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Financial Development and Countries' Production Efficiency: A Nonparametric Analysis

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Abstract: This paper examines the effect of financial development on countries' production efficiency levels. By applying a probabilistic framework it develops robust (Order-m) time-dependent conditional nonparametric frontier estimators in order to measure 87 countries' production efficiency levels over the period 1970–2014. In order to examine the effect of time and domestic credit on countries' production efficiency levels, a second-stage nonparametric econometric analysis is performed. Specifically, generalized additive models with tensor products and cubic spline penalties are applied in order to investigate the potential nonlinear behavior of financial development on countries' production efficiency levels. The results reveal that the effect of financial development on production efficiency is nonlinear. Specifically, the effect is positive up to a certain credit level after which it becomes negative. Finally, the evidence suggests that the effect is influenced by a country's financial system, institutional, and development characteristics.

Keywords: financial development; production efficiency; nonparametric frontiers; generalized additive models; tensor products; cubic spline penalty

1. Introduction

The empirical evidence on countries' economic growth paths emphasize the existence of nonlinear trends which are of great importance for policy implications and for further investigation (Liu and Stengos 1999; Kalaitzidakis et al. 2001; Maasoumi et al. 2007). Such a nonlinear trend is also evident when examining the impact of financial development on countries' economic growth levels (Rousseau and Wachtel 2011; Arcand et al. 2015). Since countries' different development, institutional and financial system arrangements differentiate the way financial development impacts countries' growth levels (Arestis and Demetriades 1997), asymmetric phenomena can arise, which in turn, are worth the investigation using nonparametric econometric tools. Shen (2013) provides evidence of such nonlinear effects among financial development and economic growth, whereas, Beck et al. (2014) suggests that the provision of credit has a positive influence on the output growth only up to a point, after which the influence becomes negative. On the other hand, Ang (2011) provides evidence of a positive effect of financial development on innovation. Mallick et al. (2016) using a probabilistic framework of directional distance functions, provide evidence of a nonlinear effect of financial development on countries' technological change and technological catch-up levels. Based on this stream of research, this study further examines the effect of financial development on countries' growth levels, by investigating in a robust nonparametric frontier setting its effect on countries' production efficiency levels.

Specifically, by using Order-m (robust) frontier estimators (Cazals et al. 2002*)* and the recent developments on the probabilistic approach of nonparametric frontier analysis (Daraio and Simar 2005, 2007a, 2007b; Bădin et al. 2010, 2012, 2014), we develop in a first-stage analysis robust time-dependent conditional measures (Mastromarco and Simar 2015). By doing so, we evaluate 87

countries' production efficiency levels under the effect of both time and financial development over the period 1970–2014. As has been asserted by Daraio et al. (2018), the adopted approach does not assume that the restrictive "separability" assumption between the financial development, time and the input/output set holds. A vast majority of nonparametric efficiency and productivity studies in different research fields (i.e., production economics, environmental economics, banking/finance, hospitality, transport, etc.) estimate in a first-stage analysis different efficiency scores. Then, in a second-stage analysis the estimated efficiency scores are regressed on some environmental/exogenous factors[1] using different parametric/nonparametric regression approaches. However, these studies wrongly assume that the 'separability' assumption among the environmental/exogenous factors and the frontier of the attainable set holds. This assumption has been proven by Simar and Wilson (2007, 2011) that in the majority of times it is unrealistic since it implies that these factors do not influence: 'neither the shape nor the level of the boundary of the attainable set' but they affect only the distribution of the estimated inefficiencies (Daraio et al. 2018). Simar and Wilson (2011) assert that the studies which do not account properly for the 'separability' assumption, are applying questionably defined statistical models describing the data-generating process (DGP). As a result, the absence of inference does not lead to meaningful efficiency measurements. The lack of a coherent statistical model on such measurements leads to "unknown" estimations which are meaningless both for evaluating factors affecting DMUs' performance levels, but also for managerial and policy implications (Simar and Wilson 2011, p. 206). Following those arguments, the applied conditional probabilistic approach does not assume that the 'separability' assumption holds. Specifically, in a second-stage analysis we investigate the effect of financial development and time on the estimated time-dependent conditional Order-m efficiencies. We apply a generalized additive model (Hastie and Tibshirani 1990) with smooth functions (tensor products with cubic spline penalties) as has been analyzed by Wood (2002, 2003, 2004, 2006, 2017). As such the adoption of robust nonparametric frontier methods alongside the nonparametric econometric advances will enable us to reveal potential nonlinear phenomena of the examined relationship. The remainder of the paper is as follows: Section 2 describes the data and the methodologies adopted, whereas, Section 3 provides the findings of our analysis. Finally, the last Section concludes our paper.

2. Materials and Methods

2.1. Probabilistic Approach of Countries' Production Frontier

Based on the activity analysis by Debreu (1951), countries' production function can be characterized by a set of inputs $x \in \mathbb{R}_+^p$ and by a set of outputs $y \in \mathbb{R}_+^q$. In our case the inputs are: Capital stock at current PPPs (in mil. 2011 US dollars) and the number of total labor force (in millions), whereas, the output is the output-side real GDP at current PPPs (in mil. 2011 US dollars). The data are covering 87 countries[2] over the period 1970-2014 and have been extracted from the latest version of Penn World Tables-PWT v9.0 (Feenstra et al. 2015).[3] We argue that countries' production process can be affected by the different levels of domestic credit to the private sector (% of GDP), which is

[1] The environmental/exogenous factors are referring to those factors which are not under (or partially under) the control of the decision maker.

