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 development. 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

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 between 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      | CA → P                     |
| Petrick (2004)        | Poland  | 2000         | Cross section      | CA → P                     |
| O’Toole et al. (2014) | Ireland | 1997–2010    | Panel data         | CA → P                     |
| 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         | CA → P                     |
| 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 (1996) | 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                           | FD ↔ EC                    |
| Balamoune-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; LRC$A$ is the credit to agriculture, in US $, at constant prices, while LGA$O$ 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. ANNs 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 → \( x \in \mathbb{R}^D \)
2: output → \( y \in \mathbb{R}^J \)
3: output vector in \( n \) levels → \( a^l \in \mathbb{R}^{M_l} \) with each layer 1, 2, ..., \( L \)
4: weight matrix → \( W^l \in \mathbb{R}^{M_l \times M_{l-1}} \) with \( M_0 = D; M_L = K \)
5: bias vector → \( u^l \in \mathbb{R}^{M_l} \)
6: \( \gamma = (W^l e^{\mathbb{R}^{M_l \times M_{l-1}}}) + u^l \in \mathbb{R}^{M_l} \)
7: \( \delta(\cdot) : \mathbb{R} \rightarrow \mathbb{R} \)

Our NN can be written as:
8: \( f(x, \gamma) = a^l \)
9: \( a^l = \delta \left( a^{l-1} + u^l \right) \) where \( a^l = W^l a^{l-1} + u^l \)
10: \( u^0 = x \)

Our activation functions can be linear or nonlinear with \( L = n \). In the first case:
11: \( f(x, (W^l e^{\mathbb{R}^{M_l \times M_{l-1}}}) + u^l) \in \mathbb{R}^{M_l} = \sigma^v = \delta(W^v \sigma^1) = \delta(W^v \delta(W^1 x)) \) \[11\]

If \( \delta \) is a linear function → \( \delta(u^l) = k_l u^l \) where \( f(x, \gamma) = \delta(W^v k x + \theta_1) + \theta_n = W x + \hat{a} \).

If we choose, in an arbitrary way, to use a non-linear activation function, we have:
12: \( \delta(x) = \frac{1}{1+e^{-x}} \)
13: \( \delta(x) = \frac{1}{1-u(x)} \)
14: \( \tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \)
15: \( \tanh'(x) = 1 - \tanh^2(x) \)

Thus, with rectified linear unit, we have:
16: \( \text{Relu}(x) = \begin{cases} x & \text{for } x > 0 \\ 0 & \text{for } x \leq 0 \end{cases} \)

In our NN, MSE will be:
17: \( \text{MSE}(\tau) = \frac{1}{N} \sum_{n=1}^{N} \| f(x_n, \tau) - t_n \|_2^2 \)

In [17]:
18: \( \| f(x_n, \tau) - t_n \|_2^2 = (L_2 n)^2 \rightarrow \| V \|_2^2 = \sum_{k=1}^{n} V_k^2 \)

Now, the Log-Likelihood (LL) will be:
19: \( LL([x_n] = \frac{1}{N} \sum_{n=1 \text{ or } n=n}^{N} \log P(x_n) \)
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.

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(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, LAGTPDF 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.
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.

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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 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
Specificity: 0.992
False Positive Rate: 0.007

Sources: our elaborations in Oryx 2.0.8.

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.

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. 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
Specificity: 0.964
False Positive Rate: 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 through 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.

