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ISSN 1822-8038 (online)
INTELEKTINĖ EKONOMIKA
INTELLECTUAL ECONOMICS
2022 , No 16(1), p. 58-80

EFFICIENCY ANALYSIS ON THE CONSUMPTION OF SOFTWARE PIRACY IN OECD COUNTRIES

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DOI: 10.13165/IE-22-16-1-04

Acknowledgements: *This research was carried out with the financial support of grant PGC2018- 095786-B-I00 of the Spanish Ministry of Science, Innovation and Universities.*

Conflicts of Interest: *The authors have no conflicts of interest to declare that are relevant to the content of this article. All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript. The authors have no financial or proprietary interests in any material discussed in this article.*

Abstract. *This paper focuses on one of the topics of copyright economics: the study of software piracy and its determinants. The efficiency of OECD countries regarding the consumption of illegal software is analyzed. In this vein, efficiency is associated with the minimal consumption of software piracy according to the socioeconomic characteristics of a nation. Data Envelopment Analysis is the methodology employed, which assigns an efficiency score to the countries in order to establish a ranking of efficiency. Additionally, a relationship is established between the legal origin of the copyright law of a country and its efficiency level. The results of the efficiency analysis show that the efficient countries are Austria, Hungary, Japan, Korea, Mexico and Slovakia; this leads to the affirmation that the countries with lower levels of piracy are not always efficient. According to the legal origin of copyright law, countries with a German origin are the most efficient. Consequently, the efficiency score is not related to the level of software piracy but to the legal origin.*

Keywords: *software piracy, copyright economics, efficiency assessment, data envelopment analysis, efficiency ranking.*

JEL Classification: *C14; O34; Z10.*

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1. Introduction

In 2017, unlicensed software accounted for 37% of the software installed on computers worldwide, resulting in losses of around US$46 billion according to the Business Software Alliance (BSA). This data depends on the region: countries with a lower piracy rate are in North America and Western Europe (their piracy rates are 16% and 26%, respectively), while in the other regions more than half of the software used is illegal (BSA, 2018).

Software[2] piracy has become a global phenomenon driven by the emergence of digital technologies, which reduce copying costs and facilitate their distribution and perfection (Andrés, 2006a; Yang et al., 2009). The BSA defines software piracy as "the illegal use and/or distribution of software protected under intellectual property laws."

The study of software piracy forms part of the economics of copying[3] (Landes & Posner, 1989), where one of the main (and most commonly studied) topics is the analysis of the determinants of piracy (Banerjee et al., 2005; Yang et al., 2004). According to existing studies, the level of piracy depends on multiple elements, such as wealth, education, culture, and regulation.

These determinants explain that, for example, pirated software in Mexico constitutes 49% of use, (Mexico ranks top in the world piracy ranking) against 15% in the USA – the latter being the country with the lowest software piracy rate.

We raise the following questions: Given the determinant factors of illegal software of a country, could the rates of piracy software be reduced? In other words, are resources/policy being used efficiently by governments/countries in order to reduce the consumption of illegal software?

Scholars have focused on determinants and consequences of the consumption of illegal software (Proserpio et al., 2005; Goel & Nelson, 2009; Andrés & Goel, 2011; Dias Gomes et al., 2018), but no studies have analyzed the consumption of software piracy using the efficiency approach. In this context, efficiency is associated with the minimal consumption of software piracy according to the socioeconomic characteristics of a nation. Striving to address this gap, this paper analyses efficiency in terms of reducing consumption levels of software piracy in several countries. To this end, a methodology employed in studies of efficiency measurement is applied, which uses a non-parametric method based on mathematical programming, known as Data Envelopment Analysis (DEA). Through efficiency scores, the methodology of DEA evaluates the relative efficiency of a set of units (countries in our case) that are comparable, while the resources they consume (determinants of software piracy) and the productions they generate (variable on the level of piracy) are similar (the variables for all the countries are the same in our case).

The DEA methodology was developed by Farrell (1957), who defined a frontier of the best practices composed of the most efficient units of the sample in order to obtain efficiency measures for each unit. Since the relative efficiency scores are obtained by comparing the data of each

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[2] Software forms part of the information or knowledge goods, their characteristics are (Shapiro & Varian, 1999): a) high production costs versus very low reproduction costs; b) experience goods; c) decreasing marginal utility; d) technological dependence (lock-in); e) network effects (feedback); f) intellectual property. Copyright goods can be found within knowledge goods: the main difference between them is the perception of copyright goods as public goods (Watt, 2009). Software belongs to information and copyright goods.

[3] Copying economics is an area of copyright economics (Plant, 1934); while the first "analyzes the effects of new technologies on the process of copying and reproduction", the economics of copyright "focuses on the impacts of the legal framework" (Towse et al., 2011, p. 31).

unit with those of the rest, specifically with "best practices," once the methodology has been applied to the set of units, these units can be ordered to establish a ranking of efficiency. As regards the literature on ranking Decision Making Units (DMUs) in DEA, several reviews exist, such as those by Adler et al. (2002), Jahanshahloo et al. (2008), and Hosseinzadeh Lofti et al. (2013).

The main contribution of this paper is the application of the DEA methodology as a tool that can promote the design of effective copyright policies. Specifically, DEA is applied to the 36 member nations of the Organization for Economic Co-operation and Development (OECD) for the years 2009, 2013, 2015, and 2017. This methodology will identify which countries are not efficient (a high consumption of illegal software compared with the socioeconomic structure) and which must modify the copyright protection framework in order to improve the efficiency score.[4] So, the results of this study will shed light on the quality of the management of copyright policy. Additionally, it will be studied whether the efficiency level of a country is associated with the legal origin of its copyright protection system.

The structure of this paper is as follows. Section 2 presents the formalization of the methodology proposed, the sample, and a literature review of software piracy in order to select the study variables. Section 3 reports the results of datasets from different years. Finally, the last section provides a summary and the conclusions.

2. Methodology, selection of sample, and variables

2.1. Methodology

DEA is a well-known non-parametric methodology for the assessment of the relative efficiency of a sample of homogeneous DMUs on the basis of data regarding the input consumption and the output production. DEA models typically assign a normalized efficiency score to each DMU in order to distinguish between efficient and inefficient units.

The standard input-oriented CCR DEA model (Charnes et al., 1978) is defined as follows.

Suppose there are m independent DMUs, j in $M=\{1, 2,\ldots,m\}$, each of which consume k different inputs, i in $I=\{1,2,\ldots,k\}$, in quantities x_{ij}, to generate h different outputs in quantities y_{rj} (r in $H=\{1,2,\ldots,h\}$).

