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Using an Artificial Neural Networks Experiment to Assess the Links among Financial Development and Growth in Agriculture

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Abstract: Financial development, productivity, and growth are interconnected, but the direction of causality remains unclear. The relevance of these linkages is likely different for developing and developed economies, yet comparative cross-country studies are scant. The paper analyses the relationship among credit access, output and productivity in the agricultural sector for a large set of countries, over the period 2000–2012, using an Artificial Neural Networks approach. Empirical findings show that these three variables influence each other reciprocally, although marked differences exist among groups of countries. The role of credit access is more prominent for the OECD countries and less important for countries with a lower level of economic de-elopement. Our analysis allows us to highlight the specific effects of credit in stimulating the development of the agricultural sector: in developing countries, credit access significantly affects production, whereas in developed countries, it also has an impact on productivity.

Keywords: credit access; TFP; economic growth; agricultural sector; Artificial Neural Networks

JEL Classification: C23; O13; Q14

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1. Introduction

The economic development of the agricultural sector is tightly linked to innovations and to the use of capital-intensive inputs, both requiring capitals and investments, which are often not available to farmers. Credit access is key in driving economic development, because it allows farmers to purchase inputs, plan investments, and face monetary shocks. As argued in several studies [1], "economies with credit rationing tend to experience slower growth [...] than will an otherwise identical economy with perfect credit markets".

The need for credit access is particularly important for farmers who face a time lag between expenditure on crop cultivation (i.e., multi-year crops) and the realization of revenues from sale of their products. Despite its importance, the total credit to agriculture disbursed by commercial banks has been below 3% in 2017, which is lower than the contribution of the agricultural sector to the global Gross Domestic Product (GDP). Put differently, the agricultural sector receives less money than the value it generates. [2] provided several theoretical arguments that explain market failures (e.g., imperfect information and learning curve) and favor policy interventions to improve credit access in rural economies, but concluded that "it is impossible to be categorical that an intervention in the credit market is justified".

The relationships between credit access and economic growth is well-established in the empirical literature [3], but the causal link has not been established, in that while economic growth spurs credit access, it is also true that credit access can spur growth. [4] reviewed the basic empirical associations and concluded that the link from credit access to economic growth cannot be explained merely by reverse causation. Several cross-country regression analyses support the tight link be-tween credit access and economic growth [5,6], and this has been shown in developed and developing economies [7,8]. Recent cross-countries studies also conclude on a reciprocal effect [9,10]. In short, while the empirical literature is conclusive on the linkages between financial development and economic growth, there is little evidence on the direction of causality.

In addition to studying the relationships between credit access and economic growth, a large strand of the literature has investigated how credit access, agricultural output, and agricultural productivity are linked together [11–14]. A vast majority of studies on the agricultural sector concern country-specific analyses and focus on the relationships between two of these three variables.

Ref. [15] showed that gift giving is mainly used to build personal trust, which facilitates access to informal lending for risk-sharing purposes. Ref. [16] divided the determinants of credit access into observable and unobservable factors. The former can be households' socio-economic characteristics as well as factors that affect lenders' decisions, while the latter are social capital/networks that interact with both actors in the framework. Ref. [17] conducted a survey of 292 farming households in Afghanistan. The results of the double hurdle model reveal that the financial activities of the households were positively determined by crop diversity, education, number of adults in a household, size of land, and access to extension. Non-agricultural income decreases the likelihood of participation. The results of the analysis of credit constraints indicate that formal credit did not help small-scale and remoter farming households; however, these households relied on informal credit, especially when they faced income shock.

Ref. [18] applied Stochastic Frontier Analysis (SFA) to analyze the growth of agricultural total factor productivity (TFP) in 15 south and southeast Asian countries, over the period 2002–2016. The results revealed that the sample countries witnessed an overall decline in agricultural productivity. Ref. [19] quantified the spatial–temporal heterogeneity of cropland productivity from 2000 to 2015 in China. The results showed that the cropland GPP significantly increased in northern China and markedly decreased in southern China.

Ref. [20] highlighted that expenditures on education may lead to better technological outcomes, unlike expenses on health. The tax burden inhibits innovation and technological progress, but total governmental revenues positively affect technological performance.

However, the literature has left two topics in question: the extent to which credit access, agricultural output, and agricultural productivity are jointly determined, and the direction of causality across these linkages. Our empirical analysis is conducted on a large dataset of 114 countries for which we collected data from 2000 to 2012. To the best of our knowledge, this is the first paper on this topic that uses an Artificial Neural Networks (ANNs) approach in Machine Learning (ML).

Besides the introduction, the rest of the paper is organized as follows. Section 2 gives a brief survey of the literature. Section 3 contains an overview of the econometric methodology and a brief discussion of the data used. Section 4 discusses the applied findings. Section 5 presents some concluding remarks and suggestions for future studies.

2. Literature Review

2.1. Productivity and Credit Access

The rate of credit access in the agricultural sector is heterogeneous across countries and tends to be relatively lower with respect to non-agricultural sectors. Its role on the sector dynamics has been investigated in several studies. From a theoretical point of view, [12] provided an effective model showing how limited financial capabilities undermine the adoption of highly productive innovations, reducing the capabilities of advancing the production possibility frontier. This effect is supported by the empirical analysis of [11], who concluded that limited credit access leads to a suboptimal use of inputs. The results are also confirmed by [13]: credit constraints lower profits by inducing a suboptimal allocation of inputs. The results are supported also by several recent studies [21–23].