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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    |
|----------|--------|--------|-------|----------|----------|--------|---------|--------|
|          |        |        |       |          |          |        |         |        |
| 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   | 5.7267 | 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 |
|          |        |        |       |          |          |        |         |        |
| Least Developed | |        |       |          |          |        |         |        |
| 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  | 2.9966   | 3.0951 | 2.2940  | 3.0950 |

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

Figure A1. Target Linear Regression Test (LAGTFP-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 $\chi^2$ Test | Kolmogorov–Smirnov Test |
|-----------------|------|-----|----------------|--------------------|-------|------------------------|---------------|---------------------|---------------------|---------------------|------------------------|
| 1. LAGTFP       |      |     |                |                    |       |                        |               |                     |                     |                     |                        |
| Non-OECD        | 4.72 | 1955| 0.0043         | 0.1912             | −3.18 | 396.77                 | −3.233        | (0.0012)          | (0.0012)           | 10.452              | 7.66                   | 14.453                 | 0.1290                |
| OECD            | 4.75 | 276 | 0.0096         | 0.1588             | −3.072| 3.64                   | 3.233         | (0.0057)          | (0.0057)           | 7.689               | 0.959                  |                        |                      |
| 2. LAGTFP       |      |     |                |                    |       |                        |               |                     |                     |                     |                        |
| Developing      | 4.73 | 1955| 0.0040         | 0.1753             | −1.43 | 311.51                 | −1.753        | (0.0797)          | (0.0796)           | 3.612               | 4.97                   | 12.803                 | 0.1547                |
| Non-NFID       | 4.73 | 1725| 0.0047         | 0.1952             | 2.49  | 995.09                 | 3.162         | 13.050             | (0.0003)          | (0.0003)           | (0.029)               | (0.000)              | (0.000)              |
| 3. LAGTFP       |      |     |                |                    |       |                        |               |                     |                     |                     |                        |
| Non-NFID       | 4.73 | 506 | 0.0071         | 0.1588             | 0.0003| 0.0000                 | 0.578         | 33.436             | (0.0001)          | (0.0001)           | (0.000)               | (0.000)              | (0.000)              |
| 4. LAGTFP       |      |     |                |                    |       |                        |               |                     |                     |                     |                        |
| LD              | 4.70 | 552 | 0.0071         | 0.1679             | 4.21  | 1067.55                | 15.42         | 27.433             | (0.0001)          | (0.0000)           | (0.0000)             | (0.0000)             | (0.0000)             |
| 5. LRCA         |      |     |                |                    |       |                        |               |                     |                     |                     |                        |
| Non-OECD       | 9.97 | 885 | 0.2589         | 7.7008             | −28.20| 901.43                 | −14.956       | 223.675            | (0.0000)          | (0.0000)           | (0.0000)             | (0.0000)             | (0.0000)             |
| OECD            | 18.16| 107 | 0.1310         | 1.3555             | 11.382| 129.55                 | 50.22         | 79.620             | (0.0000)          | (0.0000)           | (0.0000)             | (0.0000)             | (0.0000)             |
| 6. LRCA         |      |     |                |                    |       |                        |               |                     |                     |                     |                        |
| Non-OECD       | 14.99| 144 | 0.5948         | 7.1382             | 7.41  | 202.02                 | 9.239         | 87.224             | (0.0000)          | (0.0000)           | (0.0000)             | (0.0000)             | (0.0000)             |
| OECD            | 10.16| 484 | 0.2608         | 7.5960             | 11.382| 129.55                 | 50.22         | 79.620             | (0.0000)          | (0.0000)           | (0.0000)             | (0.0000)             | (0.0000)             |
| 7. LRCA         |      |     |                |                    |       |                        |               |                     |                     |                     |                        |
| Non-NFID       | 8.66 | 313 | 0.4140         | 7.3240             | 6.31  | 634.11                 | 9.339         | 87.224             | (0.0000)          | (0.0000)           | (0.0000)             | (0.0000)             | (0.0000)             |
| 8. LRCA         |      |     |                |                    |       |                        |               |                     |                     |                     |                        |
| LD              | 13.10| 733 | 0.2171         | 5.8784             | 6.31  | 634.11                 | 9.339         | 87.224             | (0.0000)          | (0.0000)           | (0.0000)             | (0.0000)             | (0.0000)             |
| 9. LGAO         |      |     |                |                    |       |                        |               |                     |                     |                     |                        |
| Non-OECD       | 13.97| 2139| 0.0492         | 2.2755             | −26.51| 542.34                 | −17.794       | 316.638            | (0.0000)          | (0.0000)           | (0.0000)             | (0.0000)             | (0.0000)             |
| OECD            | 16.37| 276 | 0.0759         | 1.2610             | 7.502 | 56.275                 | 34.11         | 49.715             | (0.0000)          | (0.0000)           | (0.0000)             | (0.0000)             | (0.0000)             |
| 10. LGAO        |      |     |                |                    |       |                        |               |                     |                     |                     |                        |
| Non-OECD       | 14.97| 299 | 0.1520         | 2.6275             | 5.19  | 362.21                 | (0.0000)      | 162.95             | (0.0000)          | (0.0000)           | (0.0000)             | (0.0000)             | (0.0000)             |
| OECD            | 14.14| 2116| 0.0488         | 2.2467             | 11.699| 136.871                | 68.403        | 147.478            | (0.0000)          | (0.0000)           | (0.0000)             | (0.0000)             | (0.0000)             |
| 11. LGAO        |      |     |                |                    |       |                        |               |                     |                     |                     |                        |
| NFID           | 13.30| 667 | 0.0879         | 2.2702             | 12.66 | 1183.98                | 162.95        | 88.883             | (0.0000)          | (0.0000)           | (0.0000)             | (0.0000)             | (0.0000)             |
| 12. LGAO        |      |     |                |                    |       |                        |               |                     |                     |                     |                        |
| LF               | 13.47| 1863| 0.0583         | 2.5163             | 6.54  | 1730.31                | 7.772         | 60.401             | (0.0000)          | (0.0000)           | (0.0000)             | (0.0000)             | (0.0000)             |

