Balkan Journal of Social Sciences

BJSS

Derginin ana sayfası: https://dergipark.org.tr/bsbd

Araştırma Makalesi ● Research Article

Does Software Piracy Mitigate Poverty?: Evidence from Developing and Latin America Countries

Yazılım Korsanlığı Yoksulluğu Hafifletir Mi?: Gelişmekte Olan Ülkeler ve Latin Amerika Ülkelerinden Kanıt

Mustafa Unver [a*], Julide Yalcinkaya Koyuncu [b]

[a] Assoc. Prof. Dr., Kirikkale University, Faculty of Economics and Adninistrative Sciences, Department of Public Finance, Kirikkale/Turkey.
ORCID: 0000-0002-0491-3080
[b] Prof. Dr., Bilecik Şeyh Edebali University, Faculty of Economics and Adninistrative Sciences, Department of Economics, Bilecik/Turkey.
ORCID: 0000-0001-7930-4901

MAKALEBİLGİSİ

Makale Geçmişi:
Başvuru tarihi: 20 Mart 2022
Düzeltme tarihi: 23 Mayıs 2022
Kabul tarihi: 17 Haziran 2022

Anahtar Kelimeler:
Yazılım Korsanlığı
Yoksulluk
Gelişmekte Olan Ülkeler
Latin Amerika Ülkeleri
Panel Çalışma

ÖZ

Bu çalışma korsan yazılım kullanımının yoksulluk üzerindeki etkisini gelişmekte olan ekonomiler ve Latin Amerika ülkeleri için altı farklı yoksulluk göstergesi kullanarak analiz etmektedir. Çalışmanın modellerinde dengesiz panel yardımıyla 2003-2017 dönemi verileri kullanılmıştır. Çalışmanın temel hipotezi; korsan yazılım kullanımındaki artışın yoksulluk seviyesini hafifleteceğidir. Birinci olarak, tek değişkenli analiz sonuçlarında; tüm farklı yoksulluk modellerinde korsan yazılım kullanımı ile yoksulluk değişkenleri arasında istatistiksel olarak anlamlı ve negatif ilişki elde edilmiştir. İkinci olarak; işsizlik, sağlık harcamaları ve beşerî sermaye kontrol değişkenlerinin kullanıldığı çok değişkenli modellerde korsan yazılım kullanımı ile yoksulluk arasında istatistiksel olarak anlamlı negatif ilişki bulunmuştur. Diğer bir deyişle; tüm modeller de korsan yazılım kullanımının gelişmekte olan ülkeler ve Latin Amerika ülkelerinde yoksulluk üzerinde istatistiksel olarak anlamlı negatif etkisi bulunmaktadır. Kontrol değişkenleri düşünüldüğünde; sağlık harcamaları ve beşerî sermaye değişkenleri yoksulluk değişkeni üzerinde istatistiksel olarak anlamlı negatif katsayıya sahipken işsizlik değişkeninin yoksulluk üzerinde pozitif ve istatistiksel olarak anlamlı etkiye sahip olduğu sonucuna ulaşılmıştır.

ARTICLEINFO

Article history:
Received March 20, 2022
Received in revised form May 23, 2022
Accepted June 17, 2022

Keywords:
Software Piracy
Poverty
Developing Countries
Latin America Countries
Panel Study

ABSTRACT

This study analyzes the effect of usage of pirated software on poverty by using six prominent poverty indicators for the samples of developing and Latin America countries. The data utilized in models is unbalanced and employ the period between 2003 and 2017. Our hypothesis asserts that increases in usage of pirated software diminish poverty in developing and Latin America countries. Firstly, univariate analyses are conducted, and the results of univariate analyses are demonstrated that there is a statistically significant opposite relationship between usage of pirated software and poverty in all six distinct poverty models. Secondly, three control variables (i.e., unemployment, health expenditure, and human capital) were included to our six poverty models to find out if the finding of univariate analyses retains its validity. The statistically significant reverse relationship between usage of pirated software and poverty remained the same after the inclusion of the three covariates. In other words, usage of pirated software maintains its negative significant effect on poverty in all models for both developing and Latin America countries samples. In consideration of the control variables, statistically significant negative coefficients were obtained for health expenditure and human capital whereas a positive coefficient was obtained for unemployment.