[2] OECD countries (20): Australia, Canada, Chile, Denmark, Finland, Iceland, Ireland, Israel, Italy, Japan, Mexico, Netherlands, New Zealand, Norway, Republic of Korea, Sweden, Switzerland, Turkey, United Kingdom and United States. Non-OECD countries (67): Argentina, Bahamas, Benin, Bolivia, Botswana, Brazil, Burkina Faso, Burundi, Cameroon, Central African Republic, Chad, Colombia, Congo, Costa Rica, Côte d'Ivoire, D.R. of the Congo, Dominican Republic, Ecuador, Egypt, El Salvador, Fiji, Gabon, Gambia, Ghana, Guatemala, Honduras, India, Iran, Jamaica, Jordan, Kenya, Kuwait, Madagascar, Malawi, Malaysia, Mali, Malta, Mauritius, Morocco, Nepal, Niger, Nigeria, Oman, Pakistan, Panama, Paraguay, Peru, Philippines, Qatar, Saudi Arabia, Senegal, Sierra Leone, Singapore, South Africa, Sri Lanka, Sudan, Suriname, Swaziland, Syrian Arab Republic, Thailand, Togo, Trinidad and Tobago, Tunisia, Uganda, Uruguay, Venezuela and Zambia.

[3] The codenames of the variables which have been extracted from PWT v9.0 are: "ck", "emp" (inputs) and "cgdpo" (output).

used as a proxy of financial development.[4] Then the vector of domestic credit to private sector (PCR) can be noted as $C \in \mathcal{C} \subset \mathbb{R}^r$, and the production attainable set can be represented as:

$$\Omega = \{(x, y) | x \; can \; produce \; y\}, \tag{1}$$

whereas, the conditional attainable set (i.e., under the effect of domestic credit to private sector) can be presented as:

$$\Omega^c = \{(x, y) | C = c, x \; can \; produce \; y\}. \tag{2}$$

Based on Daraio and Simar (2005, 2007a, 2007b), we have $\Omega = \bigcup_{c \in \mathcal{C}} \Omega^c$ so that we can have for all $C \in \mathcal{C}, \Omega^c \subseteq \Omega$.

According to the work of Farrell (1957) and Shephard (1970), countries' output-oriented efficiency at (x_0, y_0) level can be defined as:

$$\psi(x_0, y_0) = sup\{\psi > 0 | (x_0, \psi y_0) \in \Omega\}. \tag{3}$$

As has been shown by Cazals et al. (2002), countries' production process can be characterized by the probability function $Z(x, y)$ as:

$$Z(x, y) = Prob(X \leq x, Y \geq y). \tag{4}$$

As a result, the output oriented efficiency measure in (3) can be presented as:

$$\psi(x_0, y_0) = sup\{\psi | Z(x_0, \psi y_0) > 0\}. \tag{5}$$

Following Daraio and Simar (2005), $Z(x, y)$ can be decomposed as:

$$Z(x, y) = P(Y \geq y | X \leq x) P(X \leq x) = \Gamma_{Y|X}(y|x) F_x(x). \tag{6}$$

Then countries' output-oriented efficiency measure at point $(x_0, y_0) \in \Omega$ can be defined by the support of the survival function $\Gamma_{Y|X}(y_0|x_0) = Prob(Y \geq y_0 | X \leq x_0)$ as:

$$\psi(x_0, y_0) = sup\{\psi | \Gamma_{Y|X}(\psi y_0 | x_0) > 0\}. \tag{7}$$

As a result, in the presence of domestic credit to the private sector, the conditional distribution can be defined as:

$$Z(x, y|c) = Prob(X \leq x, Y \geq y | C = c), \tag{8}$$

which signifies the probability of a country operating at level (x, y) to be dominated by countries having the same domestic credit conditions. Then we can have an additional decomposition of (8) as:

$$Z(x, y|c) = Prob(Y \geq y | X \leq x, C = c) Prob(X \leq x | C = c) = \Gamma_{Y|X,C}(y|x, c) F_{X|C}(x|c), \tag{9}$$

Then by following the relative literature (Bădin et al. 2010, 2012, 2014) a country's conditional efficiency measure operating at level (x_0, y_0) under the domestic credit conditions $C = c_0$, can be expressed as:

$$\begin{aligned} \psi(x_0, y_0 | c_0) &= sup\{\psi > 0 | (x_0, \psi y_0) \in \Omega^{c_0}\} \\ &= sup\{\psi > 0 | \Gamma_{Y|X,C}(\psi y_0 | X \leq x_0, C = c_0) > 0\}.^5 \end{aligned} \tag{10}$$

Recently, Mastromarco and Simar (2015) considered the above output-oriented efficiency measure in a time-dependent framework by considering time T as an additional conditional variable alongside with C. As a result the conditional probability will take the form:

$$\Gamma^t_{X,Y|C}(x, y|c) = Prob(Y \geq y | X \leq x, C = c, T = t), \tag{11}$$

and a country's conditional efficiency measure operating at level (x_0, y_0) under the domestic credit conditions $C = c_0$ and at a period $T = t_0$, can be expressed as:

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[4] The data for domestic credit to the private sector (% of GDP) has been extracted from World Development Indicators.