The efficiency of a given DMU, j_0 in M, can be computed as follows:

$$
\begin{aligned}
E(j_0) = \ & \min \theta_{j_0} \\
& s.t. \quad \sum_{j \in M} \lambda_j x_{ij} \le \theta_{j_0} x_{ij_0} && \forall i \in I \\
& \qquad \sum_{j \in M} \lambda_j y_{rj} \ge y_{rj_0} && \forall r \in H \\
& \qquad \lambda_j \ge 0 && \forall j \in M \\
& \qquad \theta_{j_0} \quad free
\end{aligned}
$$

DMU j ... n the reformulated model below, s^-_{ij0}, i i...

$$
\begin{aligned}
& \min \theta_{j_0} - \varepsilon \left(\sum_{i \in I} s^-_{ij0} + \sum_{r \in H} s^+_{rj0}\right) \\
& s.t. \quad \sum_{j \in M} \lambda_j x_{ij} = \theta_{j_0} x_{ij_0} - s^-_{ij0} && \forall i \in I \\
& \qquad \sum_{j \in M} \lambda_j y_{rj} \ge y_{rj_0} + s^+_{rj0} && \forall r \in H
\end{aligned}
$$

[4] There are tw... t. The second option is not ... ent level of a country, and, ... ncreasing the legal consum...

Efficient units are assigned a score of 1, whereas inefficient units obtain a score which reflects their degree of inefficiency (a value less than 1 and greater than 0). These efficiency scores can be used to establish a ranking of DMUs. The ranking is incomplete, however, since efficient DMUs cannot be differentiated in these terms. Various approaches exist to rank all the DMUs and not only the efficient DMUs: in general, three major categories of approaches can be distinguished. These are outlined below, but this list is not exhaustive.

One category corresponds to methods based on cross-efficiency (XE). In this type of method, the conventional CCR DEA model is first solved to compute the efficiency score of each DMU, which is then imposed as a constraint in a secondary-goal DEA model.

A second important category of DEA ranking methods is formed of those based on the computation of a Common Set of Weights (CSW) for all DMUs, which can then be used to rank all DMUs. Different criteria can be used to choose the CSW (e.g. compromise programming, regression analysis and deviation from weight profiles of efficient DMUs).

A third major category of DEA ranking methods are those based on super-efficiency (SE). Such methods generally use DEA models, and the key feature of this approach is that the DMU being ranked is dropped from the set of DMUs that define the technology. This can lead, in the case of extremely efficient DMUs, to SE scores larger than unity, which can be used to rank those DMUs. Since for inefficient units these SE scores coincide with conventional efficiency scores, this method is applied only to rank efficient DMUs. A variety of metrics can be used to measure the distance of an efficient DMU to the corresponding SE frontier (obtained when the DMU is dropped from the set of DMUs that define the technology), such as radial, the slacks-based measure, the L1 norm, and the Tchebycheff norm.

In order to differentiate between the performance of efficient DMUs, we use the super-efficiency method because in XE methods it may occur that an efficient DMU is ranked below an inefficient DMU, and in CSW methods a previous criterion must be defined to choose the weights. Moreover, the most common metric is employed here: the radial metric.

For the standard input-oriented CCR DEA model, the super-efficiency of a given DMU, j_0 in M, can be computed as follows:

$$
\begin{aligned}
E^{super}(j_0) = \quad & \min \theta_{j_0} \\
s.t. \quad & \sum_{j \in M \setminus \{j_0\}} \lambda_j x_{ij} \leq \theta_{j_0} x_{ij_0} \quad \forall i \in I \\
& \sum \lambda_j y_{rj} \geq y_{rj_0} \quad \forall r \in H
\end{aligned}
$$

Our CCR DEA model assumes constant returns to scale (CRS). Models assuming variable returns to scale (VRS) can be obtained by adding to the CRS model (1) and (3) the following constraints: and , respectively. However, in this paper, the CCR model where CRS are assumed is used because the CRS super-efficiency DEA model is usually feasible, while the VRS super-efficiency DEA model can be infeasible. Seiford & Zhu (1999) show the condition under which the VRS model is infeasible.

2.2. Selection of sample

The sample includes the 36 member nations of the OECD[5] in order to supply an international framework for the study.

Furthermore, the research time covers the years 2009, 2013, 2015, and 2017.[6] This will enable intertemporal comparisons to be made.

2.3. Selection of variables

DEA is a non-parametric method which enables multiple variables, inputs, and outputs measured in different units to be integrated. Furthermore, since it is a non-parametric method, it is not necessary to define or justify the functional form of the production between inputs and outputs. However, the selection of the variables has been made through a meticulous study of the determinants of software piracy to ensure that the analysis has a solid foundation.

2.3.1. Output variable

As noted earlier, the efficiency of the use of resources to combat piracy, given the determining factors, is studied in this paper. Therefore, an efficient protection is that which minimizes the volume of pirated product according to its determinants.

With the aim of gauging the piracy of software in a nation, statistical data provided by the BSA is used; this is the reference database of the main work related to software piracy. The BSA is an American organization that measures the rate of pirated software (SPR).[7] This rate varies

[5] Australia, Austria, Belgium, Canada, Chile, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, the United Kingdom, the United States.

[6] The selection of these years is explained by the availability of data on software piracy which is offered by the BSA (2012, 2014)

[7] Software Piracy Rate (SPR) = Unlicensed software units \ Total software units installed, where Total software units installed = PC receiving software x Software units per PC.

between 0% and 100%; where 0% reflects the non-existence of piracy, while 100% indicates all the consumed software has been pirated.

According to the properties of the DEA analysis, in this paper, instead of SPR, we will use the rate of legal software (LSR).[8] Therefore, when the value of the LSR is 0%, this means that all software is pirated; an LSR of 100% indicates the total absence of piracy.

2.3.2. Input variables

In line with some of the most representative work in the piracy framework (Proserpio et al., 2005; Goel & Nelson, 2009; Andrés & Goel, 2011; Dias Gomes et al., 2018), determinants of software piracy can be classified into four dimensions or categories[9]: economic, institutional, educational, and cultural.

Table 1 compiles the bibliographic references of software piracy determinants, which explain the selection of input variables.

- Economic dimension

Most studies regarding software piracy agree that the wealth of a nation is negatively related to the level of software piracy. This can be explained because intellectual property rights (IPR) are more protected, and have lower piracy rates, in nations with higher per capita incomes (Rapp & Rozek, 1990; Park & Ginarte, 1997).

This research will use GDP per capita in constant dollars 2011 (GDPpc). Data has been collected from the World Bank online database.