The evidence on the relationships between investments and credit access is mixed: Ref. [13] concluded that limited credit access does not prevent investments, whereas [14,24] supported opposite findings. The use of credit is more complex and is diverted to "purpose other than productive investments" [24].

The impacts on productivity and investments have implications on the growth of the sector. In line with studies on other sectors [5,25], the evidence suggests that developing credit markets facilitates the growth of the agricultural sector [26,27]. An exception is represented by [28], who concluded that the effect of credit on the agricultural sector development is limited. We have summarized some studies on the relation between credit access and productivity in Table 1.

Table 1. Summary of literature between credit access and productivity.

Author(s)	Country	Study Period	Empirical Strategy	Direction of Relationships
Rozelle et al. (1999)	China	1995	Cross section	CA → P
Feder et al. (1990)	China	1987	Cross section	CA → P
Foltz (2004)	Tunisia	1995	Cross section	CA → P
Kochar (1997)	India	1981–1982	Cross section	
Petrick (2004)	Poland	2000	Cross section	
O'Toole et al. (2014)	Ireland	1997–2010	Panel data	
Guirkinger and Boucher (2008)	Peru	1997 and 2003	Panel data	CA → P
Ali et al. (2014)	Rwanda	2011	Cross section	CA → P
Hartarska et al. (2015)	USA	1991–2010	Panel data	
Dong et al. (2012)	China	2008	Cross section	CA → P
Rehman et al. (2017)	Pakistan	1960–2015	Time series	

Notes: CA: Credit Access; P: Productivity. Source: our elaborations.

2.2. Financial Development and Economic Growth

The relationship between financial development and economic growth has received particular attention from applied studies, remaining an important issue of debate. The theoretical underpinnings of this relationship can be traced back to the work of [29]. The alternative causality flows between financial development and growth were denominated by [30] as the "supply–leading" and "demand–following" hypothesis. The former hypothesis suggests a causal relationship running from financial development to economic growth, with financial institutions influencing economic growth. On the other hand, the "demand–following" hypothesis indicates the existence of the opposite link, from economic growth to financial development. These theoretical debates highlight the lack of a consensus on the effect of financial development in the economic growth process, as well as the direction of causal inference between these macroeconomic variables.

Some economists argued that financial systems promote economic growth with a significant role, in line with the "supply–leading" hypothesis. Refs. [31,32] emphasized the positive role of financial systems in economic growth. For applied panel data studies, ref. [25], using data on 80 countries over the 1960–1989 period, showed that initial levels of financial development are relevant in explaining subsequent growth. Ref. [33] analyzed a dataset of about 100 countries during 1960–1985, concluding that financial development fosters growth performance. Ref. [34] analyzed the empirical relation between the index of stock market development and economic growth in the long-run for 41 countries in the years 1976–1993. They included a variety of macroeconomic indicators (the ratio of government consumption expenditures to GDP, the inflation rate, and the black market exchange rate premium). The results of IVs regressions show a strong association between the two variables. Ref. [7] used a panel dataset of 74 countries over the period of 1960–1995 with GMM techniques, showing that reforms that boost financial intermediary development are able to consequently stimulate economic growth. Ref. [35] studied data for Korea during 1971–2002, providing empirical support in favor of the "supply–leading" hypothesis. Refs. [36–38] provided further support to this hypothesis.

While [5] concluded that the development of the financial sector facilitates the growth of the corporate sector, ref. [39], using data on firms and bank branches of 18 emerging European economies, illustrated that credit access has a positive effect on local economic growth.

On the other hand, refs. [40,41] stated that financial development has a negligible and over-stressed effect on economic growth, so that the engines of growth should be sought elsewhere. Refs. [42–44] casted doubt on the importance of the financial system in promoting economic growth. Additionally, refs. [45,46] gave support to the "demand–following" hypothesis. Ref. [9], using Sims–Geweke causality tests on about 74 countries covering the period 1961–1995, found that economic growth precedes financial development.

Finally, refs. [10,47–49] found evidence of bidirectional causality and reverse causation. On the other hand, ref. [50] reached inconclusive results, with a panel of fifteen MENA countries for the period 1980–2007.

As regards time-series studies, refs. [51–53] showed evidence that finance predicts growth, while [54] provided results in line with the feedback hypothesis, with a bidirectional causality.

An appealing summary of efforts to measure and analyze the impact of access to finance is due to [55]. Ref. [56] indicated that higher bank competition increases firms' access to finance, while [57] discovered that only obstacles related to finance, crime, and policy instability directly affect firm growth.

In Table 2, we synthetized some applied findings on the financial development–economic growth nexus.

Table 2. Summary of literature between financial development and economic growth.