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: $\chi^2$ test with ties. Pearson $\chi^2$ test: Median test, continuity corrected. Kolmogorov–Smirnov test: Two-sample test for equality of distribution functions.
References

1. Azariadis, C.; Drazen, A. Threshold externalities in economic development. Q. J. Econ. 1990, 105, 501–526. [CrossRef]

2. Besley, T. How do market failures justify interventions in rural credit markets? World Bank Res. Obs. 1994, 9, 27–47. [CrossRef]

3. Karlan, D.; Morduch, J. Access to finance. In Handbook of Development Economics; Elsevier: Amsterdam, The Netherlands, 2010; Volume 5, pp. 4703–4784.

4. Levine, R. Finance and growth: Theory and evidence. In Handbook of Economic Growth; Elsevier: Amsterdam, The Netherlands, 2005; Volume 1, pp. 865–934.

5. Rajan, R.G.; Zingales, L. Financial dependence and growth. Am. Econ. Rev. 1998, 88, 559–586.

6. Beck, T.; Levine, R.; Loayza, N. Finance and the sources of growth. J. Financ. Econ. 2000, 58, 261–300. [CrossRef]

7. Levine, R.; Loayza, N.; Beck, T. Financial intermediation and growth: Causality and causes. J. Monet. Econ. 2000, 46, 31–77. [CrossRef]

8. Winter-Nelson, A.; Temu, A.A. Liquidity constraints, access to credit and pro-poor growth in rural Tanzania. J. Int. Dev. 2005, 17, 867–882. [CrossRef]

9. Zang, H.; Kim, Y.C. Does financial development precede growth? Robinson and Lucas might be right. Appl. Econ. Lett. 2007, 14, 15–19. [CrossRef]

10. Balamoune-Lutz, M. Financial Development and Income in African Countries. Contemp. Econ. Policy 2013, 31, 163–175. [CrossRef]

11. Feder, G.; Lau, L.J.; Lin, J.Y.; Luo, X. The relationship between credit and productivity in Chinese agriculture: A microeconomic model of disequilibrium. Am. J. Agric. Econ. 1990, 72, 1151–1157. [CrossRef]

12. Rozelle, S.; Taylor, J.E.; DeBrauw, A. Migration, remittances, and agricultural productivity in China. Am. Econ. Rev. 1999, 89, 287–291. [CrossRef]