1. Introduction

Today's information and communication technologies age imposes to prefer using software to get more information from the world and to be integrated with business sectors in the economic activities. From the cost perspective, it seems that the market prices of the software are extremely high while this process is a key factor in the increasing globalization. In this regard, users in countries where need to compete through economic activities can prefer a copy of software due to high costs of the software. In addition to users' cost perspective, software publishers attempt to combat the global software piracy because global software piracy leads to important losses in the software publishing companies in the advanced countries. In this regard, it is a reality although there are many deterrent and preventive control mechanisms to combat

* *Sorumlu yazar/Corresponding author*.
e-posta: mustafaunver@kku.edu.tr
e-ISSN: 2149-4622. © 2019 Tekirdağ Namık Kemal Üniversitesi İktisadi ve İdari Bilimler Fakültesi. TÜBİTAK ULAKBİM DergiPark ev sahipliğinde. Her hakkı saklıdır. [Hosting by TUBITAK ULAKBIM JournalPark. All rights reserved.]

software piracy that influences the costs of individual and institutional users.

The literature on the software piracy has made many substantial contributions to the investigation of economic, social, demographic and institutional factors. For example, Goel and Nelson (2009) attempt to examine the economic, institutional, and technological determinants of software piracy. The outcomes reveal that countries' development levels and the quality of governance have an impact on the frequency of software piracy. In addition, more economic and political freedoms have negative effects on software piracy. They see evidence for positive diffusion effect of increased internet and computer technologies with legal use of software while demographic factors are insignificant on the piracy of software (see also Asongu and Meniago, 2018; Asongu, 2021).

The literature on how software piracy is impacted by economic variables contains Traphagan and Griffith (1998); Lau (2003); Andres (2006); Robertson et al., (2008); Asongu (2014); Schmuhl and Na (2019). For example, the study of Goel and Nelson (2012), based on a sample of 100 nations between 2004 and 2007, find that shadow economy causes higher software piracy rates.

In addition, there is a rich of literature on the fight against poverty. More specifically, a significant main of empirical papers has examined the determinants of poverty (Koyuncu and Okşak, 2019; Özen and Koyuncu, 2020). From country sample perspective, many papers attempt to examine the determinants of poverty (Oluoko-Odingo, 2009; Akanbi, 2015; Islam et al., 2017; Mohamoud and Bulut, 2020).

Recent papers have also examined the association among economic growth and poverty (Donaldson, 2008; Ferreira et al., 2010; Breunig and Majeed, 2020). For example, Kouadio and Gakpa (2022) examines relationship between economic growth and poverty in West Africa. Their test findings show that economic growth has statistically significant and positive impact on poverty reduction. In addition, Yilmaz and Koyuncu (2010) find there is sufficient evidence to indicate that imports from China lead to the decrease in the poverty level, using data from 1994 to 2006 (see also Koyuncu and Yilmaz, 2013; Koyuncu and Unal, 2020). There is a number of literatures on ICT – poverty reduction (Diga et al., 2013; Mbuyisa and Leonard, 2017; Yilmaz and Koyuncu, 2018). This paper aims to analyze the effect of software piracy on poverty in developing and Latin America economies over the period 2003-2017. It also contributes to the present literature in two ways. First, we include six poverty indicators as a measure of dependent variable. Second, we also use a large sample, including developing and Latin America countries.

The rest of the study is classified as follow. Section 2 offers the empirical framework. In section 3, we present empirical results. Finally, in section 4, it concludes.

2. Empirical Structure

This paper interrogates the effect of usage of pirated software on poverty by using six poverty indicators for the case of developing and Latin America economies. The period under study is between 2003 and 2017 and the data are unbalanced. Usage of pirated software may alleviate poverty through two channels. Firstly, users of pirated software will save as much as the market price of the software. Secondly, using pirated software may enhance efficiency and volume of business that pirated software user does. Therefore, we hypothesize that increases in usage of pirated software lessen poverty.

