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CALCULATING MODELS FOR TOTAL FACTOR PRODUCTIVITY MEASUREMENT

MODELOS DE CÁLCULO PARA A PRODUTIVIDADE TOTAL DOS FATORES

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Abstract: Productivity measures the level of efficiency a particular economy presents in producing goods and services. Thus, increasing productivity is the fastest route to achieve economic growth and social well-being. This article aims to estimate and compare four Total Factor Productivity (TFP) measurement models. The models chosen were: Olley & Pakes - OP (1996); Levinsohn & Petrin – LP (2003); Wooldridge - Wool (2009); and Ackerberg, Caves & Frazer - ACF (2015). Per capita energy consumption was employed as the intermediate input. The results suggest that the ACF (2015) model is an improvement form the OP and LP models, while presenting statistically significant results. The Wool (2009) model is also an improvement and, once more, presented similar results. Considering the ACF model presents high dispersion, the Wool model is the preferred TFP measurement model.
Keywords: Productivity; Efficiency; Countries;

Resumo: A produtividade mede o nível de eficiência que uma economia apresenta em produzir bens e serviços. Assim, aumentar a produtividade é a maneira mais rápida de se atingir crescimento econômico e bem-estar social. Este estudo busca estimar e comprar quatro modelos diferentes para o cálculo da Produtividade Total dos Fatores (Total Factor Productivity - TFP).

Os modelos escolhidos foram: Olley & Pakes, 1996 - OP; Levinsohn & Petrin, 2003 - LP; Wooldridge, 2009 - Wool; e, Ackerberg, Caves e Frazer, 2015 - ACF. Os resultados sugerem que o modelo ACF (2015) é um aprimoramento dos modelos OP e LP, além de apresentar resultados com significância estatística. O modelo Wool (2009) também é um aprimoramento e, novamente, apresenta resultados similares. Como o modelo ACF apresenta maior dispersão, o modelo Wool apresenta-se como a melhor escolha.

Palavras-chaves: Produtividade; Eficiência; Países Desenvolvidos; Países Emergentes.

1.Introduction

In an economic context characterized by the globalization, along with the steady increase in international trade, the manner through which knowledge and technologies spread among countries becomes strategic, as well as how Total Factor Productivity (TFP) is influenced.

Productivity measures the degree of efficiency, which is how an economy uses its resources to produce consumer goods and services (Vecchia et al., 2021; Beca et al., 2019; Filho & Moori, 2019; Messa, 2013). Increasing productivity is the fastest way to achieve economic growth and social welfare, as such production gains reflect the effectiveness of the productive sector as well as the degree of development of a society (Mirza et al., 2021; Feng et al., 2018; Felema, Raiher & Ferreira, 2013).

Historically, productivity is based on the relationship between the product (output) and single input, which is known as partial technology productivity. In this sense, the most common productivity benchmark is the partial labor productivity measured by output per worker or output per worked hour.

One justification for using this productivity measure is that it does not require the calculation of capital as another input, anda capital data is often missing. Therefore, questionable proxies are used. However, the most significant limitation of the method is that it measures output per unit of work rather than output per unit of all combined inputs (Vallejos and Valdivia, 2000).

The first to associate the aggregate production function with productivity was Tinbergen (1942). However, the seminal contribution to this theme was given by Solow (1956), by creating a link between the production function and a productivity index number. Assuming constant returns to scale, Solow measured the change in the production function given capital and labor levels.

Then, by arranging the terms of the production function, Solow obtained what he called relative Hicksian Efficiency, that is, a more general indicator of output per unit of input, which later became known as Total Factor Productivity (TFP) or Solow Residue, which reflects technological progress and other elements that act as determinants of economic growth.

Thus, TFP intends to measure the efficiency of an economy when combining all its resources to generate a product. Based on this concept, the dynamics of the indicator is the result of technological progress in the economy (Messa, 2013). It means that productivity occurs by getting higher output with the same amount of resources employed or using fewer resources to achieve the same output. There are no different ways of looking at productivity. There is only one thing: to do more with less.

Thus, the classic production function has become inefficient in representing the productive transformations in modern economies (Buesa et al., 2010; Hausmann et al., 2014). Several studies have developed production functions adapted using different types of variables, such as labor productivity (Feng et al., 2018; Sarbu, 2017), sustainability (Liu et al., 2016; Wei et al., 2020; Zhang et al., 2020; Chen & Golley, 2014; Husniah &Supriatna, 2016), knowledge proxies (Bhattacharya et al., 2021; Lenox and King, 2004; Hidalgo and Hausmann 2009; Elmawazini, 2014), and energy (Mirza et al., 2021; Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Wooldridge, 2009; Ackerberg, Caves and Frazer, 2015).