Reviews of most relevant work that studies the connection between this dimension and software piracy are shown in Table 1. As can be observed, there is a negative relationship between SPR and GDPpc, so it can be said that the link between GDPpc and LSR is positive.

- Institutional dimension

According to Knack and Keefer (1995) and Hall and Jones (1996), nations with stronger institutions are those which provide a greater protection of the IPR. Therefore, countries with weaker institutions have greater piracy rates, and vice versa (Marron & Steel, 2000).

In this context, corruption is a way of gauging the quality of the institutional framework. Nations with the highest corruption are those that encourage piracy more, because in these nations, hackers enjoy greater opportunities for operating outside the law.

In line with the reviews shown in Table 1, this paper will use the Corruption Perceptions Index (CPI). This is an indicator built by Transparency International (n.d.), which reflects levels of corruption perceived in each nation according to valuations and opinion polls of experts in the field. The range of this indicator varies between 0 and 100; a value of 100 indicates the absence of corruption, and vice versa.

Table 1: *References of software piracy determinants*

[8] Legal Software Rate (LSR) = 100 − SPR.

[9] Technology is usually considered as another dimension. Since the results of studies are not concise with respect to this factor, this factor is excluded from this paper.

Reference	Study	Output	Dimension/Input	Link output-input
Husted (2000)	Software piracy, cross-section analysis for 37 nations in 1996	SPR	Economic: GDP pc	(-)
			Cultural: Individualism	(-)
Marron & Steel (2000)	Software piracy, cross-section analysis for 77 nations with averages from 1994–1997	SPR	Economic: GDP pc	(-)
			Educational: Average years of schooling in population >25 years	(-)
			Cultural: Individualism	(-)
Ronkainen & Guerrero-Cusumano (2001)	Software piracy, cross-section analysis for 50 nations in 1997 and 1998	SPR	Economic: GDP pc	(-)
			Institutional: CPI	(-)
Depken & Simmons (2004)	Software piracy, cross-section analysis for 65 nations in 1994	SPR	Economic: GDP pc	(-)
			Educational: Literacy rate	(+)/(-)
			Cultural: Individualism	(-)
Banerjee et al. (2005)	Software piracy, panel data analysis for 53 nations from 1994–1999	SPR	Economic: GDP pc	(-)
			Institutional: CPI	(-)
Proserpio et al. (2005)	Software, movies and music piracy; cross-section analysis for 76 nations with averages from 1999–2002	SPR	Economic: GDP pc	(-)
			Institutional: CPI	(-)
			Educational: Average years of schooling in population >25 years	(-)
			Cultural: Individualism	(-)
Shadlen et al. (2005)	Software piracy; panel data analysis for 80 nations from 1994–2002	SPR	Economic: GDPpc	(-)
			Educational: Combined primary, secondary, and tertiary gross enrollment ratio	(-)
Andrés (2006a)	Software piracy; panel data analysis for 23 nations in 1994, 1997 and 2000	SPR	Economic: GDP pc	(-)
Andrés (2006b)	Software piracy; cross-section analysis for 34 nations in 1995	SPR	Economic: GDP pc	(-)
Moores (2008)	Software piracy; cross-section analysis for 57 nations with averages from 1994–2002	SPR	Economic: GDP pc	(-)
			Cultural: Individualism	(-)

Robertson et al. (2008)	Software piracy; cross-section analysis for 88 nations in 1999	SPR	Economic: GNP pc	(-)
			Institutional: CPI	(-)
Goel & Nelson (2009)	Software piracy; cross-section analysis for 80 nations in 2004	SPR	Economic: GDP pc	(-)
			Institutional: CPI	(-)
			Educational: Literacy rate	(+)
Yang et al. (2009)	Software piracy; panel data analysis for 59 nations from 2000–2005	SPR	Economic: GDP pc	(-)
			Cultural: Individualism	(-)
Andrés & Goel (2011)	Software piracy; cross-section analysis for 100 nations in 2007	SPR	Economic: GDP pc	(-)
			Institutional: CPI	(-)
Dias Gomes et al. (2018)	Software piracy; panel data analysis for 81 nations from 1995–2010	SPR	Economic: GDP pc	(-)
			Institutional: CPI	(-)
			Educational: Duration of primary education (years)	(-)

Source: *Author's own*

Regarding the results of the references in Table 1, it can be stated that there is a negative relationship between SPR and CPI; in other words, the connection between LSR and CPI is positive.

- Educational dimension

The majority of studies on software piracy that analyze this dimension found the relationship between educational level and software piracy to be negative (Marron & Steel, 2000; Depken & Simmons, 2004; Proserpio et al., 2005; Shadlen et al., 2005; Goel & Nelson, 2009; Dias Gomes et al., 2018).

A population with a higher educational level becomes more aware of the need to protect IPR, and hence demand major protection.

Research, such as that by Marron and Steel (2000), Proserpio et al. (2005), and Andrés (2006b), uses the average years of schooling in populations over 25 years of age as their study variable. However, in line with Dias Gomes et al. (2018), this paper will use the duration in primary education (DPE).[10] Data is provided by the World Bank online database.

Since the link between DPE and SPR is negative, then the relationship between DPE and LSR is positive.

- Cultural dimension

Features of a culture provide information on the customs and practices of a society. In this respect, there are studies which conclude that culture affects attitudes towards software piracy.

According to Hofstede (1997), there are five dimensions that explain the attitude of a society in economic and social aspects: 1) power distance, 2) individualism, 3) masculinity, 4) un-

[10] Dias Gomes et al. (2018) did not apply the average years of schooling in the population aged over 25 due to the non-availability of data in recent years (this is a variable obtained by Barro and Lee in 1996), hence they used DPE.

certainty avoidance, and 5) long-term orientation. A number of studies have linked Hofstede's dimensions with piracy. Individualism[11] (IND) is the single dimension that is significantly connected with software piracy.

In line with the results of references shown in Table 1, there is a negative connection between individualism and software piracy. Consequently, nations of a more individualistic nature have a lower level of software piracy since collectivist nations are more concerned about social harmony and group welfare. This greater emphasis based on sharing also occurs in software frameworks, and hence illegal products circulate more readily in a collectivist society. Therefore, there is a positive link between IND and LSR. Table 2 reflects the connection between the output (LSR) and input variables.

Table 2: *Links between output and input variables*

Output	Input	Link
LSR (Legal Software Rate)	GDPpc (GDP per capita)	Positive (+)
	CPI (Corruption Perceptions Index)	Positive (+)
	DPE (Duration of primary education)	Positive (+)
	IND (Individualism)	Positive (+)

Results and discussion

In this paper, the ranking of the 36 member nations of the OECD is applied across several years in order to consolidate the results, since the variables analyzed do not change abruptly for each nation over short periods.

