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The effect of technology on income inequality. Implications of the digital gap; Evidence for OECD member countries

El efecto de la tecnología en la desigualdad de ingresos. Implicaciones de la brecha digital; evidencia para los países miembros de la OCDE

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Abstract

Income inequality continues to be one of the main problems to be solved in economies and access to technologies has become a transcendental element in reducing said inequalities. In this context, the objective of this research is to determine the effect of Information and Communication Technologies (ICTs), and the use of the Internet on income inequality for 20 member countries of the Organization for Economic Cooperation and Development. Economic (OECD) during 2004-2017. The data is obtained from the World Bank Development Indicators (2020). Panel data and Generalized Least Squares (GLS) models and dynamic models are used. The results obtained show that the increase in imports of ICTs and the use of the internet do not contribute to the reduction of income inequality, due to the negative effects of the existing digital divide in the economies analyzed. The economic policy could focus on the greater use of ICTs, in addition, the flexibility in tariffs would facilitate the obtaining of technological resources. Finally, the expansion of digital coverage would play a relevant role in reducing the existing digital divide.

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Resumen

La desigualdad de ingresos sigue siendo uno de los principales problemas a resolver en las economías y el acceso a tecnologías se ha convertido en un elemento trascendental en la reducción de dichas desigualdades. En este contexto, el objetivo de esta investigación es determinar el efecto que tienen las tecnologías de la información y la comunicación (TICs), y el uso del internet sobre la desigualdad de ingresos para 20 países miembros de la Organización para la Cooperación y el Desarrollo Económico (OCDE) durante 2004-2017. Los datos se obtienen de los indicadores del desarrollo del Banco Mundial (2020). Se utilizan datos panel y modelos de mínimos cuadrados generalizados (GLS) y modelos dinámicos. Los resultados obtenidos muestran que el incremento de las importaciones de las TICs y el uso del internet no contribuyen a la reducción de la desigualdad de ingresos, debido a los efectos negativos de la brecha digital existente en las economías analizadas. La política económica podría enfocarse a la mayor utilización de las TICs, además, la flexibilidad en los aranceles facilitaría la obtención de recursos tecnológicos. Finalmente, la ampliación de la cobertura digital tendría un papel relevante en la reducción de la brecha digital existente.

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Palabras clave: tecnología; internet; desigualdad; datos panel; OCDE

Introduction

Inequality is a concept related to the scarce availability of income. It usually refers to the differences in income between people and is measured by comparing the income received by certain percentages of the population with higher and lower income, as mentioned in Cinca (2011). Consequently, it has become one of the main problems nations face worldwide since there is a concentration of income in certain population sectors. Therefore, as this situation arises, the gap between rich and poor increases steadily. According to Keeley (2018), one of the problems that can occur is that "socioeconomic inequality appears to play a central role in the incidence of criminal victimization, as disadvantaged people are more likely to perpetrate or be victims of crime." Similarly, this problem is primarily synonymous with social upheaval, so governments must reduce this income level gap.

Nevertheless, income inequality, measured by the Gini coefficient covering 90% of the world population, has shown a downward trend. In 1980, it presented a value of approximately 0.68, which means a greater income inequality; nonetheless, for 2017, this value has become 0.56, a non-significant decrease, so there is still much to do. Considering 20 countries that make up the Organization for Economic Cooperation and Development (OECD), the trend they present is constant over time, so that for 2017, countries such as Austria, Belgium, Denmark, Spain, and Turkey record values of this coefficient of 0.30, 0.27, 0.29, 0.35, and 0.41 respectively, with this last country recording a slightly high Gini coefficient, but it can be seen that they maintain low values for the most part (World Bank, 2020).