In view of the context presented, this paper aims to compare four models to measure TFP. The tested models were the Olley and Pakes – OP (1996); Levinsohn and Petrin – LP (2003); Wooldridge – Wool (2009); and Ackerberg, Caves & Frazer – ACF (2015). It was used as an intermediate input the per capita energy consumption. Countries were classified into two groups (developed and emerging or developing economies) in order to obtain more homogeneous data since the groups have different socioeconomic conditions. Therefore, it was assumed that each group has more expressive characteristics.

Through the econometric results, the models were compared in terms of statistical significance, and one model was selected the best. In this sense, this paper contributes to future studies by helping them to choose the best and most significant method to measure productivity.

This article is organized into four sections beyond this introduction. In the second section, there is a theoretical review on the empirical papers on TFP. The third section the Method used in this study. In the fourth section, it was discussed the findings. Finally, the main considerations are found in the fifth section of this article.

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2. Literature Review

2.1 Total Factor Productivity (TFP)

Several studies have theoretically and empirically identified factors that determine TFP in developed and developing countries. The theoretical literature suggests that human capital affects the growth of TFP, facilitating the adoption and implementation of new technologies exogenously (Nelson & Phelps 1966; Romer 1990) and/or facilitating the domestic production of technological innovations (Aghion & Howitt, 1998; Romer, 1990).

However, the ability to adopt (adapt and implement) foreign technology depends not only on the quantity but also on the quality of education. By implication, it means that for low-income countries with low government spending on education, low education, poor quality education, and low investment in research and development (R&D), human capital may not have a positive impact the growth of TFP.

It is noteworthy that the literature has argued that productivity gains will be linked to the absorption capacity of the regions. Thus, innovative producers are more receptive to new technologies and thus can maximize gains and reduce costs (Felema, Raiher & Ferreira, 2013). Table 1 summarizes some TFP determinants for the literature.

Table 1 – Determinants of TFP according to the literature

Author(s)/Year	**Determinants of TFP**
Bhattacharya et al. (2021)	Export; Trade in imported inputs; Capital goods; Foreign Direct Investment
Gao et al. (2021)	Gross Domestic Product; Labor force; Physical capital based on time-varying depreciation rate; Physical capital based on constant depreciation rate; Physical capital based on constant depreciation rate
Mirza et al. (2021)	Unit sold; Number of customers; Network length; Peak load
Danska-Borsiak (2018)	R&D activities; Infrastructure; Physical capital; Structural change; Financial system; Location of the region; Per capita income
Otsuka (2017)	Share capital; Population agglomeration
Otsuka &Natsuda (2016)	IDE; R&D; Human capital; Technology employed
Kim (2016)	Exports; Imports; R&D; Salary; Quality of work; Work hours
Akinlo and Adejumo (2016)	Commercial opening; Foreign Direct Investment; Inflation; Human capital; Unemployment rate
Harris & Moffat (2015)	Real gross production; Actual intermediate entries; Job; Capital; Age; Single plant
Giovanis & Ozdamar (2015)	Age; Size; Short term debt; Long term indebtedness; Liquidity; Value added index; Active relationship for sales; Risk proxy; Market share; Business entry; Company departure; Industry average growth
Arazmuradov et al. (2014)	GDP; Human capital; IDE; Import of machinery and equipment
Castiglionesi and Ornaghi (2013)	Index of use of new technologies; Salary; Percentage of R&D employees in total workforce; Quotas of students with higher education in relation to the total workforce; Human capital; R&D Expenses
Sheng & Song (2012)	Participation in R&D; Market share; Herfindahl Index; Export Quota
Dańska-Borsiak & Laskowska (2012)	Human capital level; R&D; Investments
Kim (2011)	Job; Capital; Training cost per skilled worker; Skilled worker; Number of higher education employment; R&D

Source: Authors.

To obtain the TFP measurements, the methods proposed by Ackerberg et al. (2015) and Wooldridge (2009) that are similar to the semi-parametric approaches developed by Olley & Pakes (1996) and Levinsohn & Petrin (2003) are used.

The approach of Ackerberg et al. (2015) is used to obtain robust productivity measures because this approach does not suffer from functional dependency problems such as Olley and Pakes (1996) and Levinsohn and Petrin (2003).

Olley & Pakes (1996) developed a two-stage procedure where, in a first stage, a reduced production function is estimated with the investment used as a proxy for the productivity shocks observed by the company and correlated with variable inputs.

Levinsohn & Petrin (2003), in turn, pointed out that the approach suggested by Olley and Pakes (1996) can be problematic due to the fact that capital is an expensive input to adjust, probably leading to irregular investments and data sets with a considerable share of zero investments.

Wooldridge (2009) proposes a new estimation configuration, showing how to obtain LP estimator within a GMM (Generalized Method of Moments) econometric system, which can be estimated in a single step, and shows the appropriate moment conditions.