13. Foltz, J.D. Credit market access and profitability in Tunisian agriculture. Agric. Econ. 2004, 30, 229–240. [CrossRef]

14. O’Toole, C.M.; Newman, C.; Hennessy, T. Financing constraints and agricultural investment: Effects of the Irish financial crisis. J. Agric. Econ. 2014, 65, 152–176. [CrossRef]

15. Zhang, T.; Liu, H.; Liang, P. Social Trust Formation and Credit Accessibililty—Evidence from Rural Households in China. Sustainability 2020, 12, 667. [CrossRef]

16. Linh, T.N.; Long, H.T.; Chi, L.V.; Tam, L.T.; Lebailly, P. Access to rural credit markets in developing countries, the case of Vietnam: A literature review. Sustainability 2019, 11, 1468. [CrossRef]

17. Moshid, M.; Maharanj, K.L. Factors Affecting Farmers’ Access to Formal and Informal Credit: Evidence from Rural Afghanistan. Sustainability 2020, 12, 1268. [CrossRef]

18. Liu, J.; Wang, M.; Yang, L.; Rahman, S.; Sriboonchitta, S. Agricultural Productivity Growth and Its Determinants in South and Southeast Asia. J. Dev. Econ. 2020, 1268. [CrossRef]

19. Niu, Z.; Yan, H.; Liu, F. Decreasing Cropping Intensity Dominated the Negative Trend of Cropland Productivity in Southern China in 2000–2015. Sustainability 2020, 12, 10070. [CrossRef]

20. Sadeh, A.; Radu, C.F.; Feriesser, C.; Borşa, A. Governmental Intervention and Its Impact on Growth, Economic Development, and Technology in OECD Countries. Sustainability 2021, 13, 166. [CrossRef]

21. Guirkinger, C.; Boucher, S.R. Credit constraints and productivity in Peruvian agriculture. Agric. Econ. 2008, 39, 295–308. [CrossRef]

22. Dong, F.; Lu, J.; Featherstone, A.M. Effects of credit constraints on household productivity in rural China. Agric. Financ. Rev. 2012, 72, 402–415. [CrossRef]

23. Ali, D.A.; Deininger, K.; Duponchel, M. Credit Constraints, Agricultural Productivity, and Rural Nonfarm Participation: Evidence from Rwanda; The World Bank: Washington, DC, USA, 2014.

24. Petrick, M. Farm investment, credit rationing, and governmentally promoted credit access in Poland: A cross-sectional analysis. Food Policy 2004, 29, 275–294. [CrossRef]

25. King, R.G.; Levine, R. Finance and growth: Schumpeter might be right. Q. J. Econ. 1993, 108, 717–738. [CrossRef]

26. Hartarska, V.; Nadolyanyak, D.; Shen, X. Agricultural credit and economic growth in rural areas. Agric. Financ. Rev. 2015, 75, 302–312. [CrossRef]

27. Rehman, A.; Chandio, A.A.; Hussain, I.; Jingdong, L. Is credit the devil in the agriculture? The role of credit in Pakistan’s agricultural sector. J. Financ. Data Sci. 2017, 3, 38–44. [CrossRef]

28. Kochar, A. An empirical investigation of rationing constraints in rural credit markets in India. J. Dev. Econ. 1997, 53, 339–371. [CrossRef]

29. Schumpeter, J.A. The Theory of Economic Development; Harvard University Press: Cambridge, MA, USA, 1911.

30. Patrick, H.T. Financial development and economic growth in underdeveloped countries. Econ. Dev. Cult. Chang. 1966, 14, 174–189. [CrossRef]

31. McKinnon, R.I. Money and Capital in Economic Development; The Brookings Institute: Washington, DC, USA, 1973.

32. Shaw, E.S. Financial Deepening in Economic Development; Oxford University Press: New York, NY, USA, 1973.

33. De Gregorio, J.; Guidotti, P.E. Financial development and economic growth. World Dev. 1995, 23, 433–448. [CrossRef]

34. Levine, R.; Zervos, S. Stock market development and long-run growth. World Econ. Rev. 1996, 110, 323–340. [CrossRef]
35. Yang, Y.Y.; Yi, M.H. Does financial development cause economic growth? Implication for policy in Korea. *J. Policy Model.* 2008, 30, 827–840. [CrossRef]