[5] Note that $1 \leq \psi(x_0, y_0 | c_0) \leq \psi(x_0, y_0)$ since $c_0 \in \mathcal{C}, \Omega^{c_0} \subseteq \Omega$.

$$\psi_t(x_0, y_0|c_0) = sup\{\psi > 0|(x_0, \psi y_0) \in \Omega_t^{c_0}\} = sup\{\psi > 0|\Gamma_{X,Y|C}^t(\psi y_0|X \leq x_0, C = c_0, T = t_0) > 0\}. \quad (12)$$

As has been proposed by the relative literature (Daraio and Simar 2005, 2007a, 2007b; Bădin et al. 2010, 2012, 2014), smoothing techniques via kernel-based methods need to be applied in order to estimate $\Gamma_{X,Y|C}^t(x, y|c)$ conditioning on $X \leq x$, both time $T = t$ and domestic credit $C = c$. Using the techniques by Hall et al. (2004) and Li and Racine (2007) we can estimate $\Gamma_{X,Y|C}^t(x, y|c)$ as:

$$\hat{\Gamma}_{X,Y|C}^t(x, y|c) = \frac{\sum_{s=(i,v)} I(x_s \leq x, y_s \geq y) K_{h_C}(c_s - c) K_{h_t}(v - t)}{\sum_{s=(i,v)} I(x_s \leq x) K_{h_C}(c_s - c) K_{h_t}(v - t)}. \quad (13)$$

In Equation (13) $I(\cdot)$ is an indicator function and $K(\cdot)$ represents kernels with compact support (in our case we have use Epanechnikov kernels). Finally, optimal bandwidths (h) are selected using the least squares cross-validation (LSCV) criterion (Li and Racine 2007).[6] It must be noted that the time-dependent conditional full frontier efficiency measure in (12) is a Free disposal hull (FDH) estimator which is not robust (Deprins et al. 1984) and can be obtained by plugging into its formula the nonparametric estimator presented in (13). Another point that needs to be emphasized is the treatment of time in Equation (13). Obviously time is a discrete variable and discrete kernels can be used (De Witte and Kortelainen 2013). However, as indicated by Li and Racine (2007) and Mastromarco and Simar (2015, p. 830), continuous kernels are more appropriate when the discrete variables take many different values. In our case, T takes the values from 1 to 45 (i.e., from 1970 to 2014) and, therefore, continuous kernels have been applied. Another point that needs to be considered is the $i.i.d.$ structure of our data. The independence of observations cannot be assumed in our case (especially with the time variable). However, as has been analyzed by Hart (1996), if the kernel used has the support on $[-1, 1]$, then the estimator uses only the observations determined by the bandwidth window. Therefore the dependency is deteriorated among the small 'window' and makes the data in that window "essentially independent" from the rest of the data. This is what Hart (1996, p. 117) refers to as the principle of "whitening by windowing".

2.2. Robust (Order-m) Conditional Frontiers

The Order-m (robust) estimators were first introduced by Cazals et al. (2002) and were further developed by Daraio and Simar (2005, 2006, 2007a, 2007b). In our paper we apply these estimators since they are less sensitive to outliers/extreme values producing, therefore, robust production efficiency estimates. For a given level of countries' inputs x in the interior of the support of X, let us consider $m, i.i.d.$ random variables $Y_i, i = 1, \ldots, m$ which have been generated by the conditional $q - variate$ distribution function $\Gamma_{Y|X}(y|x_0) = Prob(Y \leq y_0|X \leq x_0)$. Then a random set can be defined as:

$$\Omega_m(x_0) = \left\{(x', y) \in \mathbb{R}_+^{p+q} \middle| x \leq x_0, y \leq Y_i, i = 1, \ldots, m\right\}, \quad (14)$$

whereas similar to (3) we can define:

$$\tilde{\psi}_m(x_0, y_0) = sup\{\psi > 0|(x_0, \psi y) \in \Omega_m(x_0)\} = \max_{i=1,\ldots,m} \left\{ \min_{j=1,\ldots,q} \frac{Y_i^j}{y_0^j} \right\}. \quad (15)$$

Then countries' robust output-oriented production efficiency measure can be presented as:

$$\psi_m(x_0, y_0) = \mathbb{E}\left(\tilde{\psi}_m(x_0, y_0) \middle| X \leq x_0\right). \quad (16)$$

Moreover, the original $\psi_m(x_0, y_0)$ and the time-dependent conditional efficiency measures $\psi_{t,m}(x_0, y_0|c_0)$ can be estimated as:

$$\hat{\psi}_m(x_0, y_0) = \int_0^\infty \left[1 - \left(1 - \hat{\Gamma}_{Y|X}(uy_0|X \leq x_0)\right)^m\right] du = \hat{\psi}(x_0, y_0) - \int_0^{\tilde{\psi}(x_0, y_0)} \left(1 - \hat{\Gamma}_{Y|X}(uy_0|X \leq x_0)\right)^m du, \quad (17)$$

[6] For computational details see Bădin et al. (2010, p. 640).

$$\hat{\psi}_{t,m}(x_0, y_0|c_0) = \int_0^{\infty} \left[1 - \left(1 - \hat{F}^t_{X,Y|C}(uy_0|X \leq x_0, C = c_0, T = t_0)\right)^m\right] du = \hat{\psi}_t(x_0, y_0|c_0) - \int_0^{\hat{\psi}_t(x_0,y_0|c_0)} \left(1 - \hat{F}^t_{X,Y|C}(uy_0|X \leq x_0, C = c_0, T = t_0)\right)^m du. \quad (18)$$