3. Method

3.1 TFP calculation

The measurement of TFP evolution from Solow's (1957) work is obtained from a Cobb-Douglas type production function with constant returns to scale and neutral technical progress.

$$Y = AL^{\alpha}K^{\beta} \qquad (1)$$

Where Y = the production volume; L = the work stock; K = the capital stock. In logarithmic terms, equation 1 can be described as:

$$Ln\ Y = lnA + \alpha lnK + (1-\alpha)LnN \qquad (2)$$

Where α and β are parameters with β = (1-α) and A is the exogenous technological parameter (TFP). Making the time derivatives of equation (2) is obtained (3):

$$\frac{dA}{A} = \frac{dY}{Y} - \left(\alpha\frac{dL}{L} + \beta\frac{dk}{k}\right) = R = TFP \qquad (3)$$

Where R is the Solow residue (i.e., the product growth rate not explained by the growth of inputs). Thus, equation (3) provides a measure of the evolution of TFP as the difference between the change in output and the change in capital and labor stocks. Therefore, it is the measure of the evolution of production that is not explained by the growth of factor stocks, but by the evolution of its productivity.

Equation 3 provides a measure of the evolution of TFP, or Solow Residue (R), as the difference between the change in output and the change in capital and labor stocks. Thus, TFP intends to indicate the efficiency with which the economy combines all its resources to generate the product. From this conceptualization, the dynamics of the indicator would be a result of the technological progress of the economy.

It is noteworthy that the primary factors of production are those that facilitate production, but are not significantly transformed by production processes, nor become part of the final product, and intermediate inputs are those created during and fully used in production. Capital and labor are considered primary factors of production, while most energy is considered an intermediary that can be "produced" by some combination of capital and labor investment (more technology) (Ayres & Warr, 2010).

The Solow model was extended by adding the energy factor and allowing a technical change of factor increase (Azar & Dowlatabadi, 1999; Löschel, 2002; Acemoglu et al., 2012). There are also examples in the relevant literature of modeling approaches that recognize and allow the role of intermediate inputs - namely energy - to directly impact economic growth (Stern & Kander, 2012).

The correct estimation of TFP is a crucial issue in economics and is the central theme of many seminal papers. Although the models generally consider only capital and labor as independent factors of production, they are unable to explain economic growth with only these two factors fully. Solow's pioneering paper (1957) revealed that after recognizing the contributions of capital and labor to a growth accounting framework, an exogenous residual term is needed to explain more than 85 percent of US economic growth (1909-1949). It is noteworthy that TFP encompasses many components, some desired (effects of technical and organizational innovation), others unwanted (measurement error, omitted variables).

Thus, Olley & Pakes (1996) introduced a semiparametric method that controls these biases, allowing to estimate the parameters of the production function consistently and thus to obtain reliable yield estimates. Later, based on the paper of Olley & Pakes (1996), Levinsohn & Petrin (2003) developed an estimator that uses intermediate inputs to represent the term of unobservable productivity. Most factory-level data sets include data on the use of intermediate inputs such as energy and materials. Therefore, the Levinsohn & Petrin estimator does not suffer from the truncation bias induced by the Olley and Pakes estimator, which requires companies to have nonzero investment levels. Thus, they used intermediate inputs as instruments rather than investment for lack of information.

Given this, several adaptations and extensions of the Olley and Pakes estimator were developed. Recently, the time assumptions underlying the semi-parametric estimators of Olley & Pakes and Levinsohn and Petrin have been questioned by Ackerberg, Caves, & Frazer (2015) who suggest an alternative two-step estimator, where all relevant parameters are retrieved in the second stage, in which the addition of polynomial terms into the regression generates a better estimate. Wooldridge (2009), on the other hand, focuses on the inefficiencies associated with the two-step estimation procedure of existing methodologies and proposes a framework in which estimates of the production function can be obtained in one step. Its structure allows the temporal assumptions of the original semiparametric estimators and the adapted structure of Ackerberg, Caves and Frazer.

Thus, this paper will compare three TFP calculation methods: Levinsohn & Petrin (2003); Wooldridge (2009); and Ackerberg, Caves & Frazer (2015). As intermediate input, the energy consumption per capita is chosen, as pointed out in the literature. It is noteworthy that for the OP model, the investment variable was used as an intermediate input and later criticized by LP, who used the energy proxy.

For the calculation of country TFP, the variables in Table 2 were selected for the four above methods.

Table 2 – Variables for the calculation of TFP

Variables	Definition
Constant GDP (Dependent Variable)	GDP at purchaser's prices is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without deducting the depreciation of manufactured goods or from the depletion and degradation of natural resources. Dollar to GDP values is translated from national currencies using the official 2010 exchange rates (World Bank Group, 2017).
Economically active population	The proportion of the population aged 15 and over that is economically active: All persons who provide labor for the production of goods and services during a specific period (World Bank Group, 2017).
Electricity consumption (kWh per capita)	Electricity consumption measures the production of power plants and combined heat and power plants, less transmission, distribution and transformation losses, and own use by power and heating plants (World Bank Group, 2017).
Gross Fixed Capital Formation (% of GDP)	Gross fixed capital formation includes land improvements (fences, ditches, drains, and so on); purchase of machinery, equipment and equipment; and the construction of roads, railways and the like, including schools, offices, hospitals, private residences, and commercial and industrial buildings (World Bank Group, 2017).