Empirical evidence shows that inequality can be reduced through different factors, including education, high economic growth, and adequate public policies focused on better income redistribution. Nevertheless, recent literature also shows that factors associated with technologies and the use of the Internet can generate some impact in favor of reducing inequalities and the achievement of the Millennium Development Goals (Galperin & Mariscal, 2016). Nonetheless, although several works have studied this relation, a clear consensus on the incidence and relation between variables has not yet been defined, and the effects, in general, may be associated with the case study or the characteristics of each economy.

Mushtaq and Bruneau (2019), for example, in an analysis of 61 countries, found a negative relation of access to ICT with poverty and inequality, observing that ICT dimensions, when used as instruments for financial inclusion, accelerate economic growth and reduce poverty and inequality. Also, Mora-Rivera and García-Mora (2021) show, with high statistical reliability, that internet access is a tool that can help reduce the number of poor people. Nevertheless, it is mentioned that digital innovation benefits higher income groups and is accompanied by a parallel expansion of low-paid jobs and wage polarization, so this translates into high-income inequality and a widening of the digital divide, although this will depend on the income level of households, due to the capacity they have to adapt to such changes (Bauer, 2018; Van Reenen, 2011; Ali et al., 2019). Pakistan (2011) also emphasizes that the time factor is an element to be considered, especially in developing countries where the gap widens rapidly over time. The authors suggest that investment in computer acquisition should be well leveraged. Similarly, Dasgupta et al. (2001) point out that digital reforms could drastically reduce the digital divide for low-income countries such as those in Africa, Asia, and Latin America.

Furthermore, according to data from the OECD Digital Government Index for 2019, there are encouraging statistics (an index of 0.5) that reflect the progress of these countries toward digital government, providing political and operational support that has made it possible to generate digital reforms. Unfortunately, despite these figures, it is clear that there is still a persistent gap in expanding the impact and reach of government (OECD, 2020). In this context, it is essential to determine the effect of investment in Internet and technology programs on inequality. Since governments disburse large amounts of investment to improve the population’s welfare, it is important to optimize and prioritize the use of resources. In particular, this research focuses its analysis on the case study of the OECD countries.

Therefore, this research aims to identify the effect of Information and Communication Technologies (ICT) imports and internet use on income inequality for 20 OECD member countries during 2004-2017. The paper’s hypothesis states that technology inversely influences income inequality for this group of countries. In order to provide an answer, use is made of the World Bank database (2020). A panel data econometric strategy, using different tests to detect diagnostic problems, is applied, and a generalized least squares (GLS) model and a dynamic model, specifically MG and PMG estimators, which include control variables such as urban population and Gross Domestic Product per capita, are estimated.

The results indicate that the fact that these countries manage to increase ICT imports and that more people make use of the Internet generates a reducing effect on income inequality, as does economic growth; in contrast, the increase in the urban population increases the level of inequality, according to the GLS model. Nevertheless, if the dynamic GLS model is considered, including the effect of the control variables mentioned above, it can be seen that the only variable that contributes to the reduction of income inequality in the long term is Internet access, corroborating that although factors such as the increase in technology imports and the improvement in the standard of living of the countries have a positive effect in the short term, this effect is no longer significant in the reduction of income inequality in the long term.

This paper is divided into five sections plus the introduction: the second section discusses the previous literature on the subject; the third section presents the data used and the econometric strategy; the fourth section discusses the results; finally, the fifth section presents the conclusions and economic policy implications; it also includes the respective bibliographical references used.

Review of the literature

Given the current growing interest in identifying the factors that influence the growing inequality in developed and developing countries in technology-related issues in the context of the digital economy, it has been suggested that greater imports of technological goods and greater individual access to the Internet decrease income inequality. Thus, Canh et al. (2020) found that internet use has a relevant effect and can help reduce income inequality; the effects are mostly evident at the global level and for middle and low-income countries, while for high-income countries, the effect is weak in the long term. On the other hand, analyzing urbanization processes in middle- and low-income countries, it is observed that these present a negative relation with income inequality, and, on the contrary, GDP has a much less relevant effect in reducing inequality. These results coincide with Asongu et al. (2019), Mora-Rivera and García-Mora (2021), and Chahuara and Trelles (2014), who point out that Internet access in the Mexican and Peruvian population constitutes a tool that can help reduce the number of poor people, especially in the most vulnerable population. This effect is more pronounced if accompanied by high-impact social programs.