Both the unconditional (17) and the time-dependent conditional (18) robust frontiers take as benchmark the expectation of best performing countries (among m countries) drawn randomly from the population of countries using less input factors of production than x_0. Finally, as proven by Cazals et al. (2002), both $\hat{\psi}_m(x_0, y_0)$ and $\hat{\psi}_{t,m}(x_0, y_0|c_0)$ are $\sqrt{n} - consistent$ estimators[7], which means that the they convergence to the true values similar to the parametric estimators, whereas, they do not suffer from the curse of dimensionality in comparison to the standard DEA and FDH estimators.

2.3. Analysing the Effect of Domestic Credit

By using time-dependent conditional efficiency estimates in a second-stage nonparametric regression analysis we evaluate the effect of both time and domestic credit on countries' production efficiency levels (Bădin et al. 2012; Daraio et al. 2015). Relevant studies using a second-stage nonparametric regression analysis used either a local constant and/or a local linear estimator in order to reveal nonlinear phenomena (Daraio and Simar 2005; Jeong et al. 2010). According to Stone (1985), the fundamental properties of such statistical models are their ability: To provide accurate data fits (flexibility), to minimize the increase of variance due to an increase in dimensionality (curse of dimensionality), and finally, to effectively reveal the underlying structure (interpretability). Compared to the local linear and local constant estimators, generalized additive models (GAM) appear to cope better with the problem of dimensionality since they use a sum of nonparametric functions over the components (Carroll et al. 1997). Moreover, since the Order-m estimators do not suffer from the curse of dimensionality (relative to the FDH and the DEA estimators), it appears that GAM models are suited most to our analysis. Therefore, we apply a generalized additive model as was initially introduced by Hastie and Tibshirani (1990) and was further developed by Wood (2002, 2003, 2004, 2017). In its general form the model can be expressed as:

$$g(\varphi_i) = X_i^* \vartheta + f_1(C_i) + u_i \; i = 1, \ldots, n \quad (19)$$

where $\varphi_i \equiv \mathbb{E}(\psi_{t,m,i})$.

In Equation (19), $\psi_{t,m,i}$ is the depended variable, whereas, X_i^* represents the parametric part of the model with their parameters defined by ϑ. The $f(\cdot)$ are the smooth functions of the associated C_i. In our case the smooth functions are tensor products which are invariant to linear rescaling of covariates (Wood 2006).

In order to illustrate the smooth functions applied, let us assume a situation where we have three covariates x_1, x_2 and x_3 and their low-rank bases of smooth functions in their general form can be represented as:

$$\int_{x_1}(x_1) = \sum_{i=1}^{I} \alpha_i b_{1i}(x_1), \; \int_{x_2}(x_2) = \sum_{j=1}^{J} \beta_j b_{2j}(x_2), \text{ and } \int_{x_3}(x_3) = \sum_{k=1}^{K} \gamma_k b_{3k}(x_3), \quad (20)$$

and $b_{1i}(x_1)$, $b_{2j}(x_2)$ and $b_{3k}(x_3)$ are the basis functions, whereas $\alpha_i, \beta_j, \gamma_k$ are the parameters. Then $x_1$can be converted to smooth functions $x_1, \; x_2$ as:

$\alpha_i(x_2) = \sum_{j=1}^{J} \beta_{ij} b_{2j}(x_2)$ which results in $\int_{x_1 x_2}(x_1, x_2) = \sum_{i=1}^{I} \sum_{j=1}^{J} \beta_{ij} b_{2j}(x_2) b_{1i}(x_1)$. Similarly, the tensor product of the three covariates can be represented as:

$$\int_{x_1 x_2 x_3}(x_1, x_2, x_3) = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} \gamma_{ijk} b_{3k}(x_3) b_{2j}(x_2) b_{1i}(x_1). \quad (21)$$

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[7] The Data Envelopment Analysis (DEA) and the FDH estimators are $n^{2/(p+q+1)}$ and $n^{1/(p+q)}$ respectively-consistent estimators (Daraio and Simar 2006).

Now let $\Theta_{\cdot}$ matrices contain the coefficients and let α, β and γ represent the coefficients of the marginal smooths. As a result, the quadratic form of the wiggliness function can be respectively presented as:

$$J_{x_1}(f_{x_1}) = \alpha^{\mathrm{T}}\Theta_{x_1}\alpha,\ J_{x_2}(f_{x_2}) = \beta^{\mathrm{T}}\Theta_{x_2}\beta,\ J_{x_3}(f_{x_3}) = \gamma^{\mathrm{T}}\Theta_{x_3}\gamma. \tag{22}$$

Then the cubic spline penalty can be defined as:

$$J_{x_1}(f_{x_1}) = \int\left(\partial^2 f_{x_1}/\partial {x_1}^2\right)^2 dx_1.$$