Source: Prepared by the authors according to the World Bank Group (2017). * Data are in US dollars for constant GDP and Gross Fixed Capital Formation. ** The Gross Fixed Capital Formation variable was depreciated at an annual rate of 10% as used in the literature.

The analysis used log-linear regressions because it is possible to interpret the parameters as elasticities as well as the use of panel data techniques. The software used for descriptive and econometric analysis consists of Stata15®. Data for the calculation of TFP was taken from The World Bank website for the years 1995-2015. Only per capita, electricity consumption data for 2015 were extracted from the CIA World Factbook website.

3.2 Descriptive Statistics - TFP

Table 3 presents descriptive statistics for all countries (n = 124) and for groups G1 (developed countries) and G2 (emerging and developing countries).

Table 3 –Descriptive statistics

Variables		**Mean**	**Standard Deviation**	**Minimum Amplitude**	**Maximum Amplitude**
GDP	*Total sample*	4.58e+11	1.47e+12	2.07e+09	1.67e+13
	G1	1.16e+12	2.51e+12	5.56e+09	1.67e+13
	G2	1.92e+11	5.88e+11	2.07e+09	8.91e+12
Economically active population	*Total sample*	2.24e+07	7.96e+07	131770	7.87e+08
	G1	1.43e+07	2.78e+07	146501	1.61e+08
	G2	2.54e+07	9.17e+07	131770	7.87e+08
Cap.deprec	*Total sample*	8.69e+10	3.14e+11	5.75e+07	4.36e+12
	G1	2.03e+11	4.46e+11	6.95e+08	3.23e+12
	G2	4.17e+10	2.29e+11	5.75e+07	4.36e+12
Cons.energ.pc	*Total sample*	3922.554	5318.351	13.517	54799.2
	G1	8681.331	6855.619	1992.9	54799.2
	G2	2105.567	3034.158	13.517	21508.45

Source: Authors. Total sample (124 countries), G1 and G2. *Raw data. Data are in US dollars for constant GDP and depreciated capital. The results obtained through the xtsum (Stata) command provide a further basis for the adoption of panel data models and the application of several estimators.

Another essential operation is the correlation of variables (Pearson's correlation test) in which it was performed for the total sample and both groups (Table 4).

Table 4 – Pearson correlation test

Variables	GDP_cons (Total)	GDP_cons (G1)	GDP_cons (G2)
Economically A. Pop.	0.4133	0.9906	0.8113
Cap.deprec	0.9247	0.9894	0.9184
Cons.Energ.pc	0.2243	0.0819	0.0678

Source: Authors.

Based on Table 4, the Economically Active Population variable was strongly correlated in G1 and G2, and with moderate correlation in the total sample. The Depreciated Capital variable provided a high correlation in the three samples. Intermediate input (Energy Consumption), in turn, showed a low correlation with constant GDP; however, the total sample showed a higher correlation.

As for the collinearity analysis between the explanatory variables, the variables Depreciated Capital and Economically Active Population presented a high correlation when analyzed in groups. However, in the total sample, they showed a moderate correlation (0.54). Intermediate input, however, showed a low correlation with Depreciated Capital and Economically Active Population.

The multicollinearity issue occurs when the independent variables have a high level of linear association with each other, which may result in a significant loss of precision of the estimators (Brooks, 2008). To avoid multicollinearity, it was used the full sample to calculate the TFP.

4. Results and Discussion

In this section, is presented the estimates for the TFP of the selected models: Olley and Pakes (1996); Levinsohn & Petrin (2003); Wooldridge (2009); Ackerberg, Caves & Frazer (2015).

4.1 Estimated model parameters

Productivity is often estimated as the deviation between observed production and forecasted production by an Ordinary Least Squares (OLS) estimated Cobb-Douglas production function. It was found similar results between the Olley & Pakes (OP) and Levinsohn & Petrin (LP) estimates. However, the OP model was calculated only for comparison with the other models, because LP is an enhancement of the OP model. Thus, in the OP model, the variable Investment was used as an intermediate input, which is criticized by the LP model.

The LP results show that the Economically Active Population and Depreciated Capital variables have a positive and statistically significant effect on the constant GDP. In other words, the 1% increase in the economically active population impacts 0.33% of GDP and the 1% increase in depreciated fixed capital impacts GDP by 0.36%. The LP model was statistically significant at 1% level (F statistic).

Levinsohn and Petrin (2003) argue that the productivity shock seems to vary in units over time. Thus, LP proposes a modification of the OP approach to solving the problem of irregular investment through the use of intermediate inputs to represent unobserved productivity.

Therefore, Wooldridge (2009) proposes an improvement for such methods (OP and LP). The results of the Wooldridge (2009) model also showed similar estimates to the OP and LP models. In this sense, the 1% increase in the Economically Active Population has a 0.34% impact on GDP, and the 1% increase in depreciated capital impacts the GDP by 0.37%. The WOOL model was also statistically significant at 1% level.