Author(s)	Country	Study Period	Empirical Strategy	Direction of Relationships
King and Levine (1993)	80 countries	1960–1989	Cross-country regressions	FD → EC
De Gregorio and Guidotti (1995)	80 countries	1960–1985	Cross-country regressions	FD → EC
Demetriades and Hussein (1996)	16 countries	1960–1993	Time series	FD ↔ EC
Demetriades and Luintel (1996)	Nepal	1960–1992	Time series	FD ↔ EC
Levine and Zervos (1996)	41 countries	1976–1993	Cross-country regressions	FD → EC
Neusser and Kugler (1998)	13 countries	1970–1991	Time series	FD → EC
Rajan and Zingales (1998)	55 countries	1980–1990	Cross-country regressions	FD → EC
Luintel and Khan (1999)	10 countries		Time series	FD ↔ EC
Beck et al. (2000)	63 countries	1960–1995	Cross-country and panel data	FD → EC
Levine et al. (2000)	74 countries	1960–1995	Cross-country and panel data	FD → EC
Rousseau and Wachtel (2000)	47 countries	1980–1995	Panel data	FD → EC
Calderón and Liu (2003)	109 countries	1960–1994	Geweke decomposition test on pooled data	FD ↔ EC
Yang and Yi (2008)	Korea	1971–2002	Time series	FD → EC
Zang and Kim (2007)	74 countries	1961–1995	Panel data	FD ← EC
Kar et al. (2011)	MENA countries	1980–2007	Panel data	Mixed results
Baliamoune-Lutz (2013)	18 African countries	1960–2001	Time series	FD ↔ EC
Magazzino (2018)	Italy	1960-2014	Time series	FD → EC

Notes: EC: Economic Growth; FD: Financial Development. Source: our elaborations.

3. Materials and Methods

LAGTFP represents agricultural TFP indexes (base year 1961 = 100) over 1961–2012 using primarily FAO data; *LRCA* is the credit to agriculture, in US $, at constant prices, while *LGAO* is the gross agricultural output for each country, where annual fluctuations have been smoothed by the Hodrick–Prescott filter. The applied analysis uses annual data from 2000 to 2012 for 114 countries, including both developed and developing countries, located in several continents (We gratefully acknowledge the comment of a reviewer who has stressed the importance of exploring the differences across groups of countries. While of great relevance, this is beyond the scope of the present article. In a subsequent analysis, we have shown that the degree of development matters). The data are derived from the World Development Indicator database (see, for more details: http://www.econstats.com/wdi/wdic_MNA.htm (accessed on 1 June 2019)). The data starting period was dictated by credit to agriculture data availability. Moreover, we avoid the more recent years, since the current economic–financial crisis has substantially affected the estimated relationships. We derived the log-transformation of all variables. Table A1 in the Appendix A summarizes the variables considered in the empirical analysis.

A graphical analysis of the three variables of interest (Figure 1) allows us to conclude overall correlations. The scatterplot matrices show that the gross agricultural output and the agricultural TFP indexes tend to be positively correlated. The relationships of credit to the agricultural sector with the two variables are non-linear. In particular, the credit to agriculture is not very correlated with agricultural TFP indexes; while low value of credit access (i.e., for values below one, which turn out to be negative after log transformation) are associated with average values of TFP, the highest value of credit access relates to very heterogeneous values of TFP. A similar dichotomy is observed for the gross agricultural output: low values of credit access correspond to relatively lower values of gross agricultural output, whereas higher values of credit access are positively correlated with gross agricultural output.

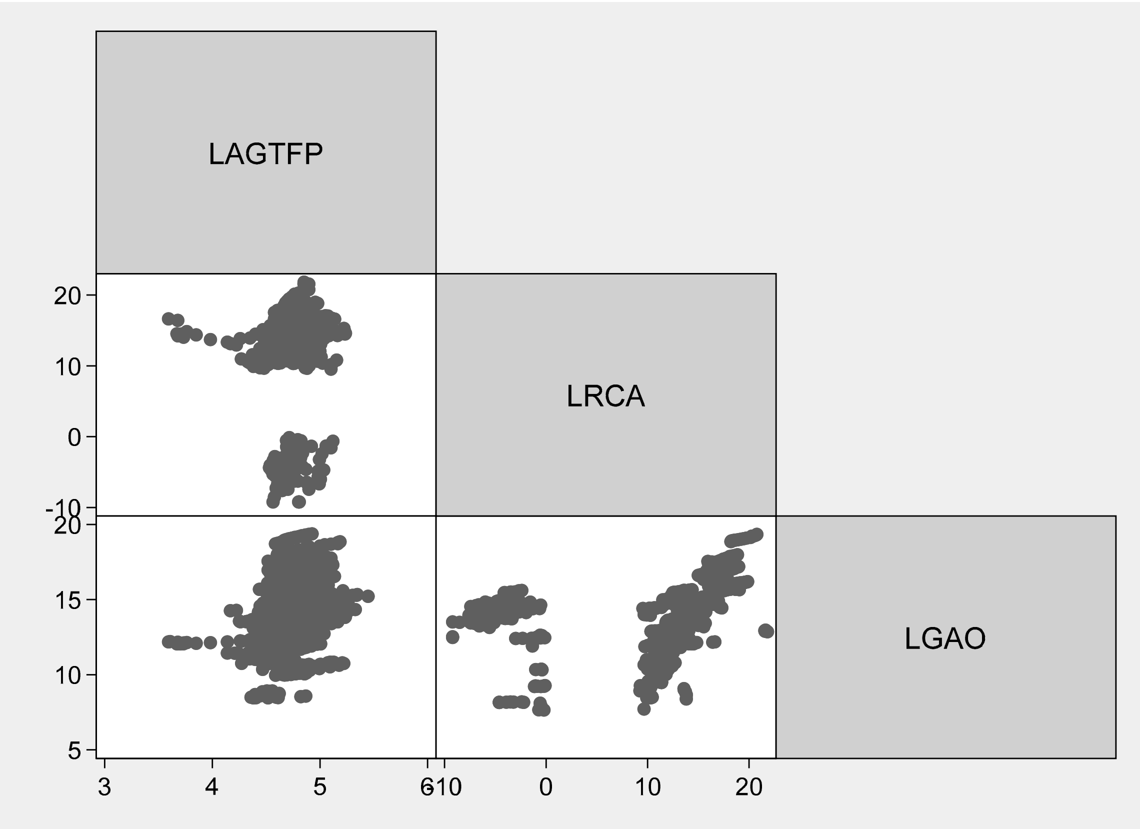

Figure 1. Agricultural TFP indexes, credit to agriculture, and gross agricultural output in 114 countries (2000–2012, log-scale). Sources: WDI data.