As previously stated, the CRS super-efficiency model has been used since it is always feasible. The VRS super-efficiency model cannot be used in our case because the model is infeasible for certain countries.

Table 3 shows the efficiency scores and the ranking of countries for the period studied.

As can be observed, for 2017 there were six efficient nations (Austria, Hungary, Japan, Korea, Mexico and Slovakia), which are ordered according to the super-efficiency score as follows: Korea, Mexico, Austria, Hungary, Japan, and Slovakia. These countries and Portugal were also efficient in 2015, where the ranking is the following: Korea, Mexico, Austria, Slovakia, Hungary, Japan, and Portugal. For 2013, the efficient nations were the same as in 2015, but Hungary and Portugal moved up one position and Slovakia and Japan moved down one position. Finally, in 2009, there were also eight efficient nations (Austria, the Czech Republic, Hungary, Japan, Korea, Mexico, Portugal, and Slovakia), which coincide with the efficient nations of 2013. These efficient nations are ordered according to the super-efficiency score as follows: Korea, Austria, Hungary, Mexico, Japan, Slovakia, Portugal, and the Czech Republic. Note that the same order is maintained as in 2013 for these countries, except for Mexico and Japan, which are in 4th and 5th place for 2009 and in 2nd and 7th place for 2013, respectively.

[11] Individualism refers to the level of individuality valued over group ideals. Data of this variable has been extracted from Hofstede (1997).

Table 3: *Efficiency scores and positions of the nations in different years*

OECD countries	2017		2015		2013		2009	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank
Australia	0.8043	24	0.7988	24	0.7611	29	0.7593	33
Austria	1.1182	3	1.1216	3	1.1348	3	1.1430	2
Belgium	0.8280	18	0.8160	22	0.8072	19	0.8697	19
Canada	0.8131	23	0.7863	27	0.7759	24	0.7929	30
Chile	0.8691	13	0.8294	19	0.7990	20	0.8289	25
Czech Re-public	0.9327	11	0.9442	11	1.0238	8	1.0150	8
Denmark	0.7693	29	0.7620	31	0.7519	31	0.8050	27
Estonia	0.8161	22	0.8383	18	0.7823	22	0.8573	21
Finland	0.8660	14	0.8671	16	0.8555	14	0.8727	18
France	0.8181	20	0.7994	23	0.7760	23	0.7705	31
Germany	0.9880	9	0.9906	8	0.9870	9	0.9984	9
Greece	0.6348	35	0.6284	35	0.7156	34	0.9057	14
Hungary	1.0699	4	1.0743	5	1.0958	4	1.1108	3
Iceland	0.5680	36	0.5747	36	0.5606	36	0.5486	36
Ireland	0.6945	34	0.7068	34	0.7035	35	0.6744	35
Israel	0.9530	10	0.9404	12	0.9284	11	0.9707	11
Italy	0.7967	26	0.9623	10	0.8964	13	0.9225	12
Japan	1.0465	5	1.0343	6	1.0373	7	1.0756	5
Korea	1.6452	1	1.5984	1	1.5500	1	1.4750	1
Latvia	0.8031	25	0.8230	20	0.7940	21	0.8862	16
Lithuania	0.7669	31	0.7786	29	0.7617	27	0.8768	17
Luxembourg	0.8582	17	0.8740	14	0.8541	15	0.9115	13
Mexico	1.3317	2	1.2358	2	1.1759	2	1.1093	4
Netherlands	0.7687	30	0.7614	32	0.7570	30	0.7620	32
New Zealand	0.9984	7	0.9817	9	0.9513	10	0.9737	10
Norway	0.7447	33	0.7433	33	0.7192	33	0.7400	34
Poland	0.7846	27	0.7893	26	0.7752	25	0.8226	26
Portugal	0.9929	8	1.0294	7	1.0526	6	1.0163	7
Slovakia	1.0441	6	1.0837	4	1.0767	5	1.0553	6

Slovenia	0.8886	12	0.8989	13	0.9030	12	0.8641	20
Spain	0.7549	32	0.7621	30	0.7517	32	0.7968	29
Sweden	0.8260	19	0.8179	21	0.8116	18	0.8420	23
Switzerland	0.7840	28	0.7851	28	0.7612	28	0.8033	28
Turkey	0.8163	21	0.7974	25	0.7741	26	0.8543	22
United King-dom	0.8621	16	0.8562	17	0.8318	17	0.8407	24
United States	0.8629	15	0.8698	15	0.8524	16	0.8941	15

Certain comments should be made regarding the results shown. Firstly, efficient nations, with the exception of Austria and Japan, have high software piracy rates (although all nations reduced software piracy throughout the study period); on the other hand, nations with the lowest software piracy rates have been classified as inefficient nations (the USA, Australia, Luxembourg, and Germany, for example). Therefore, using the same example as that in the introduction of this paper, Mexico uses its resources and/or applies its policies more efficiently than the USA.

Regarding the results during the study period, it can be stated that there were no major changes in the position of nations in the different efficiency rankings. However, Greece, Italy, and Lithuania suffered major variations in their positions. Tables 4–7 of the Appendix to this paper offer a dataset for the period studied. Greece dropped in the ranking, from 14th place for 2009 to 34th place for 2013; these changes could be explained by the fall of the GDPpc (it can be observed that the other input variables have no significant fluctuations). Italy also underwent significant variation in its positions, ranking 10th for 2015 and 26th for 2017; in this case, the CPI was the input variable that experienced a major variation (while the CPI was 44 in 2015, the CPI of 2017 was 50). The drop of Lithuania in the ranking, from 17th place for 2009 to 27th place for 2013, could be explained by the variation of both the GDP and the CPI (GDP and CPI grows while the output variable has no major increase).

Therefore, according to the results offered by this study, the most efficient nation in the consumption of legal software throughout the 2009–2017 period was Korea.

However, to illustrate that, in general, there were no abrupt changes in the ranking over the different years, the strength and association between the different rankings are analyzed. To do this, Spearman's correlation between each pair of years will be used.

Spearman's correlation coefficient is a non-parametric measure of rank correlation, that is, of the statistical dependence of ranking between two different years. Spearman's correlation coefficient can take a value between +1 and −1. If Spearman's coefficient is close to 0, then the association between the two rankings is weak or null, and if it is close to +1 (or −1), then the association between the two rankings is almost perfectly positive (or negative).

Table 8 shows Spearman's correlation coefficients between the rankings of all the years.

Since all the Spearman's correlation coefficients shown in Table 8 are close to +1, the associations between the rankings of the different years are almost perfect. In this way, this analysis of the efficiency of member nations of the OECD shows consistency over the years.