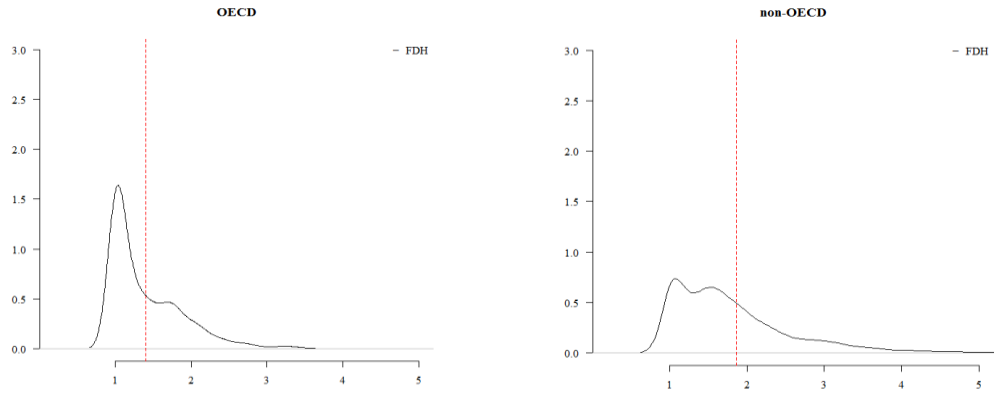
Finally, the wiggliness of $f_{x_1x_2x_3}$ can be presented as:

$$\begin{gathered} J(f_{x_1x_2x_3}) = \delta_{x_1}\int_{x_2,x_3} J_{x_1}(f_{x_1}|x_2,x_3)d_{x_2}d_{x_3} + \delta_{x_2}\int_{x_1,x_3} J_{x_2}(f_{x_2}|x_1,x_3)d_{x_1}d_{x_3} + \\ \delta_{x_3}\int_{x_1,x_2} J_{x_3}(f_{x_3}|x_1,x_2)d_{x_1}d_{x_2}, \end{gathered} \tag{23}$$

whereas $\delta_{\cdot}$ represents the smoothing parameters allowing the invariance of the penalty to the rescaling of the covariates.

3. Results

Before we analyze the effect of domestic credit and time on countries' production performance levels, we analyze the efficiency distributions as derived from the free disposal hull (FDH) estimators (Deprins et al. 1984). Figure 1 presents the density plots from the efficiencies derived from Equation (7). In our setting, efficiency is indicated with values equal to 1. However, values greater than one suggest inefficiency. It must be noted that in this setting (i.e., FDH frontiers) we envelope all countries and the estimates are derived by comparing countries of different size, development stage, institutional arrangements, etc. As has been expected, OECD countries have higher production efficiency levels compared to the non-OECD countries. In Figure 1 the red dotted line indicates countries' average efficiency levels. It is evident that OECD countries' average efficiency score is placed nearer to unity in comparison to the non-OECD countries. Furthermore, the results suggest that the larger mass of OECD countries' production efficiency estimates are located near to unity, whereas, for the non-OECD countries the larger mass of the estimates is located to the left of the unity, suggesting higher production inefficiencies.

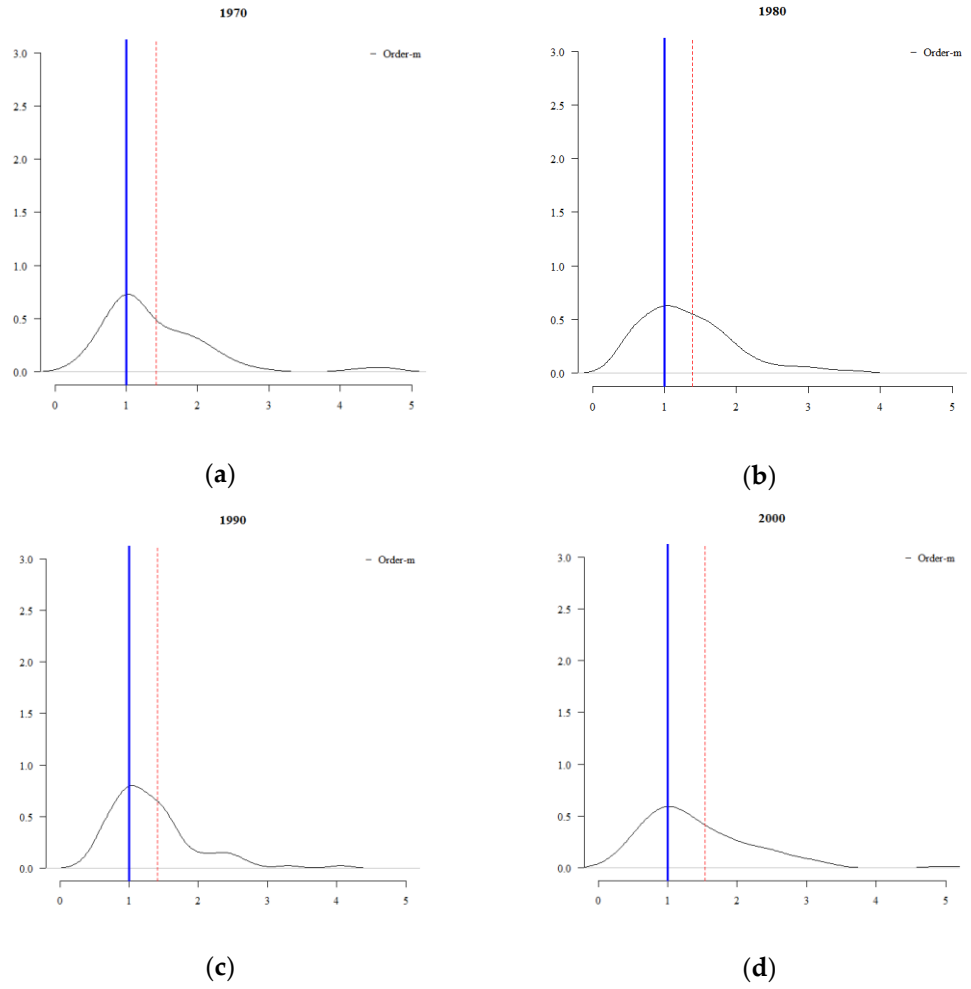


(**a**) (**b**)