The Ackerberg, Caves & Frazer (ACF) model proposes a hybrid estimate between the OP and LP approaches, along with assumptions about the timing of input choice decisions. According to the result, the model was statistically significant at 1% level, and with a positive parameter. The 1% increase in the Active Economic Population impacts 0.16% on GDP. Moreover, the 1% increase in depreciated capital affects GDP by 0.87%. Table 5 shows the results of the TFP models.

Table 5 - Results of TFP models

Variables (ln)	**Olleys and Pakes (OP) (1996)**	**Levinsohn and Petrin (LP) (2003)**	**Wooldridge (WOOL) (2009)**	**Ackerberg, Caves and Frazer (ACF) (2015)**
Economically A. Pop.	0.3354***	0.3283***	0.3410***	0.1592***
Cap.deprec	0.3598***	0.3618***	0.3656***	0.8565***

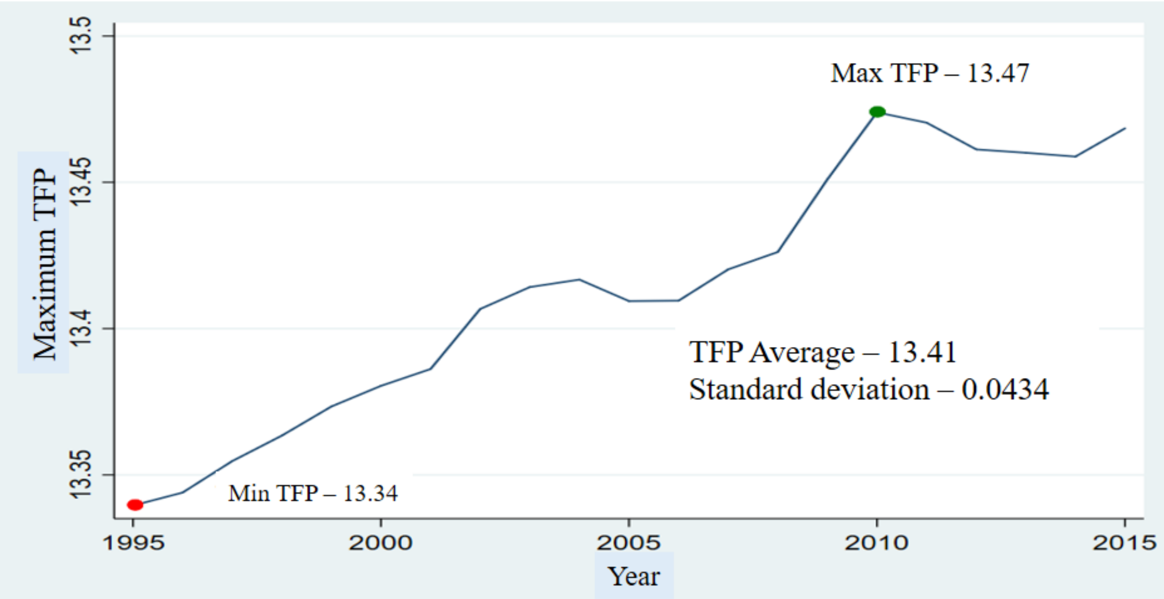
Source: Authors. Panel data (1995-2015) - Coefficients β. Consider: *** p <0.01.

4.2 Choosing the best estimate for the TFP

Although the ACF (2015) model proposes an improvement of the OP and LP models, and still presented results with statistical significance, the Wool (2009) model, besides improving the LP model, presented close results with the same. In addition, the ACF model showed large dispersion around the mean as observed. Thus, it was chose to analyze the WOOL model.

Figure 1 illustrates the maximum TFP found for developed countries. Note that the United States of America (USA) presents the largest TFP (13.47) in all years of the sample (1995-2015), thus characterizing itself as a benchmarking country.