For the case of China, Wang et al. (2020) demonstrate that the progress of internet technology facilitates employment within industry through a positive spillover effect that is direct across industries, results that coincide with Antonelli and Gehringer (2017). Similarly, Mushtaq and Bruneau (2019) found a negative relation of access to ICT with poverty and inequality, observing that ICTs for financial inclusion accelerate economic growth and reduce poverty and inequality. Furthermore, it is observed that economic growth has an inverse effect on income inequality; when a country receives a higher level of income, this enables it to conduct more social spending, allocating these resources to strategic sectors such as health and education. On the other hand, Zhang (2013) suggested that the more inequality in wealth distribution, the slower the internet adoption rate reached. This inequality gap is decreasing between high-income OECD countries and high-income non-OECD countries, while it has been increasing for low- and middle-income countries.

Indeed, Noh and Yoo (2008), in their study on the Internet, inequality, and growth, found a positive effect of Internet adoption on economic growth. Nevertheless, this will be reduced by income inequality because the existing digital divide hinders growth and thus income inequality in the countries analyzed, establishing that the spread of ICTs can be an influential tool in development. Although the existing digital divide can delay development, countries with higher incomes can make better use of these tools and obtain socioeconomic advantages. Thus, Martin (2018) finds an existing positive and statistically significant relation between Internet use and income for Colombia. In addition, Dávila Barragán (2018) adds that GDP per capita contributes significantly to the decrease in inequality, as does urbanization. This is associated with the fact that people in cities can access government benefits such as subsidies and have more opportunities to get out of or not fall into poverty.

On the other hand, Vargas and Guerrero-Riofrío (2019) found that technology at the global level has a direct effect on inequality; the same occurs for upper-middle, lower-middle, and low-income countries, with high-income countries in contrast showing a negative effect on income inequality. Digital innovation benefits higher-income groups and is accompanied by a parallel expansion of low-paid jobs and wage polarization (Bauer, 2018; Van Reenen, 2011). Similarly, Ali et al. (2019) found that when ICT affordability is high, income inequality is also high, given that it is positively associated with socioeconomic position and varies significantly with the location of households (better location, urban areas, etcetera). Hence, the ICT spending of high-income households is much higher than that of low-income households.

On the other hand, Godoy-Jaramillo and Vaca (2019) found that at the global level and by subgroups of extremely high, high, and upper-middle-income countries, urbanization is not significant, but for lower-middle-income countries, the effect is positive and statistically significant; while for low and extremely low-income countries, the effect is negative and significant, that is, the fact that there is greater urbanization in these countries enables them to decrease income inequality. Similarly, Sulemana et al. (2019), in their study of sub-Saharan Africa, found a meaningful and direct relation between income inequality and urbanization, i.e., the higher the concentration of people in the urban sector, the higher the income inequality. They quote Kuznets (1955) to explain the reasons for this effect, the first being that economic growth enabled economies to move away from agriculture to industrialize and urbanize, and the second is that rural people, who are generally less educated than their urban counterparts, are trapped in persistent poverty due to the limited economic opportunities and other barriers they encounter when migrating to cities. These results are related to those found by Gao et al. (2019) in rural China, but with the further finding that the spatiotemporal disparity in rural inequality is deeply rooted in the four-way transition process of marketization, globalization, decentralization, and urbanization.