The following one-way univariate and multivariate fixed effect models (FEM) are constructed and estimated:

$$HDI_{it} = \beta_{0i} + \beta_1 PCPIRACY + u_{it} \qquad (1.A)$$

$$HEAD_{it} = \beta_{0i} + \beta_1 PCPIRACY + u_{it} \qquad (1.B)$$

$$POVGAP_{it} = \beta_{0i} + \beta_1 PCPIRACY + u_{it} \qquad (1.C)$$

$$WATTS_{it} = \beta_{0i} + \beta_1 PCPIRACY + u_{it} \qquad (1.D)$$

$$GINI_{it} = \beta_{0i} + \beta_1 PCPIRACY + u_{it} \qquad (1.E)$$

$$MLD_{it} = \beta_{0i} + \beta_1 PCPIRACY + u_{it} \qquad (1.F)$$

$$HDI_{it} = \beta_{0i} + \beta_1 PCPIRACY + \beta_2 UNEMP + \beta_3 HEALTH + \beta_4 HUMCAP + u_{it} \qquad (2.A)$$

$$HEAD_{it} = \beta_{0i} + \beta_1 PCPIRACY + \beta_2 UNEMP + \beta_3 HEALTH + \beta_4 HUMCAP + u_{it} \qquad (2.B)$$

$$POVGAP_{it} = \beta_{0i} + \beta_1 PCPIRACY + \beta_2 UNEMP + \beta_3 HEALTH + \beta_4 HUMCAP + u_{it} \qquad (2.C)$$

$$WATTS_{it} = \beta_{0i} + \beta_1 PCPIRACY + \beta_2 UNEMP + \beta_3 HEALTH + \beta_4 HUMCAP + u_{it} \qquad (2.D)$$

$$GINI_{it} = \beta_{0i} + \beta_1 PCPIRACY + \beta_2 UNEMP + \beta_3 HEALTH + \beta_4 HUMCAP + u_{it} \qquad (2.E)$$

$$MLD_{it} = \beta_{0i} + \beta_1 PCPIRACY + \beta_2 UNEMP + \beta_3 HEALTH + \beta_4 HUMCAP + u_{it} \qquad (2.F)$$

Also, the following one-way univariate and multivariate random effect models (REM) are constructed and estimated;

$$HDI_{it} = \beta_0 + \beta_1 PCPIRACY + \varepsilon_i + u_{it} \qquad (3.A)$$

$$HEAD_{it} = \beta_0 + \beta_1 PCPIRACY + \varepsilon_i + u_{it} \qquad (3.B)$$

$$POVGAP_{it} = \beta_0 + \beta_1 PCPIRACY + \varepsilon_i + u_{it} \qquad (3.C)$$

$$WATTS_{it} = \beta_0 + \beta_1 PCPIRACY + \varepsilon_i + u_{it} \qquad (3.D)$$

$$GINI_{it} = \beta_0 + \beta_1 PCPIRACY + \varepsilon_i + u_{it} \qquad (3.E)$$

$$MLD_{it} = \beta_0 + \beta_1 PCPIRACY + \varepsilon_i + u_{it} \qquad (3.F)$$

$$HDI_{it} = \beta_0 + \beta_1 PC\,PIRACY + \beta_2 UNEMP + \beta_3 HEALTH + \beta_4 HUMCAP + \varepsilon_i + u_{it} \qquad (4.A)$$

$$HEAD_{it} = \beta_0 + \beta_1 PCPIRACY + \beta_2 UNEMP + \beta_3 HEALTH + \beta_4 HUMCAP + \varepsilon_i + u_{it} \qquad (4.B)$$

$$POVGAP_{it} = \beta_0 + \beta_1 PCPIRACY + \beta_2 UNEMP + \beta_3 HEALTH + \beta_4 HUMCAP + \varepsilon_i + u_{it} \qquad (4.C)$$

$$WATTS_{it} = \beta_0 + \beta_1 PCPIRACY + \beta_2 UNEMP + \beta_3 HEALTH + \beta_4 HUMCAP + \varepsilon_i + u_{it} \qquad (4.D)$$

$$GINI_{it} = \beta_0 + \beta_1 PCPIRACY + \beta_2 UNEMP + \beta_3 HEALTH + \beta_4 HUMCAP + \varepsilon_i + u_{it} \qquad (4.E)$$

$$MLD_{it} = \beta_0 + \beta_1 PCPIRACY + \beta_2 UNEMP + \beta_3 HEALTH + \beta_4 HUMCAP + \varepsilon_i + u_{it} \qquad (4.F)$$

where it sub-script represents the i-th country's observation value at time t for the relevant variable. β_{0i} shows country specific factors not taken into account explicitly in the regression model, that can vary among countries but not within a particular country or across time. ε_i is a time invariant stochastic term, which stands for the country specific factors not regarded explicitly in the regression model. u_{it} symbolizes disturbance term of the model.