Figure 1 – Maximum TFPs for developed countries, Wooldridge Mode



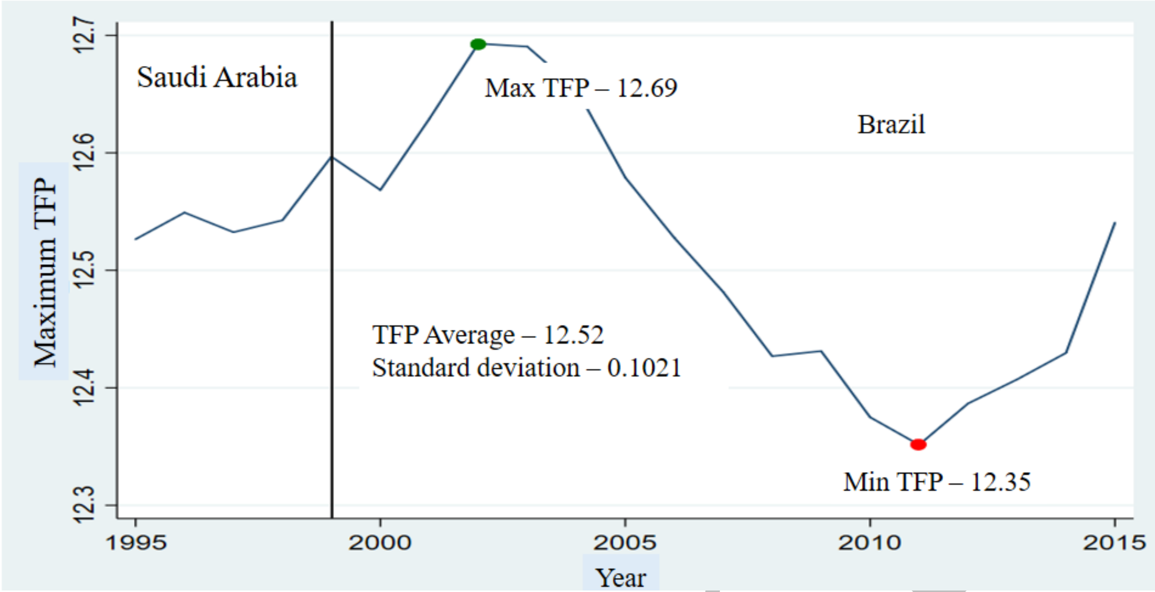
Source: Authors * Min TFP represents the lowest index among maximum TFPs.

According to Figure 1, the USA had the highest TFP (13.47) in 2010 and the lowest in 1995 (13.33). The results are similar to Alvim (2009) who also computed the TFP of some countries, where all reached productivity below the USA.

Brazil presented higher productivity than several developed countries, such as Cyprus, Slovenia, Estonia, Iceland, Latvia, Malta and Portugal, but also lower than other countries like Germany, Belgium, Canada, Italy, Japan and Norway. Brazil presented the highest TFP in 2002 (12.69292) and has an average of 12.49847 and a standard deviation of 0.108135.

For developed countries, as the USA presents the highest TFP for the total sample in all years, so it is benchmarking for developed countries. For developing countries, the maximum TFP (Wool Model) value of each year was verified and is shown in Figure 2.

Figure 21 – Maximum TFPs for developing countries, Wooldridge Model



Source: Authors. *Min TFP represents the lowest index among maximum TFPs.

According to Figure 2, Saudi Arabia is the benchmarking for developing countries from 1995 to 1999. Subsequently, from 2000 to 2015, Brazil is the benchmarking for developing countries. Brazil showed a decrease in productivity from 2002 to 2011, but after 2011 showed a growing productivity behavior.

The study by Mation (2013) analyzed the evolution of TFP in Brazil, and in light of this diagnosis, it is clear that the main explanatory factor of Brazilian economic growth was the incorporation of factors of production, especially the labor factor. As the economy is at historically high levels of employment and participation rates, it is challenging to continue sustained growth along these lines.

5. Conclusion

This article compared four models to calculate TFP using the per capita energy consumption as an intermediate input. Although the ACF (2015) model proposes an improvement of the OP and LP models, and still presented results with statistical significance, the Wool (2009) model, besides improving the LP model, presented close results with the same. In addition, the ACF model showed large dispersion around the mean as observed. Thus, it was choose the Wooldridge model (2009) as the best estimative for the database.

As a research limitation, it is possible to mention the unavailability of more recent data (above 2015), as well as the need for analysis of countries in separate groups (developed and emerging or developing) in order to obtain more homogeneous data, since the groups they have different socioeconomic conditions, and, therefore, it is assumed that each group has more expressive characteristics.

It is suggested as a future paper the calculation of Knowledge Absorption Capacity by the method developed by Girma (2005) which is defined as the level of TFP in the previous period divided by the maximum level TFP level among the units. The idea is to propose the comparison of this method with proxies for the Absorption Capacity.

Another suggestion for a future study is the calculation of TFP using the Malmquist index as some studies have proposed (Cao et al., 2017; Mu et al., 2017; Fu & Ji, 2017; Chen et al., 2016). The idea is to compare the results of the models in this work with the possible results of Malmquist.

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References

Acemoglu, D., Aghion, P., Bursztyn, L., & Hemous, D. (2007). The environment and directed technical change. ***American Economic Review,*** 102(1), 131–166.

ACKERBERG, D., CAVES, K., & FRAZER, G. (2015). Identification Properties of Recent Production Function Estimators. ***Econometrica,*** 83(6), 2411-2451.

Aghion, P., & Howitt, P. (2005). ***Endogenous growth theory.*** Cambridge, MA: MIT Press, 1998.

Akinlo, A. E., & Adejumo, O. O. (2016). Determinants of Total Factor Productivity Growth in Nigeria, 1970–2009. ***Global Business Review,*** 17(2), 257-270.