From another perspective, economic growth positively impacts the reduction of income inequality in the different regions of Peru; this was corroborated by Lazo Dioses (2018). Similarly, Diaz and Mayorga (2009) indicate that the level of the economic growth path affects the behavior of inequality in Latin America. This result implies that the higher the level of GDP per capita, the lower the degree of inequality, at least on average (perhaps excluding Brazil); similar results were found in Frasqueri and Ruiz (2014), where it is shown that economic growth turns out to be meaningful and has a negative effect on income inequality in the 18 Latin American countries, because economic growth policies generate an increase in the income share of the population of the lowest quintile, generating an increase in employment and the quality of education and productivity. Nonetheless, Córdova Ramírez (2019) found that as GDP per capita increases, income inequality grows until it reaches a threshold of economic development where the ratio becomes inverse, while in extremely high-income countries and high-income countries in the first years of analysis, income inequality decreases as GDP per capita increases until it reaches a certain level of development where the ratio becomes positive.

In upper-middle-income countries, as GDP per capita increases, income inequality also increases; conversely, in extremely low-income countries, as GDP per capita increases, income inequality decreases, and in lower-middle-income countries, the result is not significant. In the same vein, Yang and Greaney (2017) found that the inequality-GDP per capita ratio shows a positive causal relation for three out of four countries (USA, Japan, and China), indicating that economic growth stimulates higher income inequality, while for the case of South Korea, there is a negative relation. In the case of the U.S., Rubin and Segal (2015) mention that much of the increase in income inequality can be attributed to the increased importance of the stock market, along with the increased use of pay-performance clearing, which makes the labor income of top groups more closely aligned with future rate growth.

In general, internet access represents a spur for development. Galperin and Mariscal (2016) state that investment in infrastructure and the use of broadband is essential for the achievement of the Millennium Development Goals and in this argument, according to data from the Inter-American Development Bank (IDB, 2011), since 2010 there has been a meaningful increase in public investment focused on the acquisition of computers and internet access worldwide. Nevertheless, empirical evidence contradicts these positive economic and social effects, as the impact tends to be limited, with some even

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emphasizing that it can accentuate inequalities. Kenny (2011) speaks of an insignificant benefit for achieving the millennium goals. Forman et al. (2012) also provide evidence supporting this argument, highlighting that the benefits do not compensate for the investments frequently made in broadband plans and information and communication technologies, mainly for education. Nevertheless, the literature also highlights that this negative effect on inequalities is related to the high level of data aggregation that tends to limit the impact mechanisms at the organizational level using the Internet (Galperin & Mariscal, 2016).

Regarding the long-run relation between variables, Tang et al. (2022), using a Fully Modified Ordinary Least Squares (FMOLS) model, showed that technological innovation reduced inequality in the long run in high, upper-middle, and lower-middle-income countries, a result attributed to the increase in technological knowledge, which enables better social development. Likewise, Hafeez et al. (2020) and Ahmad et al. (2022), applying a Pooled Mean Group (MWG) estimator showed that in South Asia the inclusion of ICTs in the long run significantly reduced the income gap between rich and poor, and also increased women's empowerment, significantly improving their welfare. Nevertheless, Alimi and Okunade (2020), using a PMG estimator, showed that in Sub-Saharan Africa, in the long term, the adoption of mobile telephony did not improve economic conditions. Nevertheless, the spread of the Internet had beneficial effects, becoming a necessary tool to reduce poverty and inequality. Likewise, in developed countries, using FMOLS and PMG models, it was found that technological progress in the long run increased the income participation gap of the population of the top 1% (Neal, 2013).

For the case of India and Pakistan, the Autoregressive Distributed Lag (ARDL) model showed that, in the long run, technological innovation and IT services helped to decrease income inequality, rejecting the hypothesis that technological innovation increases the income gap between skilled and low-skilled workers, attributing the effect to increased access to technological services that enable improved development (Rout & Behera, 2022; Imran et al., 2021). Different results were found by Igwegbe and Amaka (2021) for the case of Nigeria, where the FMOLS model revealed that, in the long run, technological progress accentuates inequality due to the limited access to technology that characterizes developing economies.