The explained variable of the study is poverty. We utilize six different poverty indicators to check the sensitiveness of our experiential findings since empirical findings may change from one indicator to another one. If the findings remain unchanged across six distinct poverty indicators, this will imply that our findings are robust no matter which indicator is used. We displayed the list of dependent variables, their definitions, and the data sources in Table 1.

Table 1. Table of Explained Variables

Variable	Definition	Data Source
HDI	Human development index. It is scaled between 0 and 1 and higher score means improvement in human development and thus poverty alleviation. All HDI values are multiplied by -1 so that higher score means more impoverishment.	UNDP
HEAD	% of population living in households with consumption or income per person below the poverty line.	POVCALNET
POVGAP	The mean shortfall of income from the poverty line. The mean is based on the entire population treating the non-poor as having a shortfall of zero, and the shortfall is expressed as a percentage of the poverty line.	POVCALNET
WATTS index	This is the mean across the population of the proportionate poverty gaps, as measured by the log of the ratio of the poverty line to income, where the mean is formed over the whole population, counting the non-poor as having a zero-poverty gap.	POVCALNET
GINI index	A measure of inequality. 0 value mean absolute equality and 100 mean absolute inequality.	POVCALNET
MLD index	The mean log deviation (MLD) is a measure of income inequality. The MLD is zero when everyone has the same income and takes larger positive values as incomes become more unequal.	POVCALNET

We chose our explanatory variables in the light of previous studies found in the literature and our main hypothesis. The list of explanatory variables, their definitions, and the data sources are given in Table 2 below.

Table 2. Table of Explanatory Variables

Variable	Definition	Data Source
PCPIRACY	Per capita value of pirated software or per capita losses of pirated software (in US dollars)	The IDC Global Software Piracy Study
UNEMP	Unemployment in the total labor force	WDI
HEALTH	Current health expenditure (% of GDP)	WDI
HUMCAP	Human capital index	Penn World Table

A negative association between PCPIRACY variable and poverty is anticipated. As poverty worsens during the period of unemployment, we expect to have a positive coefficient for UNEMP variable. Increases in health expenditure may relieve poverty by creating a healthier society and thus a negative coefficient is anticipated for HEALTH variable. Poverty diminishes with well-educated human capital and hence a negative association between HUMCAP variable and poverty is expected.

3. Estimation Results

Univariate and multivariate estimation results for developing countries sample are reported in Table 3 and 4 respectively. In Table 3 and 4 we also report the Hausman test statistics for choosing between FEM and REM models at the 1% significance level.

As seen from Table 3, based upon Hausman test results evaluated at 1% level of significance, FEM is preferred for HEAD and GINI while REM model is chosen for HDI, POVGAP, WATTS, and MLD models. F-statistic values point out that each model is significant as a whole. As expected, we got a statistically significant negative coefficient for PCPIRACY variable at least at %5 level of significance for all models.

Table 3. Univariate Results for Developing Countries

Models ➔	HDI	HEAD	POVGAP	WATTS	GINI	MLD
C	**-0.6932**	**94.017**	**36.339**	**74.802**	**470.448**	**457.447**
Prob.	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000
PCPIRACY	**-0.000034**	**-0.3984**	**-0.1775**	**-0.2685**	**-0.2766**	**-0.6746**
Prob.	0.0328	0.0000	0.0000	0.0000	0.0000	0.0000
R-Square	0.0058	0.8409	0.3037	0.2194	0.9732	0.2939
Number of Country	69	23	23	23	23	23
Total Observations	779	179	179	179	179	179
Hausman Stat.	0.2783	69.416	18.413	26.972	149.127	26.856
Prob. of Hausman Stat.	0.5978	0.0084	0.1748	0.1005	0.0001	0.1013
F-statistic	45.660	356.210	771.929	497.437	2.442.668	736.875
Prob. of F-statistic	0.0329	0.0000	0.0000	0.0000	0.0000	0.0000
Selected Model	REM	FEM	REM	REM	FEM	REM