Alvim, C. F. (2009). A produtividade dos Fatores em Alguns Países. ***Economia & Energia,*** *73.*

Arazmuradov, A., Martini, G., & Scotti, D. (2014). Determinants of total factor productivity in former Soviet Union economies: A stochastic frontier approach. ***Economic Systems,*** 38(1), 115-135.

Ayres, R. U., & Warr, B. (2010). ***The Economic Growth Engine:*** How Energy and Work Drive Material Prosperity. Edward Elgar Publishing, Cheltenham, UK.

EXACTA Engenharia de Produção eISSN 1983-9308

Azar, C., & Dowlatabadi, H. (1999). A review of technical change in assessment of climate policy. ***Annual Review of Energy and the Environment,*** 24(1), 513–544.

Beca, A. L., Shimabuku, E., Silva, A. M., Tanaka, W. Y., & Ferreira, W. P. (2019). Aplicação da teoria das restrições no transporte público: estudo de caso em uma linha de ônibus na cidade de São Paulo. ***Exacta,*** (17(2), 119-133.

Brooks, C. (2008). ***Introductory Econometrics for Finance.*** 2 ed. Chris Brooks The ICMA Centre, University of Reading.

Bhattacharya, M., Okafor, L. E., & Pradeep, V. (2021). International firm activities, R&D, and productivity: Evidence from Indian manufacturing firms. ***Economic Modelling,*** 97, 1-13.

Buesa M., Heijs J., & Baumert, T. (2010). The determinants of regional innovation in Europe: A combined factorial and regression knowledge production function approach. ***Research Policy,*** 39, 722–735.

Cao, L., Qi, Z., & Ren, J. (2017). China's industrial total-factor energy productivity growth at sub-industry level: A two-step stochastic metafrontier Malmquist index approach. ***Sustainability (Switzerland),*** 9(8), 1384.

Castiglionesi, F., & Ornaghi, C. (2013). On the determinants of total factor productivity growth: Evidence from Spanish manufacturing firms. ***Macroeconomic Dynamics,*** 17(3), 501-530.

Chen, L. H., Tang, L., & Ni, W. J. (2016). Analysis of total factor productivity between 2003 and 2014 in tertiary hospitals in Shanghai based on Malmquist index. ***Journal of Shanghai Jiaotong University (Medical Science),*** 36(6), 912-916. Chen, S., & Golley, J. (2014). 'Green' productivity growth in China's industrial economy. ***Energy Economics,*** 44, 89-98.

Danska-Borsiak, B. (2018). Determinants of total factor productivity in Visegrad Group nuts-2 regions. ***Acta Oeconomica,*** *68*(1), 31-50.

Dańska-Borsiak, B., & Laskowska, I. (2012). The Determinants of Total Factor Productivity in Polish Subregions. Panel Data Analysis. ***Comparative Economic Research,*** 15(4), 17-29.

Elmawazini, K. (2014). FDI Spillovers, Efficiency Change and Host Country Labor Productivity: Evidence from GCC Countries. ***Atlantic Economic Journal,*** 42(4), 399-411.

Felema, J., Raiher, A. P., & Ferreira, C. R. (2013). Agropecuária brasileira: desempenho regional e determinantes de produtividade. ***Revista de Economia e Sociologia Rural,*** 51(3), 555-574.

Feng, J. C., Huang, M. B., & Wang. M. (2018). Analysis of green total-factor productivity in China's regional metal industry: A meta-frontier approach. ***Resources Policy,*** 58, 219-229.

Filho, V. A. V., & Moori, R. G. (2019). The mediating effect of resource based view (RBV) on the relationship between supply chain management and operational performance. ***Exacta,*** 17(1), 111-126.

Fu, Q., & Ji, F. (2017). Total factor productivity of food manufacturing industry in China: A DEA-Malmquist index measurement. ***Revista de la Facultad de Ingenieria,*** 32(4), 1-8.

Gao, Y., Zhang, M., & Zheng, J. ***(2021).*** Accounting and determinants analysis of China's provincial total factor productivity considering carbon emissions. China Economic Review, 65.Giovanis, E., & Ozdamar, O. (2015). Determinants of total factor productivity: Evidence from US Compustat firms and Triadic Patent Families. ***International Journal of Economics and Business Research,*** 10(3), 258-272.

Girma, S. (2005). Absorptive Capacity and Productivity Spillovers from FDI: A Threshold Regression Analysis. ***Oxford Bulletin of Economics and Statistics,*** 67(03), 281-306. Harris, R., & Moffat, J. (2015). Plant-level determinants of total factor productivity in Great Britain, 1997–2008. ***Journal of Productivity Analysis,*** 44(1), 2015.

Hausmann R., Hidalgo, C. A., Bustos, S., Coscia, M., Simoes A., & Yildirim, M. A. (2014). ***The atlas of economic complexity:*** Mapping paths to prosperity: MIT Press.

Hidalgo, C. A., & Hausmann, R. (2009). The building blocks of economic complexity. ***Proceedings of the National Academy of Sciences of the United States of America,*** 106(26), 10570-10575.