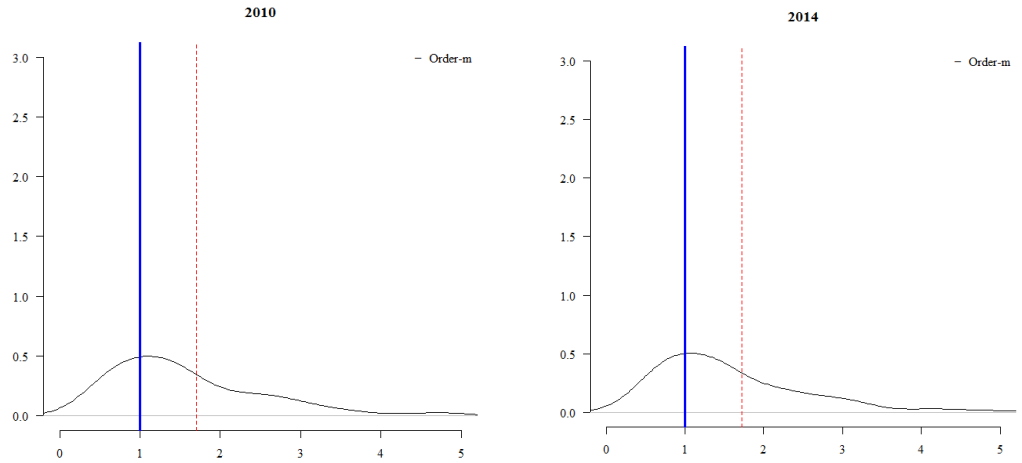
Figure 1. Density plots of unconditional countries' production efficiency levels derived from the FDH estimator: (**a**) FDH production efficiencies of OECD countries; (**b**) FDH production efficiencies of the non-OECD countries.

In contrast to the FDH analysis, Figure 2 presents our findings which have been derived from the Order-m model (Equation (17)). According to Cazals et al. (2002) and Daraio and Simar (2007a), partial frontiers (i.e., Order-m) are less sensitive to outliers. If a country is performing superior

compared to the randomly drawn m countries with $X \leq x$ (in our case $m = 20$)[8], then it is said to be a super-efficient country. In such cases, the estimated Order-m output efficiency score would take values less than one. Let us now consider a paradigm in which a country has an Order-m production efficiency score equal to 1.25. Then this score indicates that if this country would perform as efficient as the m best practice countries (with $X \leq x$), then its GDP levels could increase on average by 25%. Figure 2 presents diachronically the robust estimates for 1970, 1980, 1990, 2000, 2010 and 2014. The results suggest that on average terms countries have performed better during 1970, 1980, 1990 and 2000. For the years 2010 and 2014 greater production inefficiencies are reported which may be attributed to the negative effects of the Global Financial Crisis (Gourinchas and Obstfeld 2012). It must be highlighted that the output-oriented Order-m frontier compares each country with the *m*-peer countries which are using input levels $\leq x$. As has been emphasized by Daraio and Simar (2006, p. 523): "*The benchmark, in fact, is not made against the most efficient units in the group, but against an appropriate measure drawn from a large number of random samples of size m within the group*". In fact this property of the Order-m estimator is very appealing in our case since it will not allow the effect of domestic credit to be masked over by different country sizes (in terms of their input levels). In contrast, the benchmark of the FDH analysis is made against the most efficient units of the entire group assuming that all countries (regardless their input levels) constitute the technology set, and as a result all countries are compared to each other.



[8] The value of *m* has been chosen following Daraio and Simar (2005), suggesting that we select a value of *m* in which the number of super-efficient DMUs (in our case countries) stabilize. However, different *m* values have also been tested (i.e., 40, 50 and 80). When we increase the *m* parameter the results converge to the FDH estimator. All results which have been estimated with different *m* values are available upon request.