As indicated by Table 4, the significant explanatory power of PCPIRACY is not changed after the inclusion of the other three covariates of UNEMP, HEALTH, and HUMCAP. In other saying, PCPIRACY variable has a highly significant negative effect on poverty in all multivariate models. Meanwhile FEM model is selected for HDI, HEAD and POVGAP models whereas REM model is chosen for WATTS, GINI, and MLD models.

In regarding to the control variables, the coefficient of UNEMP variable is positive and statistically significant at least at 10% significance level in all models. HEALTH coefficient is negative and statistically significant at least at 10% significance level in all models except MLD model. HUMCAP coefficient is negative and statistically significant in all models.

In sum, the finding of a negative association between software piracy and poverty for developing countries sample is statistically significant and keeps its validity in all univariate and multivariate models

.

Table 4. Multivariate Results for Developing Countries

Models ➔	HDI	HEAD	POVGAP	WATTS	GINI	MLD
C	**-0.3244**	**368.715**	**161.534**	**250.057**	**781.609**	**1.028.327**
Prob.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
PCPIRACY	**-0.0011**	**-0.2211**	**-0.0926**	**-0.1550**	**-0.1067**	**-0.3314**
Prob.	0.0000	0.0000	0.0002	0.0005	0.0055	0.0002
UNEMP	**0.0016**	**0.2558**	**0.1013**	**0.1832**	**0.1590**	**0.3862**
Prob.	0.0000	0.0110	0.0606	0.0552	0.0553	0.0341
HEALTH	**-0.0043**	**-10.182**	**-0.3786**	**-0.5401**	**-0.4845**	**-0.6251**
Prob.	0.0000	0.0011	0.0227	0.0632	0.0554	0.2494
HUMCAP	**-0.1416**	**-90.865**	**-42.882**	**-61.488**	**-119.059**	**-221.225**
Prob.	0.0000	0.0001	0.0005	0.0023	0.0000	0.0000
R-Square	0.9806	0.8781	0.8127	0.3062	0.4598	0.4565
Number of Country	60	23	23	23	23	23
Total Observations	680	179	179	179	179	179
Hausman Stat.	415.732	196.826	193.666	67.172	54.163	25.110
Prob. of Hausman Stat.	0.0000	0.0006	0.0007	0.1516	0.2472	0.6427
F-statistic	4.947.619	421.198	253.692	191.946	370.286	365.439
Prob. of F-statistic	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Selected Model	FEM	FEM	FEM	REM	REM	REM

Univariate and multivariate estimation results for Latin America countries sample are displayed in Table 5 and 6 respectively.

Table 5. Univariate Results for Latin America Countries

Models ➔	HDI	HEAD	POVGAP	WATTS	GINI	MLD
C	**-0.7078**	**102.707**	**39.475**	**83.062**	**502.607**	**519.089**
Prob.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
PCPIRACY	**-0.000029**	**-0.4275**	**-0.1811**	**-0.2835**	**-0.2830**	**-0.6655**
Prob.	0.0349	0.0000	0.0000	0.0000	0.0000	0.0000
R-Square	0.0196	0.3924	0.2977	0.9493	0.9664	0.2942
Number of Country	19	15	15	15	15	15
Total Observations	228	130	130	130	130	130
Hausman Stat.	0.0054	12.525	0.4021	85.881	75.969	16.268
Prob. of Hausman Stat.	0.9413	0.2631	0.5260	0.0034	0.0058	0.2021
F-statistic	45.253	826.481	542.573	1.423.722	2.182.617	533.520
Prob. of F-statistic	0.0345	0.0000	0.0000	0.0000	0.0000	0.0000
Selected Model	REM	REM	REM	FEM	FEM	REM

As can be concluded from Table 6, the significant negative explanatory power of PCPIRACY remains valid after the inclusion of the covariates of UNEMP, HEALTH, and HUMCAP. In other words, PCPIRACY variable significantly and negatively affects poverty in all multivariate models. Meantime FEM model is selected for HDI, HEAD and POVGAP models whereas REM model is chosen for WATTS, GINI, and MLD models.

