7): 251-260.

Nin-Pratt A., Yu B., Fan S., 2010. Comparisons of agricultural productivity growth in China and India. *Journal of Productivity Analysis*, 33(3): 209-223.

Norton G.W., Davis J.S., 1981. Evaluating Returns to Agricultural Research: A Review. *American Journal of Agricultural Economics*, 63: 685-699.

Oğuz C., Yener A., 2018. Productivity analysis of dairy cattle farms in Turkey: Case study of Konya Province. *Custos e Agronegocio*, 14: 298-319.

Pesaran M.H., 2004. *General diagnostic tests for cross section dependence in panels*. IZA Discussion Paper no. 1240. Bonn: Institute of Labor Economics. https://docs.iza.org/dp1240.pdf (accessed: May 2021).

Psacharopoulos G., 1994. Returns to investment in education: A global update. *World Development*, 22(9): 1325-1343.

Qi Z.Y., Yang S.Y., 2021. Can government subsidies promote the TFP of enterprises? The mediating effect of R&D decisions. *Science, Technology and Society*, 26(3): 392-412.

Rahman S., Salim R. 2013. Six decades of total factor productivity change and sources of growth in Bangladesh agriculture (1948-2008). *Journal of Agricultural Economics*, 64(2): 275-294.

Rehman F.U., Islam M.M., 2023. Financial infrastructure-total factor productivity (TFP) nexus within the purview of FDI outflow, trade openness, innovation, human capital and institutional quality: Evidence from BRICS economies. *Applied Economics*, 55(7): 783-801.

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

Romer P.M., 1990. Endogenous technological change. *Journal of Political Economy*, 98(5, Part 2): S71-S102.

Saikia D., 2014. Total Factor Productivity in Agriculture: A Review of Measurement Issues in the Indian Context. *Romanian Journal of Regional Science*, 8: 45-61.

Saleem H., Shahzad M., Khan M.B., Khilji B.A., 2019. Innovation, total factor productivity and economic growth in Pakistan: a policy perspective. *Journal of Economic Structures*, 8: 7.

Salim R., Hassan K., Rahman S., 2020. Impact of R&D expenditures, rainfall and temperature variations in agricultural productivity: Empirical evidence from Bangladesh. *Applied Economics*, 52(27): 2977-2990.

Schultz T.W., 1975. The value of the ability to deal with disequilibria. *Journal of Economic Literature*, 13(3): 827-846.

Searchinger T., Waite R., Hanson C., Ranganathan J., Dumas P., Matthews E., Klirs C., 2019. *Creating a sustainable food future: A menu of solutions to feed nearly 10 billion people by 2050*. Final report. Washington, DC: World Resources Institute.

Sheng Y., Tian X., Qiao W., Peng C., 2020. Measuring agricultural total factor productivity in China: pattern and drivers over the period of 1978-2016. *Australian Journal of Agricultural and Resource Economics*, 64(1): 82-103.

Solow R.M., 1957. Technical change and the aggregate production function. *The Review of Economics and Statistics*, 39(3): 312-320.

Suer B., 1995. Technological change and productivity in the UK food, drink and tobacco industries: a translog cost function approach. *International Journal of Manpower*, 16(1): 32-45.

Suphannachart W., Warr P., 2012. Total Factor Productivity in Thai Agriculture: Measurement and Determinants. In: Fuglie K.O., Wang S.L., Ball V.E (eds.), *Productivity Growth in Agriculture: An international perspective*. Wallingford: CAB International, pp. 215-236.

Tamura R., 2002. Human capital and the switch from agriculture to industry. *Journal of Economic Dynamics and Control*, 27(2): 207-242.

Tsamadias C., Pegkas P., Mamatzakis E., Staikouras C., 2019. Does R&D, human capital and FDI matter for TFP in OECD countries? *Economics of Innovation and New Technology*, 28(4): 386-406.

USDA/ERS - United States Department of Agriculture, Economic Research Service, 2019. *International Agricultural Productivity*. https://www.ers.usda.gov/data-products/international-agricultural-productivity/ (accessed: July 2021).

USDA/ERS - United States Department of Agriculture, Economic Research Service, 2020. *Agricultural Productivity in the U.S.* https://www.ers.usda.gov/data-products/agricultural-productivity-in-the-us/summary-of-recent-findings/ (accessed: July 2021).

USDA/ERS - United States Department of Agriculture, Economic Research Service, 2021. *Productivity Growth in U.S. Agriculture (1948-2019)*. https://www.ers.usda.gov/data-products/agricultural-productivity-in-the-u-s/productivity-growth-in-u-s-agriculture-1948-2019/ (accessed: July 2021).

Wang M., Xu M., Ma S., 2021. The effect of the spatial heterogeneity of human capital structure on regional green total factor productivity. *Structural Change and Economic Dynamics*, 59: 427-441.

White H., 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica*, 48: 817-838.

Wooldridge J.M., 2010. *Econometric analysis of cross section and panel data*. Boston: MIT Press.

World Bank, 2020. *Addressing Food Loss and Waste: A Global Problem with Local Solutions*. Washington DC: World Bank. https://openknowledge.worldbank.org/handle/10986/34521 (accessed: May 2021).

World Bank, 2021. *World Development Indicators*. Washington: The World Bank. https://databank.worldbank.org/source/world-development-indicators.

Xu Q., Zhu P., Tang L., 2022. Agricultural services: Another way of farmland utilization and its effect on agricultural green total factor productivity in China. *Land*, 11(8): 1170.

Yadav M., 2020. Health as an Economic Dimension: A comparative study of India and China. *Asia Pacific Journal of Health Management*, 15(4): 86-94.

Yu Y., Alvi S., Tufail S., Nawaz S.M.N., Peng M.Y.P., Ahmad N., 2022. Investigating the role of health, education, energy and pollution for explaining total factor productivity in emerging economies. *Humanities and Social Sciences Communications*, 9(1): 79.

Zepeda L., 2001. Agricultural investment, production capacity and productivity. In: *Agricultural Investment and Productivity in Developing Countries*. FAO Economic and Social Development Paper no. 148. Rome: FAO, pp. 3-20.