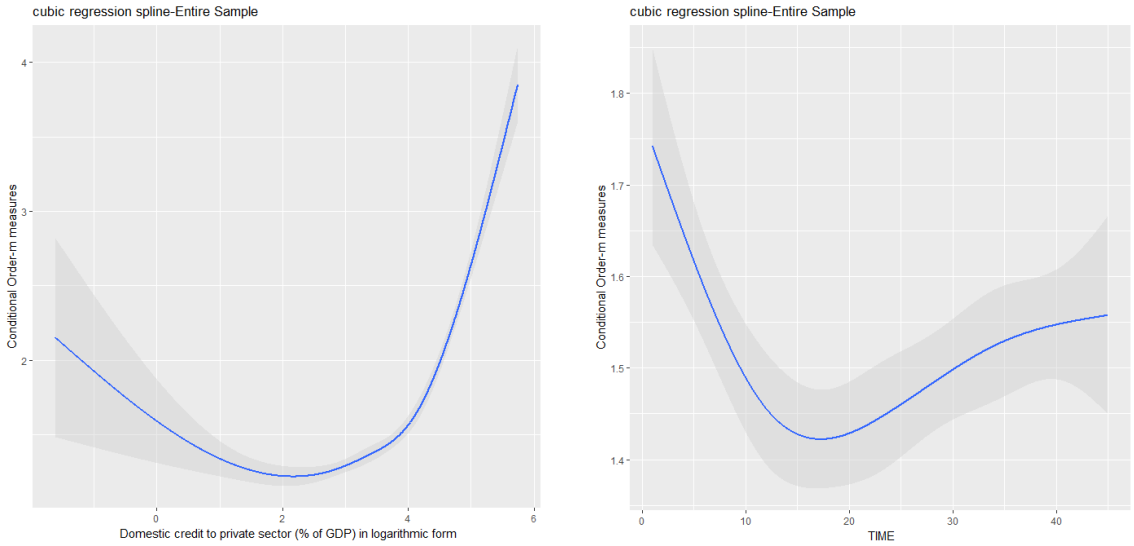
(e) (f)

Figure 2. A diachronic representation of unconditional countries' production efficiency levels derived from the Order-m estimator. Note: The red dotted line indicates the average Order-m value; The blue solid line indicates unity.

Then we apply a second-stage analysis as described in the relevant literature (Daraio and Simar 2006, 2014; Bădin et al. 2012; De Witte and Kortelainen 2013; Tzeremes 2014; Bădin et al. 2014; Daraio et al. 2015). Moreover, we regress the estimated time-dependent conditional Order-m production efficiencies on the domestic credit levels and time using the generalized additive model using tensor products as smooth factors with cubic regression splines (Wood 2006; Wood 2017). In our setting, a decreasing fitted additive nonparametric line indicates a positive effect of domestic credit and time on countries' production efficiency. From the other hand, an increasing fitted additive nonparametric regression line indicates a negative effect.[9] Figure 3 presents graphically the results from the examined effects from the entire sample. The results suggest that the effect both of domestic credit and time on countries' production efficiencies is nonlinear. It is also evident that when the domestic credit increases, the effect on countries' production efficiency levels is positive up to a certain level. After that level the effect becomes negatively indicated by an increasing nonparametric regression line. Moreover, the effect of time is also nonlinear, signifying a positive effect on countries' productive efficiencies from the 70s to 90s. However, after that period the effect becomes negative. Furthermore we check the robustness of our findings analyzing separately the effects for the OECD and the non-OECD countries. Specifically, Figure 4 in a similar manner like Figure 3 presents both the effect of domestic credit to the private sector and time on OECD countries' production efficiency levels.

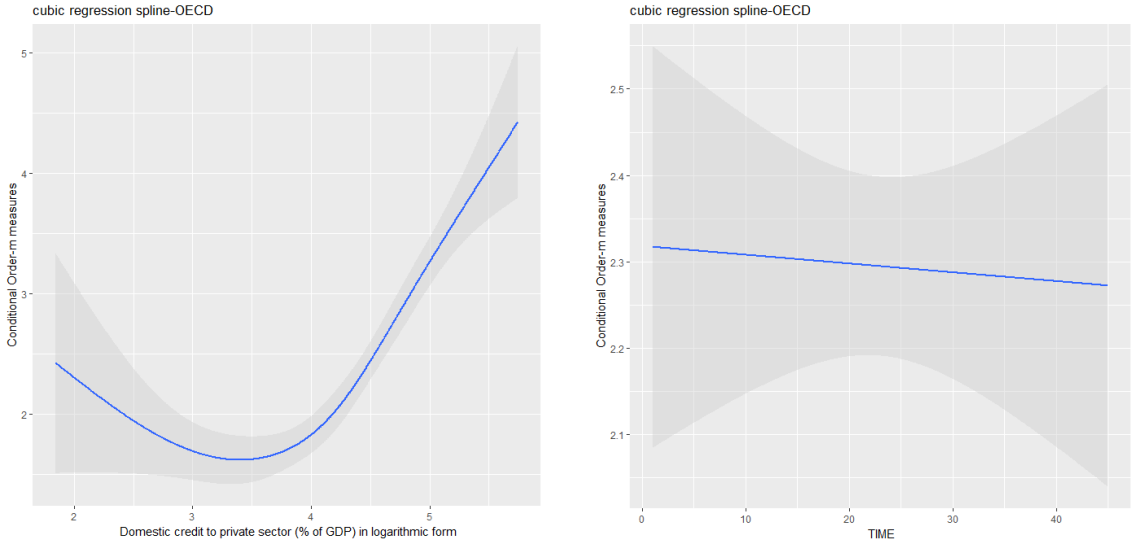
The effect of domestic credit to the private sector has a similar trend as the one presented for the case of our entire sample. However, it must be highlighted that the turning point in which the effect turns from positive to negative is higher. The contradictive finding (compared to Figure 3) is for the effect of time on countries' production efficiency levels which is positive throughout the entire period, presented by a decreasing additive nonparametric regression line.

[9] As presented previously, in the output oriented case Order-m efficiency values greater than unity indicate higher production inefficiency levels.



(**a**) (**b**)

Figure 3. The effect of domestic credit and time on countries production efficiencies (entire sample): (**a**) The effect of domestic credit to private sector (entire sample); (**b**) the effect of time (entire sample).