With regard to the control variables, the sign of UNEMP variable is positive and statistically significant at least at 10% significance level in all models, but GINI model. The coefficients of HEALTH and HUMCAP variables are negative and statistically significant at least at 10% significance level in all models.

In brief, the result of a negative association between software piracy and poverty for Latin America countries sample is statistically significant and remains valid across all univariate and multivariate models.

Table 6. Multivariate Results for Latin America Countries

Models ➔	HDI	HEAD	POVGAP	WATTS	GINI	MLD
C	**-0.3921**	**315.909**	**146.344**	**232.998**	**801.664**	**919.910**
Prob.	0.0000	0.0000	0.0002	0.0014	0.0000	0.0000
PCPIRACY	**-0.0013**	**-0.2228**	**-0.0911**	**-0.1474**	**-0.1000**	**-0.3770**
Prob.	0.0000	0.0000	0.0024	0.0062	0.0242	0.0003
UNEMP	**0.0016**	**0.7397**	**0.2843**	**0.5039**	**0.1515**	**0.6009**
Prob.	0.0009	0.0001	0.0076	0.0081	0.3321	0.0788
HEALTH	**-0.0071**	**-12.023**	**-0.4459**	**-0.6767**	**-0.6372**	**-12.872**
Prob.	0.0000	0.0012	0.0322	0.0660	0.0381	0.0493
HUMCAP	**-0.1101**	**-76.428**	**-40.026**	**-55.853**	**-119.530**	**-152.170**
Prob.	0.0000	0.0094	0.0162	0.0488	0.0000	0.0006
R-Square	0.9852	0.8608	0.7896	0.3354	0.4800	0.4127
Number of Country	17	15	15	15	15	15
Total Observations	204	130	130	130	130	130
Hausman Stat.	372.186	173.045	163.872	93.013	42.617	124.678

Prob. of Hausman Stat.	0.0000	0.0017	0.0025	0.0540	0.3718	0.0142
F-statistic	6.084.558	381.202	231.445	157.714	288.463	219.628
Prob. of F-statistic	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Selected Model	FEM	FEM	FEM	REM	REM	REM

4. Conclusion

In this study we investigate the association between usage of pirated software and poverty by utilizing six well-known poverty proxies. The analyses are conducted for developing and Latin America countries and the data are unbalanced spanning the period of 2003- 2017. The hypothesis of that increases in usage of pirated software decrease poverty is tested by using cross-section fixed effect and random effect models. Firstly, univariate analyses are implemented, and the findings of univariate analyses are disclosed that there is a statistically significant reverse relationship between usage of pirated software and poverty in all six poverty models for both developing and Latin America countries samples. Secondly, we added three control variables (i.e., unemployment, health expenditure, and human capital) to our six models in order to check the validity of the finding of univariate analyses. The statistically significant negative linkage between usage of pirated software and poverty is not altered after the inclusion of the other three covariates of unemployment, health expenditure, and human capital. Put it differently, usage of pirated software preserves its negative significant impact on poverty in all six multivariate models of developing and Latin America countries samples. With regard to the control variables, we got statistically significant negative coefficients for health expenditure and human capital while a positive coefficient for unemployment.

References

Akanbi, O. A. (2015). Structural and Institutional Determinants of Poverty in Sub-Saharan African Countries. *Journal of Human Development and Capabilities*, 16(1), 122-141.

Andrés, A. R. (2006). Software Piracy and Income Inequality. *Applied Economics Letters*, 13(2), 101-105.

Asongu, S. A. (2014). Software Piracy and Scientific Publications: Knowledge Economy Evidence from Africa. *African Development Review*, 26(4), 572-583.

Asongu, S. A. (2021). Global Software Piracy, Technology and Property Rights Institutions. *Journal of the Knowledge Economy*, 12(3), 1036-1063.

Asongu, S., & Meniago, C. (2018). Technology and Persistence in Global Software Piracy. *NETNOMICS: Economic Research and Electronic Networking*, 19(1), 43-63.