36. Mele, M.; Magazzino, C. Financial development, growth, and the distribution of income. *J. Political Econ.* 1990, 98, 1076–1107. [CrossRef]

37. Bencivenga, V.R.; Smith, B.D. Financial intermediation and endogenous growth. *Rev. Econ. Stud.* 1991, 58, 195–209. [CrossRef]

38. Roubini, N.; Sala-i Martin, X. Financial repression and economic growth. *J. Dev. Econ.* 1992, 39, 5–30. [CrossRef]

39. Diao, L.; Al-Titi, O. Local growth and access to credit: Theory and evidence. *J. Macroecon.* 2017, 54, 410–423. [CrossRef]

40. Robinson, J. The Rate of Interest and Other Essays; MacMillan: London, UK, 1952.

41. Lucas, R.E., Jr. On the mechanics of economic development. *J. Monet. Econ.* 1988, 22, 3–42. [CrossRef]

42. Stern, N. The economics of development: A survey. *Econ. J.* 1989, 100, 597–685. [CrossRef]

43. Stiglitz, J. The role of the state in financial markets. In Proceedings of the World Bank Conference on Development Economics, World Bank: Washington, DC, USA, 1994.

44. Chandavarkar, A. Of finance and development: Neglected and unsettled questions. *Econ. Dev. Cult. Chang.* 1999, 48, 333–346. [CrossRef]

45. Gurley, J.; Shaw, E. Financial structure and economic development. *Econ. Dev. Cult. Chang.* 1967, 34, 333–346. [CrossRef]

46. Goldsmith, R.W. *Financial Structure and Development*; National Bureau of Economic Research: New Haven, CT, USA, 1969.

47. Demetriades, P.O.; Hussein, K.A. Does financial development cause economic growth? Time-series evidence from 16 countries. *J. Dev. Econ.* 1996, 51, 387–411. [CrossRef]

48. Magazzino, C.; Mele, M.; Morelli, G. The relationship between renewable energy and economic growth in a time of Covid-19: A Machine Learning experiment on the Brazilian economy. *World Bank Econ. Rev.* 2020, 32, 28–43. [CrossRef]

49. Calderón, C.; Liu, L. The Direction of Causality between Financial Development and Economic Growth. *J. Dev. Econ.* 2003, 72, 321–334. [CrossRef]

50. Kar, M.; Nazhojlu, S.; Agir, H. Financial development and economic growth nexus in the MENA countries: Bootstrap panel granger causality analysis. *Econ. Model.* 2011, 28, 685–693. [CrossRef]

51. Neusser, K.; Kugler, M. Manufacturing growth and financial development: Evidence from OECD countries. *Rev. Econ. Stat.* 1998, 80, 638–646. [CrossRef]

52. Rousseau, P.L.; Wachtel, P. Equity markets and growth: Cross-country evidence on timing and outcomes, 1980–1995. *J. Dev. Econ.* 1996, 48, 355–372. [CrossRef]

53. Beck, T.; Debruyne, E.; Nuijten, M.; Demirgüç-Kunt, A. Access to Finance: An Unfinished Agenda. *World Bank Econ. Rev.* 2008, 22, 383–396. [CrossRef]

54. Demetriades, P.O.; Hussein, K.A. Does financial development cause economic growth? Time-series evidence from 16 countries. *J. Dev. Econ.* 1996, 51, 387–411. [CrossRef]

55. Magazzino, C.; Mele, M.; Morelli, G. The relationship between renewable energy and economic growth in a time of Covid-19: A Machine Learning experiment on the Brazilian economy. *World Bank Econ. Rev.* 2020, 32, 28–43. [CrossRef]

56. Love, I.; Martinhal, C. The direction of causality between financial development and economic growth. *J. Dev. Econ.* 2003, 72, 321–334. [CrossRef]

57. Stiglitz, J. The role of the state in financial markets. In Proceedings of the World Bank Conference on Development Economics, World Bank: Washington, DC, USA, 1994.