Table A2 in the Appendix A reports the summary statistics for the overall sample. The mean value of all variables is positive. The gross agricultural output variable has negative value of skewness, indicating that the distribution is left-skewed, with more observations on the right tail. In addition, it is interesting to note how our three variables show similar values for mean and median in each sub-sample, indicating that a normal distribution emerges.

Given the fact that for each variable the 10% trimmed mean values are near the mean, as well as the Standard Deviation to the Pseudo Standard Deviation, the Inter-Quartile Range (IQR) shows the absence of outliers in the observed sample. The correlation coefficients (r) are positive and significant at 1% level in each sub-sample.

In addition, in Table A3 in the Appendix A, we provide some evidence of mean or median comparisons tests. The results clearly underline how mean and median values of the different sub-samples statistically differ. In fact, the null hypothesis is rejected everywhere.

We choose to use this ANNs experiment for the following reasons. NNs work in parallel and are, therefore, able to process a lot of data simultaneously and autonomously. In contrast, in standard or econometric statistical processes, each data is treated individually and/or in time series. Even though each neuron is relatively slow, the parallelism partly explains the faster speed of the brain in performing tasks that require the simultaneous processing of a large number of data. In essence, it is a sophisticated statistical system with excellent noise immunity; if some units of the system were to malfunction, the network as a whole would have reduced performance but would hardly encounter a system crash (for more details, see [58–68]).

The characteristics of a NN model that we use are the following:

(a) The development of the "neuron system" is distributed over many elements. In other words, many neurons do the same thing;
(b) An address identifies each data of the algorithm used (a number), which is used to retrieve the knowledge necessary to perform a certain task;
(c) ANNs, unlike standard econometric models and their software, do not have to be programmed to perform a task. ANNs learn independently based on experience or with the help of an external instructor.

We use the following algorithms terms (Algorithms 1) to describe our NN process:

Algorithms 1. Algorithms terms to describe neural networks process

$1: input \ \rightarrow x \in \mathbb{R}^D$
$2: output \ \rightarrow y \in \mathbb{R}^J$
$3: output\ vector\ in\ n\ levels \rightarrow \ \sigma^l \in \mathbb{R}^{Ml}$ with each layer $1, 2 \ldots, L$
$4: weight\ matrix \ \rightarrow \ W^l \epsilon \mathbb{R}^{Ml \otimes Ml-1}$ with $M_0 = D;\ M_L = K$
$5: bias\ vector \rightarrow u^l \in \mathbb{R}^{Ml}$
$6: \gamma = (W^l \epsilon \mathbb{R}^{Ml \otimes Ml-1}) + u^l \in \mathbb{R}^{Ml}$
$7: \delta(\cdot): \mathbb{R} \rightarrow \mathbb{R}$
Our NN can be written as:
$8: f(x, \gamma) = \sigma^l$
$9: \sigma^l = \delta\left(\ a^l\right) = \delta\left(W^l \sigma^{l-1} + u^l\right)$ where $a^l = W^l \sigma^{l-1} + u^l$
$10: u^0 = x$
Our activation functions can be linear or nonlinear with $L = n$. In the first case:
$11: f\left(x,\ (W^l \epsilon \mathbb{R}^{Ml \otimes Ml-1}\right) + u^l \in \mathbb{R}^{Ml} = \ \sigma^n = \delta(W^n \sigma^1) = \delta(W^n \delta(W^1 x))$ [11]
If δ is a linear function $\rightarrow \ \delta\left(u^l\right) = k_l u^l$ where $f(x, \gamma) = k_n(W^n k x + \vartheta_1) + \vartheta_n = \ \hat{W}x + \hat{u}$.
If we choose, in an arbitrary way, to use a non-linear activation function, we have:
$12: \delta(x) = \frac{1}{1+\exp(-x)}$
$13: \delta' = \delta(x)(1 - u(x))$
$14: \tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{+x}}$
$15: tanh'(x) = 1 - \tan h^2(x)$
Thus, with rectified linear unit, we have:
$$16: Relu(x) = \begin{cases} x\ for\ x > 0 \\ 0\ for\ x <= 0 \end{cases}$$
In our NN, MSE will be:
$17: MSE(\tau) = \frac{1}{2N} \sum_{n=1}^{N} \|f(x_n,\ \tau) - t_n\|_2^2$
In [17]:
$18: \|f(x_n,\ \tau) - t_n\|_2^2 = (l_{2,n})^2 \rightarrow \|V\|_2^2 = \ \sum_{k=1\ or\ n}^{n} V_k^2$
Now, the Log-Likelihood (LL) will be:
$$19: LL([x_n] = \ \frac{1}{N} \sum_{n=1\ or\ n=n}^{N} \quad logP\ (x_n)$$

We expanded the observations through the quadratic transformations (*LRCAS*, *LAGTPS*, and *LGAOS*) and first differences of each variable (*LRCADF*, *LAGTPDF*, and *LRCADF*). In this way, our NN has worked on over 21,000 data and has guaranteed us better ML results.