Breunig, R., & Majeed, O. (2020). Inequality, Poverty and Economic Growth. *International Economics*, 161, 83-99.

Diga, K., Nwaiwu, F., & Plantinga, P. (2013). ICT Policy and Poverty Reduction in Africa. *The Journal of Policy, Regulation and Strategy for Telecommunications*, 15(5), 114-127.

Donaldson, J. A. (2008). Growth Is Good for Whom, When, How? Economic Growth and Poverty Reduction in Exceptional Cases. *World Development*, 36(11), 2127-2143.

Ferreira, F. H., Leite, P. G., & Ravallion, M. (2010). Poverty Reduction Without Economic Growth? Explaining Brazil's Poverty Dynamics, 1985–2004. *Journal of Development Economics*, 93(1), 20-36.

Goel, R. K., & Nelson, M. A. (2009). Determinants of Software Piracy: Economics, Institutions, and Technology. *The Journal of Technology Transfer*, 34(6), 637-658.

Goel, R. K., & Nelson, M. A. (2012). Shadow economy and international software piracy. *Applied Financial Economics*, 22(23), 1951-1959.

Islam, D., Sayeed, J., & Hossain, N. (2017). On Determinants of Poverty and Inequality in Bangladesh. *Journal of Poverty*, 21(4), 352-371.

Koyuncu, J. Y. & Okşak, Y. (2019). The Impact of Banking Crises on Poverty: Panel Evidence. *Studies on Balkan and Near Eastern Social Sciences*: Volume 3, Rasim Yilmaz / Günther Löschnigg (eds.), pp. 255-262, Peterlang.

Kouadio, H. K., & Gakpa, L. L. (2022). Do Economic Growth and Institutional Quality Reduce Poverty and Inequality in West Africa?. *Journal of Policy Modeling*, 44(1), 41-63.

Koyuncu, C., & Ünal, H. S. (2020). Is Economic Freedom Effective on Poverty Alleviation? *Balkan Sosyal Bilimler Dergisi*, 9(17), 146-151.

Koyuncu, C., & Yilmaz, R. (2013). Impact of Private Forest Ownership on Deforestation and Poverty. *Quality & Quantity*, 47(3), 1657-1664.

Lau, E. K. W. (2003). An Empirical Study of Software Piracy. *Business Ethics: A European Review*, 12(3), 233-245.

Mbuyisa, B., & Leonard, A. (2017). The Role of ICT Use in Smes Towards Poverty Reduction: A Systematic Literature Review. *Journal of International Development*, 29(2), 159-197.

Mohamoud, A. M., & Bulut, E. (2020). Determinants of Poverty in Somalia: A Logit Model Analysis. *Fiscaoeconomia*, 4(2), 437-451.

Oluoko-Odingo, A. A. (2009). Determinants of Poverty: Lessons from Kenya. *GeoJournal*, 74(4), 311-331.

Ozen, E. & Koyuncu, J. Y. (2020). Does Globalization Deteriorate or Alleviate Poverty? Panel Analysis. *Studies on Balkan and Near Eastern Social Sciences*: Volume 4, Rasim Yilmaz / Günther Löschnigg (eds.), pp.21-32, Peterlang.

Robertson, C., Gilley, K. M., & Crittenden, W. F. (2008). Trade Liberalization, Corruption, and Software Piracy. *Journal of Business Ethics*, 78(4), 623-634.

Schmuhl, M. A., & Na, C. (2019). Globalization and Software Piracy Within and Across 103 Countries. *Crime, Law, and Social Change*, 72(3), 249-267.

Traphagan, M., & Griffith, A. (1998). Software Piracy and Global Competitiveness: Report on Global Software Piracy. *International Review of Law, Computers & Technology*, 12(3), 431-451.

Yilmaz, R., & Koyuncu, C. (2010). China's Export Surge and World Poverty. *Transformations in Business & Economics*, 9(2), 86-94.

Yılmaz, R., & Koyuncu, J. Y. (2018). The Contribution of ICT to Poverty Reduction: A Panel Data Evidence. *Social Sciences Research Journal*, 7(4), 63-75.