Table 8: *Spearman's correlations coefficients*

	Ranking 2017	Ranking 2015	Ranking 2013	Ranking 2009
Ranking 2017		0.94311454	0.95418275	0.802574
Ranking 2015	0.94311454		0.98481338	0.87464607
Ranking 2013	0.95418275	0.98481338		0.88597169
Ranking 2009	0.802574	0.87464607	0.88597169	

Goel and Nelson (2009) and Andrés and Goel (2011) found that the legal origin of copyright protection systems could explain the level of software piracy in a country (in line with La Porta et al.,1999, there are four legal origins: English, French, German, and Scandinavian). This association motivates the research hypothesis of this work, from which it is studied whether the efficiency scores of countries are associated with their legal origins.

For this analysis, the Kruskal–Wallis test is used (Kruskal & Wallis, 1952; Brockett & Golany, 1996). This involves determining whether or not there are significant differences in the average values obtained in the efficiency scores between the various groups into which the sample of countries has been divided, in terms of their legal origin.

Table 9 shows the p-value obtained from the Kruskal–Wallis test and the average efficiency score of each group of legal origin, for each year considered.

Taking Table 9 as a reference, the Kruskal–Wallis test (with a significance level of 5\%) leads to the rejection, for every year considered, of the hypothesis of equality of means for efficiency scores in the four groups of countries proposed according to their legal origin. Through examining the average values of each group for every year considered, countries of German origin are the most efficient while countries of Scandinavian origin are the least efficient. There are hardly any significant differences between the means of the countries of English origin and the countries of French origin.

Table 9: *Legal origin – Kruskal–Wallis tests*

Year	*p*-value	Average efficiency score			
		English Origin	French Origin	German Origin	Scandinavian Origin
2017	0.016	0.85547	0.84456	1.03331	0.75479
2015	0.010	0.84857	0.84904	1.03693	0.75300
2013	0.015	0.82919	0.83502	1.03519	0.73977
2009	0.012	0.84368	0.88093	1.03979	0.76167

On the other hand, these results lead us to study whether the regional proximity of a country is also related to its efficiency level. To this end, the countries have been divided into six groups: (1) Asia Pacific; (2) Central and Eastern Europe; (3) Latin America; (4) Middle East and America; (5) North America; and (6) Western Europe.

Taking Table 10 as a reference, the Kruskal–Wallis test (with a significance level of up to

10\%) leads to the acceptance, for every year considered, of the hypothesis of the equality of means for efficiency scores in the six groups of countries proposed according to their regional proximity.

Table 10: *Regional proximity – Kruskal–Wallis tests*

Year	2017	2015	2013	2009
p-value	0.141	0.247	0.377	0.423

4. Conclusions

Numerous articles analyze software piracy and its determinant factors. This paper is based on these factors, for which a historical, well-researched, and methodologically useful review is provided. According to this review, the determinants of software piracy can be classified into four dimensions: economic, institutional, educational, and cultural.

The question that arises is whether countries make efficient use of their resources to combat piracy, given the determining factors, or whether they have room for improvement. In this paper, the DEA methodology has been used in order to analyze how efficient a country is compared to the rest of the countries in the sample. Each country is assigned a relative efficiency score, which has allowed us to establish an efficiency ranking for all the countries considered.

The analysis applied indicates that, for every year included in the sample, the efficient countries were Austria, Hungary, Japan, Korea, Mexico, and Slovakia (Portugal was efficient every year ,with the exception of 2017, and the Czech Republic was efficient in 2009 and 2013). These countries (except Austria and Japan) have a high consumption of illegal software. On the other hand, Denmark, Ireland, the Netherlands, and Norway are placed at the bottom of the ranking; these are some of the countries with the lowest levels of software piracy. Therefore, the efficiency analysis leads us to affirm that the countries with lower levels of piracy are not always efficient; however, it can happen that a country which displays high levels of piracy obtains a high score of efficiency since this country is doing everything possible to reduce the volume of piracy, given its circumstances. Consequently, the level of software piracy is not related to the efficiency score. The results of the efficiency analysis show that, with the exception of the six efficient countries, the remaining countries could reduce their piracy rates; in these cases, reducing the volume of piracy requires reforming the institutional framework and acting on the input variables.

Although these results are fully applicable to all years of the sample (see Spearman Correlations), it is appropriate to qualify that the positions in the ranking of Greece, Italy, and Slovakia suffer significant changes over the years due to fluctuation of the GDPpc (in case of Greece and Slovakia) and the CPI (in case of Italy and Slovakia). This is one of the advantages of efficiency analysis: it enables the identification of which factors must be improved in order to increase the level of efficiency.

Another relevant result concerns the relationship between efficiency score and legal origin. According to the Kruskal–Wallis test, it can been said that the legal origin of a country is related to the efficiency level. Specifically, countries with a German origin are the most efficient; in contrast, Scandinavian countries have the worst efficiency levels for all years of the sample. Nonetheless, regional proximity does not determine the efficiency level. For example, Germany and France have regional proximity, but their efficiency scores are very different; France and Chile are not geographically close countries, but they have very similar efficiency scores since they have the same legal origin.

The efficiency analysis applied in this paper enables a reflection to be made on the ability of a country to manage its fight against software piracy; furthermore, it indicates the weaknesses and/or strengths of a country as regards improvements in its efficiency level. When a country is not efficient, this means that this country could reduce its piracy consumption according to the determining factors. Therefore, this paper could serve as a guide for the design of efficient copyright policies or reforms, whose principal items include economic, institutional, educational, and cultural aspects.