After, we test, as robustness checks, the PVAR results obtained with panel data methodologies through the ANNs analyses, using the Oryx 2.0.8 software. We choose to use this ANNs experiment for the following reasons. NNs work in parallel and are, therefore, able to process a lot of data simultaneously and autonomously. In contrast, in standard or econometric statistical processes, each data is treated individually and/or in time series. Even though each neuron is relatively slow, the parallelism partly explains the faster speed of the brain in performing tasks that require the simultaneous processing of a large number of data. In essence, it is a sophisticated statistical system with excellent noise immunity; if some units of the system were to malfunction, the network as a whole would have reduced performance but would hardly encounter a system crash.

The characteristics of a NN model that we use are the following:

(a) The development of the "neuron system" is distributed over many elements. In other words, many neurons do the same thing;
(b) An address identifies each data of the algorithm used (a number), which is used to retrieve the knowledge necessary to perform a certain task;
(c) ANNs, unlike standard econometric models and their software, do not have to be programmed to perform a task. ANNs learn independently based on experience or with the help of an external instructor. Therefore, we used the same dataset as the PVAR econometric modeling; however, we expanded the observations through the quadratic transforms (*LRCAS*, *LAGTPS*, and *LGAOS*) and firsts differences of each variable (*LRCADF*, *LAGTPD,F* and *LRCADF*). In this way, our neural network has worked on over 21,000 data and has guaranteed us a better ML results.

Assuming the variable redundancy process's validity in a neural network, we obtain seven inputs (*LRCA*, *LRCAS*, *LAGTPS*, *LGA*, *LRCADF*, *LAGTPDF*, and *LRCADF*) on 10 nodes with two targets (*LAGTP* and *LGAO*).

4. Results

In the first experiment, we tested the predictive capacity of three inputs (in the seven cases) concerning 5040 combinations of targets relative to the OECD countries. We have adapted our NNs algorithm to predict the probability that each variable might cause a variation between the same variables (in the Supplementary file, we report the algorithm results).

Figure 2 shows the result of the ANNs. The data in the seven inputs used have elaborated nine different hidden layers, which represent the hidden perceptrons. The complexity, represented by the number of hidden neurons, is 15:12:10:8:6:10:6:4:2. There have been over 21,500 neural connections generated. Since the NN automatically chooses the signal to be used, there have been about 20,800 final connections. As we can see from Figure 2, among the 5040 possible combinations, the NN has chosen two Targets: *LAGTFP* and *LGAO*. Subsequently, we tested the NN model through the so-called Confusion Matrix (Table 3).

The results of Table 3 confirm the goodness of those obtained by the NN approach. In particular, the correctness in predicting the obtained results is very high. The predicted values cause a variation of the targets 99.36 times every 100 repetitions. Therefore, the probability that there are other targets, different from ours, is only 0.64% (we calculated the probability, dividing the number of positive/negative predicted events by the number of possible cases). Thus, for OECD countries, if we exclude all potential combinations (complex false combinations), credit access stimulates both productivity and production.

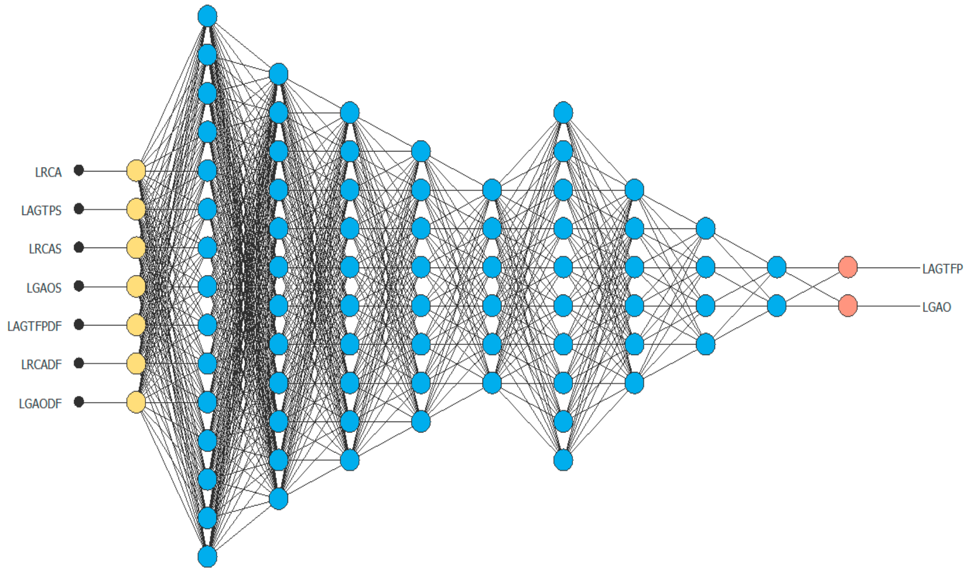

Figure 2. ANNs model (OECD countries). Sources: our elaborations in Oryx 2.0.8.

Table 3. Confusion Matrix for OECD countries.