58. Chandavarkar, A. Of finance and development: Neglected and unsettled questions. *Econ. Dev. Cult. Chang.* 1999, 48, 333–346. [CrossRef]

59. Magazzino, C.; Mele, M.; Morelli, G. The relationship between renewable energy and economic growth in a time of Covid-19: A Machine Learning experiment on the Brazilian economy. *World Bank Econ. Rev.* 2020, 32, 28–43. [CrossRef]

60. Magazzino, C.; Mele, M.; Morelli, G. The relationship between renewable energy and economic growth in a time of Covid-19: A Machine Learning experiment on the Brazilian economy. *World Bank Econ. Rev.* 2020, 32, 28–43. [CrossRef]

61. Magazzino, C.; Mele, M.; Morelli, G. The relationship between renewable energy and economic growth in a time of Covid-19: A Machine Learning experiment on the Brazilian economy. *World Bank Econ. Rev.* 2020, 32, 28–43. [CrossRef]

62. Magazzino, C.; Mele, M.; Morelli, G. The relationship between renewable energy and economic growth in a time of Covid-19: A Machine Learning experiment on the Brazilian economy. *World Bank Econ. Rev.* 2020, 32, 28–43. [CrossRef]

63. Magazzino, C.; Mele, M.; Morelli, G. The relationship between renewable energy and economic growth in a time of Covid-19: A Machine Learning experiment on the Brazilian economy. *World Bank Econ. Rev.* 2020, 32, 28–43. [CrossRef]

64. Magazzino, C.; Mele, M.; Morelli, G. The relationship between renewable energy and economic growth in a time of Covid-19: A Machine Learning experiment on the Brazilian economy. *World Bank Econ. Rev.* 2020, 32, 28–43. [CrossRef]

65. Magazzino, C.; Mele, M.; Morelli, G. The relationship between renewable energy and economic growth in a time of Covid-19: A Machine Learning experiment on the Brazilian economy. *World Bank Econ. Rev.* 2020, 32, 28–43. [CrossRef]

66. Magazzino, C.; Mele, M.; Morelli, G. The relationship between renewable energy and economic growth in a time of Covid-19: A Machine Learning experiment on the Brazilian economy. *World Bank Econ. Rev.* 2020, 32, 28–43. [CrossRef]

67. Magazzino, C.; Mele, M.; Morelli, G. The relationship between renewable energy and economic growth in a time of Covid-19: A Machine Learning experiment on the Brazilian economy. *World Bank Econ. Rev.* 2020, 32, 28–43. [CrossRef]

68. Magazzino, C.; Mele, M.; Morelli, G. The relationship between renewable energy and economic growth in a time of Covid-19: A Machine Learning experiment on the Brazilian economy. *World Bank Econ. Rev.* 2020, 32, 28–43. [CrossRef]
69. Bai, L.; Boudot, C.; Butler, A.; Eigner, J. Rural Banks and Agricultural Production: Evidence from India’s Social Banking Experiment. Work. Pap. 2018.

70. Verdoorn, P.J. Fattori che regolano lo sviluppo della produttività del lavoro. L’Industria 1949, 1, 3–10.

71. Foster, A.D.; Rosenzweig, M.R. Learning by doing and learning from others: Human capital and technical change in agriculture. J. Political Econ. 1995, 103, 1176–1209. [CrossRef]

72. Conley, T.G.; Udry, C.R. Learning about a new technology: Pineapple in Ghana. Am. Econ. Rev. 2010, 100, 35–69. [CrossRef]

73. Bardhan, P.; Udry, C. Development Microeconomics; OUP: Oxford, UK, 1999.