Appendix

Table 4: *Dataset, efficiency scores, and ranking 2017*

DMUs j=1,…,36	OECD countries	Inputs				Output LSR	Efficiency Score (E_{j0})	Super-efficiency Score (E^{super}_{j0})	Ranking order
		GDPpc	CPI	DPE	IND				
1	Australia	44781	77	7	90	82	0.8043	0.8043	24
2	Austria	45421	75	4	55	81	1.0000	1.1182	3
3	Belgium	43133	75	6	75	78	0.8280	0.8280	18
4	Canada	43871	82	6	80	78	0.8131	0.8131	23
5	Chile	22297	67	6	23	45	0.8691	0.8691	13
6	Czech Re-public	32571	57	5	58	68	0.9327	0.9327	11
7	Denmark	47555	88	7	74	80	0.7693	0.7693	29
8	Estonia	29704	71	6	60	59	0.8161	0.8161	22
9	Finland	41443	85	6	63	78	0.8660	0.8660	14
10	France	38956	70	5	71	68	0.8181	0.8181	20
11	Germany	45393	81	4	67	80	0.9880	0.9880	9
12	Greece	24602	48	6	35	39	0.6348	0.6348	35
13	Hungary	27032	45	4	80	64	1.0000	1.0699	4
14	Iceland	47840	77	7	60	56	0.5680	0.5680	36
15	Ireland	66132	74	8	70	71	0.6945	0.6945	34
16	Israel	33123	62	6	54	73	0.9530	0.9530	10
17	Italy	35491	50	5	76	57	0.7967	0.7967	26
18	Japan	38907	73	6	46	84	1.0000	1.0465	5
19	Korea	35938	54	6	18	68	1.0000	1.6452	1
20	Latvia	24859	58	6	70	52	0.8031	0.8031	25
21	Lithuania	29668	59	4	60	50	0.7669	0.7669	31
22	Luxembourg	95666	82	6	60	83	0.8582	0.8582	17
23	Mexico	17956	29	6	30	51	1.0000	1.3317	2
24	Netherlands	48809	82	6	80	78	0.7687	0.7687	30
25	New Zealand	36046	89	6	79	84	0.9984	0.9984	7
26	Norway	65014	85	7	69	79	0.7447	0.7447	33
27	Poland	27379	60	6	60	54	0.7846	0.7846	27
28	Portugal	28257	63	6	27	62	0.9929	0.9929	8

29	Slovakia	30059	50	4	52	65	1.0000	1.0441	6
30	Slovenia	31449	61	6	27	59	0.8886	0.8886	12
31	Spain	34126	57	6	51	58	0.7549	0.7549	32
32	Sweden	47261	84	6	71	81	0.8260	0.8260	19
33	Switzerland	58171	85	6	68	79	0.7840	0.7840	28
34	Turkey	25031	40	4	37	44	0.8163	0.8163	21
35	United Kingdom	40229	82	6	89	79	0.8621	0.8621	16
36	United States	54471	75	6	91	85	0.8629	0.8629	15

Table 5: *Dataset, efficiency scores, and ranking 2015*

DMUs j=1,…,36	OECD countries	Inputs				Output LSR	Efficiency Score (E_{j0})	Super-efficiency Score (E^{super}_{j0})	Ranking order
		GDPpc	CPI	DPE	IND				
1	Australia	43832.43	79	7	90	80	0.7988	0.7988	24
2	Austria	44074.95	76	4	55	79	1.0000	1.1216	3
3	Belgium	41723.12	77	6	75	77	0.8160	0.8160	22
4	Canada	42983.1	83	6	80	76	0.7863	0.7863	27
5	Chile	22536.62	70	6	23	43	0.8294	0.8294	19
6	Czech Republic	30380.59	56	5	58	67	0.9442	0.9442	11
7	Denmark	45483.76	91	7	74	78	0.7620	0.7620	31
8	Estonia	27328.64	70	6	60	58	0.8383	0.8383	18
9	Finland	38993.67	90	6	63	76	0.8671	0.8671	16
10	France	37765.75	70	5	71	66	0.7994	0.7994	23
11	Germany	43784.15	81	4	67	78	0.9906	0.9906	8
12	Greece	24094.79	46	6	35	37	0.6284	0.6284	35
13	Hungary	24831.35	51	4	80	62	1.0000	1.0743	5
14	Iceland	42674.42	79	7	60	54	0.5747	0.5747	36
15	Ireland	60944.02	75	8	70	68	0.7068	0.7068	34
16	Israel	31970.69	61	6	54	71	0.9404	0.9404	12
17	Italy	34244.71	44	5	76	55	0.9623	0.9623	10

18	Japan	37818.09	75	6	46	82	1.0000	1.0343	6
19	Korea	34177.65	56	6	18	65	1.0000	1.5984	1
20	Latvia	23057.31	55	6	70	51	0.8230	0.8230	20
21	Lithuania	26970.81	61	4	60	49	0.7786	0.7786	29
22	Luxembourg	95311.11	81	6	60	81	0.8740	0.8740	14
23	Mexico	16667.84	35	6	30	48	1.0000	1.2358	2
24	Netherlands	46353.85	87	6	80	76	0.7614	0.7614	32
25	New Zealand	34646.31	88	6	79	82	0.9817	0.9817	9
26	Norway	63669.53	87	7	69	77	0.7433	0.7433	33
27	Poland	25299.05	62	6	60	52	0.7893	0.7893	26
28	Portugal	26548.33	63	6	27	61	1.0000	1.0294	7
29	Slovakia	28254.26	51	4	52	64	1.0000	1.0837	4
30	Slovenia	29097.34	60	6	27	57	0.8989	0.8989	13
31	Spain	32215.97	58	6	51	56	0.7621	0.7621	30
32	Sweden	45488.29	89	6	71	79	0.8179	0.8179	21
33	Switzerland	56510.86	86	6	68	77	0.7851	0.7851	28
34	Turkey	23382.25	42	4	37	42	0.7974	0.7974	25
35	United Kingdom	38509.21	81	6	89	78	0.8562	0.8562	17
36	United States	52789.97	76	6	91	83	0.8698	0.8698	15

Table 6: *Dataset, efficiency scores, and ranking 2013*

DMUs j=1,...,36	OECD countries	Inputs				Output LSR	Efficiency Score (E_{j0})	Super-efficiency Score (E^{super}_{j0})	Ranking order
		GDPpc	CPI	DPE	IND				
1	Australia	42920.1	81	7	90	79	0.7611	0.7611	29
2	Austria	44161.54	69	4	55	78	1.0000	1.1348	3
3	Belgium	40780.87	75	6	75	76	0.8072	0.8072	19
4	Canada	42335.67	81	6	80	75	0.7759	0.7759	24
5	Chile	21998.31	71	6	23	41	0.7990	0.7990	20
6	Czech Republic	28379.75	48	5	58	66	1.0000	1.0238	8
7	Denmark	44564.45	91	7	74	77	0.7519	0.7519	31
8	Estonia	26148.49	68	6	60	53	0.7823	0.7823	22
9	Finland	39428.31	89	6	63	76	0.8555	0.8555	14