	Predicted Positive	Predicted Negative
Actual Positive	20,043	128
Actual Negative	143	20,020
Accuracy	0.993	
Precision	0.992	
Sensitivity	0.993	
SP	0.992	
FPR	0.007	

Sources: our elaborations in Oryx 2.0.8.

Subsequently, we analyzed—with the same dataset—the effect of the seven inputs, and of the 5040 target combinations on the developing countries. Figure 3 shows the results.

Figure 3 shows the results obtained by combining the inputs concerning the probability of generating one or more targets. The complexity, represented by the number of hidden neurons, is 15:12:10:8:5:7:6:4:1. The model only generated the *LGAO* target. This result suggests a marginal role of the other inputs to the outputs. In particular, at the level of the economic theory, we can derive that only the credit access variable (*LRCA*) could have caused a change in production (*LGAO*). We have tested this result with the Confusion Matrix again, and the results are reported in Table 4.

In general, Table 4 confirms the goodness of the result of the ANNs in Figure 3. The predicted positive values (compared to the current positive/negative values) are more significant in number. The results state that the probability of obtaining a target different from that generated in the NNs is only 1.59%. The only possible target is a variation in agricultural production. Therefore, a change in the *LRCA* variable allows only a shift of the agricultural output, but not of the productivity (resulting in the OECD countries). Since the predicted positive results are higher than the negative ones, we can say that the change in the target represents a positive acceleration.

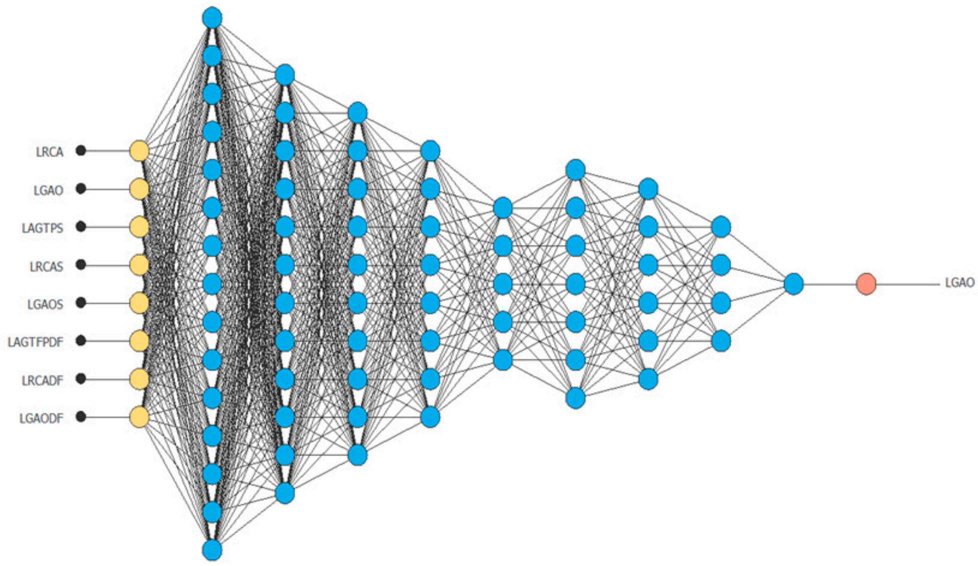

Figure 3. ANNs model (developing countries). Sources: our elaborations in Oryx 2.0.8.

Table 4. Confusion Matrix for developing countries.

	Predicted Positive	Predicted Negative
Actual Positive	19,852	319
Actual Negative	712	19,451
Accuracy	0.974	
Precision	0.956	
Sensitivity	0.984	
SP	0.964	
FPR	0.035	

Sources: our elaborations in Oryx 2.0.8.

5. Conclusions and Policy Implications

This study investigated the relationship among credit access, output, and productivity in the agricultural sector for a sample of 114 countries analyzed from 2000 to 2012. The empirical strategy used an ANNs experiment in ML.

The time-series results, confirmed by the ANNs process and the Confusion Matrix tests, show that the productivity is stimulated by credit access and the latter is facilitated by higher levels of agricultural output. Put differently, higher levels of output tend to stimulate the economic development in the agricultural sector, via higher productivity and, more importantly, by improving credit access. These results, specific for the agricultural sector, are in line with the arguments supported by [6,7] on the positive relationship between credit markets development and economic growth, and the role of productivity growth. Moreover, the discovered relationships between credit, output, and productivity are in line with earlier and recent studies [21,69]. It is interesting to note that Verdoorn's law [70] is confirmed in all our estimates: in fact, output significantly influences productivity in all tested samples.

Notably, the fundamentals of the agricultural economy follow different mechanisms across countries: the relationships among the three variables are tighter (and of longer impact) for OECD countries, where the credit stimulates both productivity and output. On the other hand, these relationships are loose (and of shorter term) in developing countries, where the stimulus of credit is only beneficial to agricultural output, and not to the productivity. A plausible explanation of our findings is provided by the well-established literature on the role of technological innovations in agriculture [71,72]). The role of credit is more important for developed economies, and advanced agricultural sectors where agricultural firms may easily exploit, through credit, the advantages of technological innovations. Differently, providing credit to firms located in developing countries is only able to boost production, exactly because technologies spread slowly though learning-by-doing and learning-from-others mechanisms, and the gains from advanced technologies cannot be exploited.