On the other hand, Ha et al. (2019), applying PMG estimators, found for 63 provinces in Vietnam that urbanization reduced income inequality in the long run because people migrating to urban areas work in factories with higher wages than rural areas. On the other hand, Adams and Klobodu (2019), applying this same methodology, found that for 21 Sub-Saharan African countries, urbanization generates an increase in income inequality. Nevertheless, they highlight that institutional quality helps moderate this effect in the long run. In contrast, Wu and Rao (2017) show a robust inverted U relation between inequality and urbanization, where the urbanization threshold is 0.53, implying that provinces in China with urbanization levels above the threshold will experience reductions in income inequality. Mishra and

Agarwal (2019), in their analysis of 9 Asian countries applying panel dynamic ordinary least squares (OLS), found that urbanization leads to increased inequality.

Likewise, Hailemariam et al. (2021), using a panel VAR model, found that national income per capita is positively and significantly associated with income inequality. Similarly, Huang et al. (2015), using a PMG model, found that higher growth volatility is positively and significantly associated with higher long-run income inequality for 48 US states, i.e., there is a positive link between income volatility and inequality only for positive economic growth. Likewise, Bahmani-Oskooee and Ardakani (2020), with an ARDL approach in 41 countries, found that economic growth worsened income distribution for 6 countries and improved for 7 countries in the long run. Nevertheless, the coefficient of GDP per capita shows a negative relation but is not relevant to the Gini coefficient, indicating that economic growth decreases income inequality in Africa (Kabiru & Shehu, 2015).

Finally, it is important to mention that to obtain a significant impact on ICTs, it is necessary to reduce the existing digital gap nationally and internationally. According to ECLAC data (2021), the average annual growth of Internet penetration was only 8% between 2010 and 2019 in Latin America and the Caribbean. In 2019 it reached a gap of 22 percentage points compared to North America. Latin America is the fourth-highest region worldwide for Internet user penetration, behind North America (88.5%), Europe (82.5%), and the countries of the Commonwealth of Independent States (CIS, 72.2%). Also, among OECD member countries, the gap has narrowed over the last two decades, leading in terms of broadband penetration until 2019 (OECD, 2021).

Hawash and Lang (2020) point out that reducing the digital gap alone is insufficient to improve growth rates significantly. The differences in Internet access by geographic area at the country level still show significant variations; at the global level, the average difference ranges from 25 to 40 percentage points (ECLAC, 2021). Indeed, the effects of the variables under analysis may be associated with the case study or the characteristics of each economy. Particularly, this study focuses on OECD countries with great progress in broadband penetration (more than 45 subscriptions per 100 inhabitants in 2019) and toward commercial 5G services. Many member countries offer diverse coverage possibilities and roaming advantages (OECD, 2020). It is interesting and relevant to determine the effect of investment in internet and technology programs on inequality since governments disburse large amounts of investment. OECD countries' investments alone have remained at an average of 202 billion in 2018 with the premise of improving the population's welfare.

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Data and methodology

Data

This research work analyzes information from the period 2004 -2017, which is taken from the World Bank database (2020). The variables extracted are the Gini coefficient as the dependent variable, the import of information and communication technology (ICT) goods, and the percentage of the population using the Internet as explanatory variables. In addition, two control variables are also included: the urban population and the Gross Domestic Product per capita, expressed in logarithms, which will improve the level of significance of the main explanatory variables and the explanatory power of the model. Given data availability, 20 of the 36 OECD countries are analyzed (see Appendix Table A4). The description of the variables and covariates chosen is available in Table 1.