Husniah H., & Supriatna A. K. (2016). Optimal number of fishing fleet for a sustainable fishery industry with a generalized logistic production function. ***Proceedings of 2015 International Conference on Industrial Engineering and Systems Management,*** IEEE IESM 2015, 7380211, 546-554.

Kim, S. (2016). Factor determinants of total factor productivity growth for the japanese manufacturing industry. ***Contemporary Economic Policy,*** 34(3), 572-586.

Kim, S. (2011). Factor determinants of total factor productivity growth in the malaysian hotel industry: A stochastic frontier approach. ***Cornell Hospitality Quarterly,*** 52(1), 35-47.

Lenox, M., & King, A. (2004). Prospects for developing absorptive capacity through internal information provision. ***Journal of Strategic Management,*** 25(4), 331-345.

Levinsohn, J., Petrin, A. (2003). Estimating Production Functions Using Inputs to Control for Unobservables. ***Review of Economic Studies,*** 70, 317-342.

Liu, B. G., Wang, B., & Zhang, N. (2016). A coin has two sides: Which one is driving China's green TFP growth? Economic Systems, 40(3), 481-498.Löschel, A. (2002). Technological change in economic models of environmental policy: a survey. ***Ecological Economics,*** 43(2), 105–126.

Mation, L. (2013). Produtividade Total dos Fatores no Brasil: impactos na educação e comparações internacionais. ***Boletim Radar*** – *IPEA*, 28, 39-46.

Messa, A. (2013). Indicadores de produtividade: Uma breve revisão dos principais métodos de cálculo. *Radar:* ***Tecnologia, Produção e Comércio Exterior***, 28.

Mirza, F. M., Rizvi, S. B., & Bergland, O. (2021). Service quality, technical efficiency and total factor productivity growth in Pakistan's post-reform electricity distribution companies. ***Utilities Policy,*** 68.

Mu, M., Tian, Y., & Duan, J. (2017). Impact of overseas listing on total factor productivity: A DEA-malmquist index measurement. ***Boletin Tecnico/Technical Bulletin,*** 55(4), 525-530.

Nelson, R., & Phelps, E. (1966). Investment in humans, technological diffusion, and economic growth. ***American Economic Review,*** 56(1/2), 69–75.

Olley, S., & Pakes, A. (1996). The Dynamics of Productivity in the Telecommunications Equipment Industry. ***Econometrica,*** 64, 1263-1295.

Otsuka, A. (2017). Regional determinants of total factor productivity in Japan: stochastic frontier analysis. ***Annals of Regional Science,*** 58(3), 579-596.

Otsuka, K., & Natsuda, K. (2016). The determinants of total factor productivity in the malaysian automotive industry: are government policies upgrading technological capacity? ***Singapore Economic Review,*** 61(4).

Romer, P. M. (1990). Endogenous technological change. ***Journal of Political Economy,*** 98(5), 71–102.

Sarbu, M. (2017). Does Social Media Increase Labour Productivity? ***Journal of Economics and Statistics,*** 237(2), 81–113.

Sheng, Y., & Song, L. (2012). China's iron and steel industry performance: Total factor productivity and its determinants. ***The Chinese Steel Industry's Transformation: Structural Change, Performance and Demand on Resources***, 69-88.

Solow, R. (1956). A contribution to the theory of economic growth. ***Quarterly Journal of Economics,*** 70(1), 65-94.

Solow, R. (1957). Technical Change and the Aggregate Production Function. ***Review of Economics and Statistics,*** 39(3), 312-320.

Stern, D. I., & Kander, A. (2012). The role of energy in the industrial revolution and modern economic growth. ***Energy Journal,*** 33(3), 125.

Tinbergen, J. (1942). A teoria do desenvolvimento econômico de longo prazo. ***Review of World Economics,*** 55(1), 511-549.

Vallejos, L., & Valdivia, L. (2000). ***Productivity growth in Peru:*** 1950 – 1998. Santiago: Interamerican Development Bank, 2000. (Serie de Documentos de Trabajo nº 355).

Vecchia, F. A. D., Volquind, R., Fernandes, E. S., Silveira, B. M., Santos, B. M., & Amaral, F. G. (2020). Lean practices in industrial production processes: innovations that provide reduction in costs and raw materials residues. ***Exacta,*** 18(1), 1-15.

Wei. W. W. L., Zhang, J. L., Wen, J. J., & Wang, S. (2020). TFP growth in Chinese cities: The role of factor-intensity and industrial agglomeration. ***Economic Modelling,*** 91, 534-549.Wooldridge, J. M. (2009). On estimating firm-level production functions using proxy variables to control for unobservables. ***Economics Letters,*** 104, 112-114.

Zhang, Y., Song, Y., & Zou, H. (2020). Transformation of pollution control and green development: Evidence from China’s chemical industry. ***Journal of Environmental Management,*** 275, 111246.