Our results favor the motivations for intervention in credit markets as a strategy to promote economic development. Following the argument of [73], who state that "agricultural credit was conceptualized as factor of production, [. . .] an increase in supply of credit would lead to an increase in production and income", we conclude that policies facilitating credit access leverage output. In addition, the evidence on the developed economies suggests that such policies may have impacts both on production and on productivity. A direct implication of our analysis is that while it is true that credit constraints tend to limit growth [1], the higher the economic development, the more agricultural development is hampered by lack of credit access. Put differently, pro-growth policy interventions in the least developed countries may not necessarily require the development of credit markets, whereas the opposite would be true in developed economies.

A limitation of our analysis is that we are not able to disentangle the mechanisms that trigger the reciprocal causality between credit and productivity. However, by observing that this link is clearly linked to the level of economic development, we raise an important research question on potential synergies that may be exploited to accelerate the economic development of the agricultural sector. Further researching the impacts that policies devoted to productivity and to credit may have in developing countries is an important issue, and deserves future research.

Supplementary Materials: The following are available online at https://www.mdpi.com/2071-1050/13/5/2828/s1, Table S1: Algorithm results.

Author Contributions: Conceptualization, C.M. and F.G.S.; methodology, C.M. and M.M.; software, C.M.; validation, C.M.; formal analysis, C.M. and M.M.; investigation, M.M. and F.G.S.; resources, F.G.S.; data curation, F.G.S.; writing—original draft preparation, C.M., M.M. and F.G.S.; writing—review and editing, C.M. and F.G.S.; visualization, C.M.; supervision, F.G.S.; project administration, C.M., M.M. and F.G.S.. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Variables' definitions.

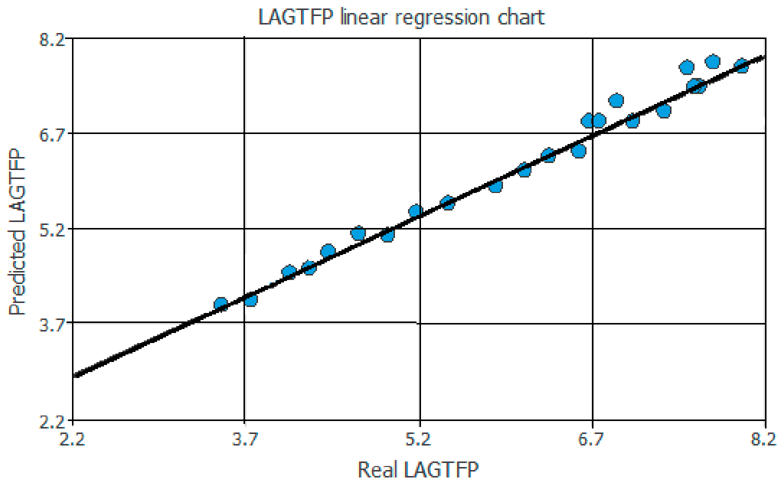
Abbreviation	Description	Source
LAGTFP	Agricultural TFP indexes (based year 1961 = 100)	WDI
LRCA	Credit to agriculture, USD, 2005 prices	WDI
LGAO	Gross agricultural output	WDI

Sources: our elaborations.

Table A2. Exploratory data analyses.

Variable	Mean	Median	SD	Skewness	Kurtosis	IQR	10-Trim	PSD
				Full sample				
LAGTFP	4.7247	4.6974	0.1878	−0.3518	7.1713	0.2259	4.7190	0.1675
LRCA	10.8572	13.3334	7.7163	−1.1710	3.0324	5.7287	11.8600	4.2470
LGAO	14.2442	14.4412	2.3128	−0.4859	2.8906	2.8957	14.3900	2.1470
				OECD				
LAGTFP	4.7539	4.7381	0.1588	0.2006	2.4794	0.2248	4.7500	0.1666
LRCA	18.1554	18.1062	1.3555	0.0825	1.6893	2.5493	18.1600	1.8900
LGAO	16.3678	17.0177	1.2610	−1.2285	3.5643	1.4994	16.5800	1.1120
				Developing				
LAGTFP	4.7275	4.6944	0.1753	0.5943	3.5870	0.2241	4.7160	0.1661
LRCA	10.1588	12.7988	7.5960	−1.1751	2.9321	4.9499	11.1600	3.6690
LGAO	14.1416	14.3401	2.2467	−0.3843	2.8372	2.7683	14.2400	2.0520
				Net Food Importing Developing				
LAGTFP	4.7083	4.6799	0.1588	1.3461	5.8767	0.1589	4.6890	0.1178
LRCA	8.6626	11.6343	7.3240	−0.9090	2.2020	14.2934	9.4100	10.6000
LGAO	13.3027	13.8673	2.2702	−0.4519	2.2996	3.0951	2.2940	3.0950
				Least Developed				
LAGTFP	4.6975	4.6581	0.1679	1.1617	5.2129	0.1642	4.6820	0.1217
LRCA	4.5156	9.9942	8.7194	−0.1587	1.1835	16.9595	4.7180	12.5700
LGAO	13.8314	14.0033	1.3480	−0.2158	2.5083	1.9594	13.8600	1.4520

Notes: SD: Standard Deviation; IQR: Inter-Quartile Range; PSD: Pseudo Standard Deviation. Sources: our calculations on WDI data.