10	France	37366.93	71	5	71	64	0.7760	0.7760	23
11	Germany	42914.48	78	4	67	76	0.9870	0.9870	9
12	Greece	23746.08	40	6	35	38	0.7156	0.7156	34
13	Hungary	23020	54	4	80	61	1.0000	1.0958	4
14	Iceland	41096.69	78	7	60	52	0.5606	0.5606	36
15	Ireland	45257.06	72	8	70	67	0.7035	0.7035	35
16	Israel	31434.88	61	6	54	70	0.9284	0.9284	11
17	Italy	34219.83	43	5	76	53	0.8964	0.8964	13
18	Japan	37148.66	74	6	46	81	1.0000	1.0373	7
19	Korea	32548.72	55	6	18	62	1.0000	1.5500	1
20	Latvia	21598.88	53	6	70	47	0.7940	0.7940	21
21	Lithuania	25147.71	57	4	60	47	0.7617	0.7617	27
22	Luxembourg	90950.09	80	6	60	80	0.8541	0.8541	15
23	Mexico	16315.86	34	6	30	46	1.0000	1.1759	2
24	Netherlands	45191.49	83	6	80	75	0.7570	0.7570	30
25	New Zealand	33841.18	91	6	79	80	0.9513	0.9513	10
26	Norway	62799.43	86	7	69	75	0.7192	0.7192	33
27	Poland	23554.79	60	6	60	49	0.7752	0.7752	25
28	Portugal	25654.61	62	6	27	60	1.0000	1.0526	6
29	Slovakia	26580.72	47	4	52	63	1.0000	1.0767	5
30	Slovenia	27629.66	57	6	27	55	0.9030	0.9030	12
31	Spain	30677.17	59	6	51	55	0.7517	0.7517	32
32	Sweden	43475.8	89	6	71	77	0.8116	0.8116	18
33	Switzerland	56252.93	85	6	68	76	0.7612	0.7612	28
34	Turkey	21650.76	50	4	37	40	0.7741	0.7741	26
35	United Kingdom	37130.28	76	6	89	76	0.8318	0.8318	17
36	United States	51008.46	73	6	91	82	0.8524	0.8524	16

Table 7: *Dataset, efficiency scores, and ranking 2009*

DMUs j=1,…,36	OECD countries	Inputs				Output LSR	Efficiency Score (E_{j0})	Super-efficiency Score (E^{super}_{j0})	Ranking order
		GDPpc	CPI	DPE	IND				
1	Australia	41207.13	87	7	90	75	0.7593	0.7593	33

2	Austria	42459.98	79	4	55	75	1.0000	1.1430	2
3	Belgium	40375.49	71	6	75	75	0.8697	0.8697	19
4	Canada	39924.2	87	6	80	71	0.7929	0.7929	30
5	Chile	18547.46	67	6	23	36	0.8289	0.8289	25
6	Czech Republic	27735.87	49	5	58	63	1.0000	1.0150	8
7	Denmark	43382.63	93	6	74	74	0.8050	0.8050	27
8	Estonia	22187.93	66	6	60	50	0.8573	0.8573	21
9	Finland	38867.8	89	6	63	75	0.8727	0.8727	18
10	France	36340.51	69	5	71	60	0.7705	0.7705	31
11	Germany	38784.45	80	4	67	72	0.9984	0.9984	9
12	Greece	30430.42	38	6	35	42	0.9057	0.9057	14
13	Hungary	22077.59	51	4	80	59	1.0000	1.1108	3
14	Iceland	40190.18	87	7	60	51	0.5486	0.5486	36
15	Ireland	44995.94	80	8	70	65	0.6744	0.6744	35
16	Israel	28569.3	61	6	54	67	0.9707	0.9707	11
17	Italy	35710.42	43	5	76	51	0.9225	0.9225	12
18	Japan	34317.5	77	6	46	79	1.0756	1.0756	5
19	Korea	28642.84	55	6	18	59	1.0000	1.4750	1
20	Latvia	18579.91	45	6	70	44	0.8862	0.8862	16
21	Lithuania	20299.2	49	4	60	46	0.8768	0.8768	17
22	Luxembourg	89098.73	82	6	60	79	0.9115	0.9115	13
23	Mexico	15011.75	33	6	30	40	1.0000	1.1093	4
24	Netherlands	45125.81	89	6	80	72	0.7620	0.7620	32
25	New Zealand	32122.84	94	6	79	78	0.9737	0.9737	10
26	Norway	62671.3	86	7	69	71	0.7400	0.7400	34
27	Poland	20952.77	50	6	60	46	0.8226	0.8226	26
28	Portugal	26743.2	58	6	27	60	1.0000	1.0163	7
29	Slovakia	23973.84	45	4	52	57	1.0000	1.0553	6
30	Slovenia	28451.55	66	6	27	54	0.8641	0.8641	20
31	Spain	32651.94	61	6	51	58	0.7968	0.7968	29
32	Sweden	40862.97	92	6	71	75	0.8420	0.8420	23
33	Switzerland	54512.98	90	6	68	75	0.8033	0.8033	28

34	Turkey	16783.44	44	5	37	37	0.8543	0.8543	22
35	United King-dom	35795.18	77	6	89	73	0.8407	0.8407	24
36	United States	48557.87	75	6	91	80	0.8941	0.8941	15

References

1. Adler, N., Friedman, L., & Sinuany-Stern, Z. (2002). Review of ranking methods in the data envelopment analysis context. *European Journal of Operational Research*, *140*(2), 249–265. https://doi.org/10.1016/S0377-2217(02)00068-1
2. Andrés, A. (2006a). Software piracy and income inequality. *Applied Economics Letters*, *13*(2), 101–105. https://doi.org/10.1080/13504850500390374
3. Andrés, A. (2006b). The relationship between copyright software protection and piracy: Evidence from Europe. *European Journal of Law and Economics*, *21*(1), 29–51. http://dx.doi.org/10.1007/s10657-006-5670-5
4. Andrés A. R., & Goel, R. K. (2011). Corruption and software piracy: A comparative perspective. *Policy and Internet*, *3*(3), 1–22. https://doi.org/10.2202/1944-2866.1088
5. Banerjee, D., Khalid, A. M. & Sturm, J. (2005). Socio-economic development and software piracy. An empirical assessment. *Applied Economics*, *37*(18), 2091–2097. https://doi.org/10.1080/00036840500293276
6. Barro, R. & Lee, J. W. (1996). International measures of schooling years and schooling quality. *The American Economic Review*, *86*(2), 218–223.
7. Brockett, P., & Golany, B. (1996). Using rank statistics for determining programmatic efficiency differences in data envelopment analysis. *Management Science*, *42*(3), 466–472.
8. Business Software Alliance. (2012). *Shadow market: 2011 BSA global software piracy study*. https://www.bsa.org/files/reports/2011_bsa_piracy_study_standard.pdf
9. Business Software Alliance. (2014). *The compliance gap: BSA global software survey, June 2014*. https://globalstudy.bsa.org/2013/downloads/studies/2013GlobalSurvey_Study_en.pdf
10. Business Software Alliance. (2018). *Software management: Security imperative, business opportunity: BSA global software survey, June 2018*. https://gss.bsa.org/wp-content/uploads/2018/05/2018_BSA_GSS_Report_en.pdf
11. Charnes, A., Cooper, W., & Rhodes, E. (1978). Measuring the efficiency of decision-making units. *European Journal of Operational Research*, *2*(6), 429–444. https://doi.org/10.1016/0377-2217(78)90138-8
12. Depken, C. A., & Simmons, L. C. (2004). Social construct and the propensity for software piracy. *Applied Economics Letters*, *11*(2), 97–100. https://doi.org/10.1080/1350485042000200187
13. Dias Gomes, N. Cerqueira, P. A., & Alçada-Almeida, L. (2018). Determinants of worldwide software piracy losses. *Technological and Economic Development of Economy*, *24*(1), 48–66. https://doi.org/10.3846/20294913.2015.1074128
14. Farrell, M. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society*, *120*(3), 253–290. https://doi.org/10.2307/2343100
15. Goel, R., & Nelson, M. (2009). Determinants of software piracy: economics, institutions, and technology. *The Journal of Technology Transfer*, *34*, 637–658. https://doi.org/10.1007/s10961-009-9119-1
16. Hall, R. E., & Jones, C. I. (1996). *The productivity of nations*. National Bureau of Economic Research, Working Paper 5812. Retrieved from https://ideas.repec.org/p/nbr/nberwo/5812.html