(**a**) (**b**)

Figure 4. The effect of domestic credit and time on countries' production efficiencies (OECD countries): (**a**) The effect of domestic credit to private sector (OECD countries); (**b**) the effect of time (OECD countries).

Finally, when examining the effects for the non-OECD countries (Figure 5), we observe a different picture of the examined relationship. For the case of time the effect is similar to our initial finding (Figure 3), suggesting a positive effect on non-OECD countries' production efficiencies up to the mid-90s. After that point again the effect turns to negative indicated by an increasing additive nonparametric regression line. The effect of domestic credit on countries' efficiency levels is highly nonlinear. The graphical evidence suggests that for the largest part of domestic credit the effect is positively signified by a decreasing additive nonparametric regression line. However, for a certain domestic credit range (i.e., from 3 to 4) the effect becomes negative, but after that point the effect turns again to positive. Therefore, our findings which are provided by the adopted nonparametric

econometric methods, suggest that even though in principle the overall effect of domestic credit is highly nonlinear, it is also attributed by countries' different stages of development, financial stability and institutional levels (Arestis and Demetriades 1997).

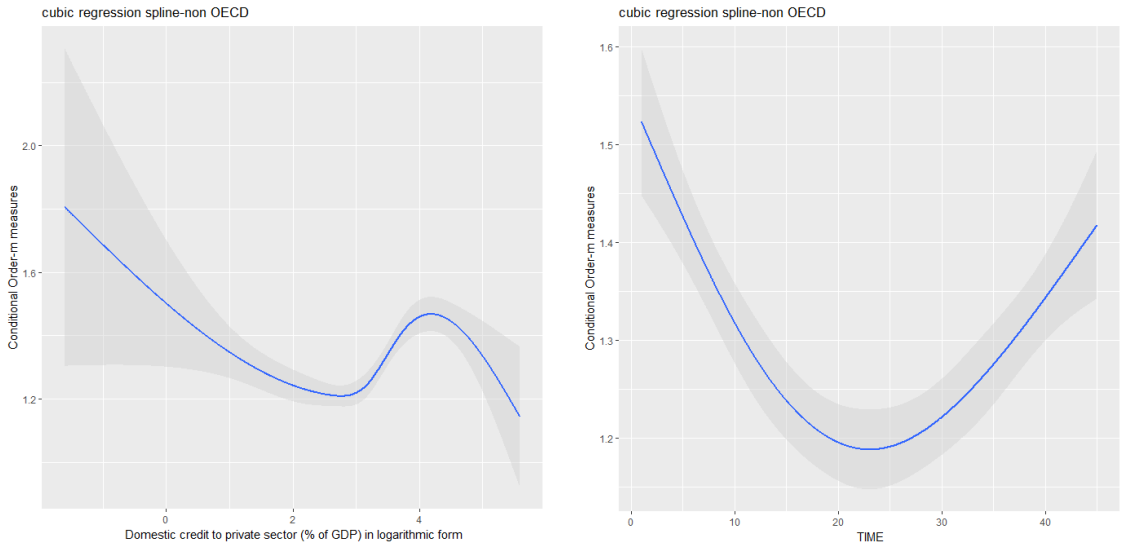


Figure 5. The effect of domestic credit and time on countries' production efficiencies (non-OECD countries): (**a**) The effect of domestic credit to the private sector (non-OECD countries); (**b**) the effect of time (non-OECD countries).

4. Conclusions

This paper investigates the effect of financial development on countries' production efficiency levels using different nonparametric statistical and econometric methods. Specifically, in a first stage analysis using different smoothing techniques and specific procedures for bandwidth selection (Bădin et al. 2010, 2012, 2014), we apply a probabilistic approach of nonparametric frontier analysis on estimating 87 countries' production efficiency levels over the period 1970–2014. For the purpose of our analysis we apply time-dependent conditional Order-m estimators incorporating in the efficiency measurement the effect both of time and countries' financial development levels. Then in a second-stage analysis, generalized additive models (Hastie and Tibshirani 1990) using tensor products with cubic spline penalties (Wood 2002, 2003, 2004, 2006, 2017) are applied.

Our findings reveal a nonlinear effect of financial development on countries' production efficiency levels. The results also suggest that the effect of financial development is positive on countries' production efficiency levels up to a certain threshold level. After that point the effect becomes negative. Our evidence is consistent with the "vanishing effect" point of view described by Rousseau and Wachtel (2011). Under this view the negative effect of financial deepening on economic growth is attributed to financial crises and to domestic banking incidences. Arcand et al. (2015) verifies empirically the "vanishing effect" and provides evidence under which the financial deepening starts having a negative effect when credit to the private sector reaches 100% of GDP. In our case, the negative effect on countries' production efficiencies starts when the level of domestic credit to the private sector reaches 50% of GDP. However, according to Arcand et al. (2015), another possible explanation of financial development's negative effect on countries' production efficiency levels may be attributed to misallocation of resources. This is apparent in the case where the cost of maintaining countries' financial stability overcomes the returns of financial development.

Overall our findings support those studies providing evidence of a nonlinear behavior among financial development and economic growth (Shen 2013; Beck et al. 2014; Arcand et al. 2015). Finally, as explained in the early study by Arestis and Demetriades (1997), the evidence suggests that this effect can be shaped also by countries' different institutional, development and financial system conditions.

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