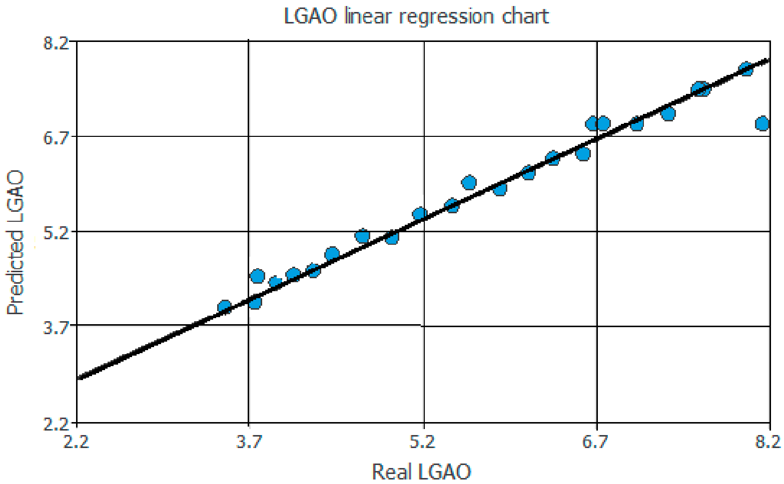


Figure A1. Target Linear Regression Test (*LAGFTFP-LGAO*).

Table A3. Paired samples statistics.

Variable	Groups	Mean	N	Standard Error	Standard Deviation	t	Satterthwaite's d.o.f.	Wilcoxon Test	Kruskal–Wallis Test	One-Way ANOVA F Test	Pearson χ^2 Test	Kolmogorov–Smirnov Test
1. LAGTFP	Non-OECD	4.72	1955	0.0043	0.1912	−3.18	396.77	−3.233	10.452	7.66	14.453	0.1290
	OECD	4.75	276	0.0096	0.1588			(0.0012)	(0.0012)	(0.0057)	(0.000)	(0.001)
2. LAGTFP	Non-Developing	4.70	276	0.0156	0.2591	−1.43	311.51	1.753	3.072	3.64	7.689	0.0959
	Developing	4.73	1955	0.0040	0.1753			(0.0797)	(0.0796)	(0.0565)	(0.006)	(0.023)
3. LAGTFP	Non-NFID	4.73	1725	0.0047	0.1952	2.49	995.09	3.612	13.050	4.97	12.803	0.1547
	NFID	4.71	506	0.0071	0.1588			(0.0003)	(0.0003)	(0.0259)	(0.000)	(0.000)
4. LAGTFP	Non-LD	4.73	1679	0.0047	0.1931	4.21	1067.55	5.782	33.436	15.42	27.433	0.1502
	LD	4.70	552	0.0071	0.1679			(0.0000)	(0.0001)	(0.0001)	(0.000)	(0.000)
5. LRCA	Non-OECD	9.97	885	0.2589	7.7008	−28.20	901.43	−14.956	223.675	120.20	117.705	0.8305
	OECD	18.16	107	0.1310	1.3555			(0.0000)	(0.0001)	(0.0000)	(0.000)	(0.000)
6. LRCA	Non-Developing	14.99	144	0.5948	7.1382	7.41	202.02	11.382	129.556	50.22	79.620	0.5559
	Developing	10.16	848	0.2608	7.5960			(0.0000)	(0.0001)	(0.0000)	(0.000)	(0.000)
7. LRCA	Non-NFID	11.87	679	0.2950	7.6874	6.31	634.11	9.339	87.224	38.38	78.883	0.3204
	NFID	8.66	313	0.4140	7.3240			(0.0000)	(0.0001)	(0.0000)	(0.000)	(0.000)
8. LRCA	Non-LD	13.10	733	0.2171	5.8784	14.70	344.39	15.498	240.190	310.74	147.478	0.4778
	LD	4.52	259	0.5418	8.7194			(0.0000)	(0.0001)	(0.0000)	(0.000)	(0.000)
9. LGAO	Non-OECD	13.97	2139	0.0492	2.2755	−26.51	542.34	−17.794	316.638	294.65	214.734	0.6072
	OECD	16.37	276	0.0759	1.2610			(0.0000)	(0.0001)	(0.0000)	(0.000)	(0.000)
10. LGAO	Non-Developing	14.97	299	0.1520	2.6275	5.19	362.21	7.502	56.275	34.11	49.715	0.3286
	Developing	14.14	2116	0.0488	2.2467			(0.0000)	(0.0001)	(0.0000)	(0.000)	(0.000)
11. LGAO	Non-NFID	14.60	1748	0.0533	2.2269	12.66	1183.98	11.699	136.871	162.95	68.403	0.2228
	NFID	13.30	667	0.0879	2.2702			(0.0000)	(0.0001)	(0.0000)	(0.000)	(0.000)
12. LGAO	Non-LD	14.37	1863	0.0583	2.5163	6.54	1730.31	7.772	60.401	23.00	80.174	0.2869
	LD	13.83	552	0.0574	1.3480			(0.0000)	(0.0001)	(0.0000)	(0.000)	(0.000)

Notes: unequal variances assumed, after some checks. After ANOVA, Sidak multiple-comparison test has been performed. P-Values in parentheses. Wilcoxon test: Two-sample rank-sum Mann–Whitney test. Kruskal–Wallis test: χ^2 test with ties. Pearson χ^2 test: Median test, continuity corrected. Kolmogorov–Smirnov test: Two-sample test for equality of distribution functions.

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