17. Hofstede, G. (1997). *Cultures and organizations: software of the mind*. McGraw Hill: New York.
18. Hosseinzadeh Lotfi, F., Jahanshahloo, G.R., Khodabakhshi, M., Rosdtamy-Malkhlifeh, M., Moghaddas, Z., & Vaez-Ghasemi, M. (2013). A review of ranking models in data envelopment analysis. *Journal of Applied Mathematics*, *2013*, Article ID 492421. https://doi.org/10.1155/2013/492421
19. Husted, W. B. (2000). The impact of national culture on software piracy. *Journal of Business Ethics*, *26*, 197–211. https://doi.org/10.1023/A:1006250203828
20. Jahanshahloo, G.R., Hosseinzadeh Lotfi, F., Sanei, M., & Fallah Jelodar, M. (2008). Review of ranking models in data envelopment analysis. *Applied Mathematical Sciences*, *2*(29), 1431–1448.
21. Knack, S., & Keefer, P. (1995). Institutions and economic performance: Cross-country tests using alternative institutional measures. *Economics and Politics*, *7*(3), 207–227. https://doi.org/10.1111/j.1468-0343.1995.tb00111.x
22. Kruskal, W.H., & Wallis, W.A. (1952). Use of ranks in one-criterion variance analysis. *Journal of the American Statistical Association*, *47*(260), 583–621. https://doi.org/10.2307/2280779
23. La Porta, R., Lopez-de-Silanes, F., Shleifer, A., & Vishny, R. W. (1999). The quality of government. *Journal of Law, Economics, and Organization*, *15*(1), 222–279.
24. Landes, W. M., & Posner, R. A. (1989). An economic analysis of copyright law. *The Journal of Legal Studies*, *18*(2): 325–363.
25. Marron, D., & Steel, D. (2000). Which countries protect intellectual property? The case of software piracy. *Economic Inquiry*, *38*(2), 159–174. http://dx.doi.org/10.1111/j.1465-7295.2000.tb00011.x
26. Moores, T. (2008). An analysis of the impact of economic wealth and national culture on the rise and fall of software piracy rates. *Journal of Business Ethics*, *81*, 39–51. https://doi.org/10.1007/s10551-007-9479-0
27. Park, W., & Ginarte, J. (1997). Intellectual property rights and economic growth. *Contemporary Economic Policy*, *15*(3), 51–61. https://doi.org/10.1111/j.1465-7287.1997.tb00477.x
28. Plant, A. (1934). The economic aspects of copyrights in books. *Economica*, *1*(2), 167–195. https://doi.org/10.2307/2548748
29. Proserpio L., Salvemini, S., & Ghiringhelli, V. (2005). Entertainment pirates: Understanding piracy determinants in the movie, music and software industries. *International Journal of Arts Management*, *8*(1), 33–47.
30. Rapp, R. T., & Rozek, R. P. (1990). Benefits and costs of intellectual property protection in developing countries. *Journal of World Trade*, *24*(5), 75–102.
31. Robertson, C., Gilley, K. M., & Crittenden, W. F. (2008). Trade liberalization, corruption, and software piracy. *Journal of Business Ethics*, *78*(4), 623–634. http://dx.doi.org/10.1007/s10551-007-9372-x
32. Ronkainen, I. A., & Guerrero-Cusumano, J. L. (2001). Correlates of intellectual property violation. *Multinational Business Review*, *9*(1), 59–65.
33. Seiford, L. M., & Zhu, J. (1999). An investigation of returns to scale in data envelopment analysis. *Omega*, *27*(1), 1–11. https://doi.org/10.1016/S0305-0483(98)00025-5
34. Shadlen, K., Schrank, A., & Kurtz, M. (2005). The political economy of intellectual property

protection: The case of software. *International Studies Quarterly*, *49*(1), 45–71. https://doi.org/10.1111/j.0020-8833.2005.00334.x

35. Shapiro, C., & Varian, H. R. (1999). *Information rules: A strategic guide to the network economy*. Boston, Massachusetts: Harvard Business School Press.
36. Towse, R., Handke, C., & Stepan, P. (2011). La Economía de la Ley de Propiedad Intelectual: Inventario de Publicaciones. In Watt, R. (ed.), *Teoría Económica y Derechos de Autor* (pp. 15–56). Madrid: Datautor.
37. Transparency International. (n.d.). Corruption Perceptions Index. Retrieved from https://www.transparency.org/en/cpi
38. Watt, R. (2009). An empirical analysis of the economics of copyright: How valid are the results of studies in developed countries for developing countries? In WIPO (ed.), *The economics of intellectual property. Suggestions for further research in developing countries and countries with economics in transition* (pp. 65–108). http://dx.doi.org/10.34667/tind.28197
39. World Bank. (n.d.). World Development Indicators. Retrieved from https://databank.worldbank.org/source/world-development-indicators
40. Yang, D., Sonmez, M., & Bosworth, D. (2004). Intellectual property abuses: How should multinationals respond? *Long Range Planning*, *37*(5), 459–475. https://doi.org/10.1016/j.lrp.2004.07.009
41. Yang, D., Sonmez, M., & Fryxell, G. (2009). Global software piracy: Searching for further explanations. *Journal of Business Ethics*, *87*, 269–283. https://doi.org/10.1007/s10551-008-9884-z