Table 1
Description of variables chosen for modeling

Variables	Symbology	Description	Measuring unit
A. Dependent:			
Gini	Igini	Measures income distribution. Values close to 0 or 100 indicate lower and higher inequality, respectively.	Index
B. Independent:			
Import of ICTs	tecnlg	Includes telecommunications, audio, and video equipment; computer and related equipment; electronic components; and other ICT goods.	% of total imports of goods.
Internet usage	usinter	People who have used the Internet (from anywhere) in the last 3 months, on any device, cell phone, TV, etcetera.	% of the population
C. Control:			
Urban population	lpurb	Persons living in urban areas as defined by national statistical offices.	Number of people
GDP per capita	lpibpc	Sum of gross value added of all resident producers plus any product taxes, minus any subsidies not included in the value of products, divided by population.	US$ at constant 2010 prices

Note: The symbology will be included in the model equations
Source: created by the authors, based on information from the World Bank (2020)

Table 2 shows the descriptive statistics of the variables chosen for the 20 countries included in the analysis, highlighting that the panel is perfectly balanced. The highest standard deviation is found in the percentage of people using the Internet at the general level, between countries, and for each of them, with values of 18.65, 14.90, and 11.68, respectively. On the Gini coefficient side, there is an almost similar variation at the general level and between countries with a difference of 0.09; at each country's level, this value is even lower, 1.25. It is also important to highlight that this group of countries in particular shows low-income inequality indices since the average value is 31.60, and on the side of internet use and technology imports, there are quite significant values, with means of 68.19% and 7.56%, respectively.

Table 2
Descriptive statistics

Variable		Mean	Std. Deviation	Min	Max	Observations
Gini coefficient	Overall	31.60	4.26	23.70	42.90	N = 280
	Between		4.17	24.89	40.46	n = 20
	Within		1.25	27.92	36.42	T = 14
Import of ICTs	Overall	7.56	3.59	2.75	21.24	N = 280
	Between		3.36	3.54	16.82	n = 20
	Within		1.46	3.12	12.61	T = 14
Internet usage	Overall	68.19	18.65	14.58	98.14	N = 280
	Between		14.90	39.27	91.08	n = 20
	Within		11.68	33.73	93.61	T = 14
Log Urban population	Overall	15.67	1.33	1.89	17.92	N = 280
	Between		1.36	13.04	17.77	n = 20
	Within		0.04	15.52	15.83	T = 14
Log GDP per capita	Overall	10.28	0.66	9.11	11.63	N = 280
	Between		0.67	9.35	11.57	n = 20
	Within		0.08	9.97	10.53	T = 14

Note: N=observations at the global level; n=observations at the country level; T=number of years in the period
Source: created by the authors, based on information from the World Bank (2020)

In addition, Table 3 shows the collinearity test, which enables determining the level of independence among the variables, that is, establishing a perfect linear relation between some or all of the explanatory variables, which in turn enables validating the selection of these variables. For this, some criteria are considered, first the variance inflation factor (VIF), which shows how multicollinearity inflates an estimator. The criterion used is that if the average value is greater than 10, there is a problem of high collinearity. In this case, the average is 1.44. Therefore, there is no such problem. Considering the "tolerance" indicator, values closer to 1 than 0 are observed, and the "R-squared" values are small. These results corroborate the non-existence of perfect multicollinearity.

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Table 3
Collinearity test

Variable	VIF	SQRT VIF	Tolerance	R-Squared
Import of ICTs	1.07	1.03	0.93	0.07
Internet usage	1.84	1.36	0.54	0.46
Log urban population	1.14	1.07	0.87	0.13
Log GDP per capita	1.71	1.31	0.58	0.42
Mean	1.44			

Source: created by the authors, based on information from the World Bank (2020)

On the other hand, Figure 1 shows a heat map of the Gini coefficient for the 20 OECD member countries in 2017; the more intense gray indicates a higher level of inequality, while the low intensity of that color implies the opposite. In countries such as Portugal, Spain, and Turkey, income inequality is more notable; in contrast, in Finland and Norway this index is much lower, so it could be said that they show greater income equity in their population. The heterogeneity in this indicator is clear, given the differences presented by the territories.

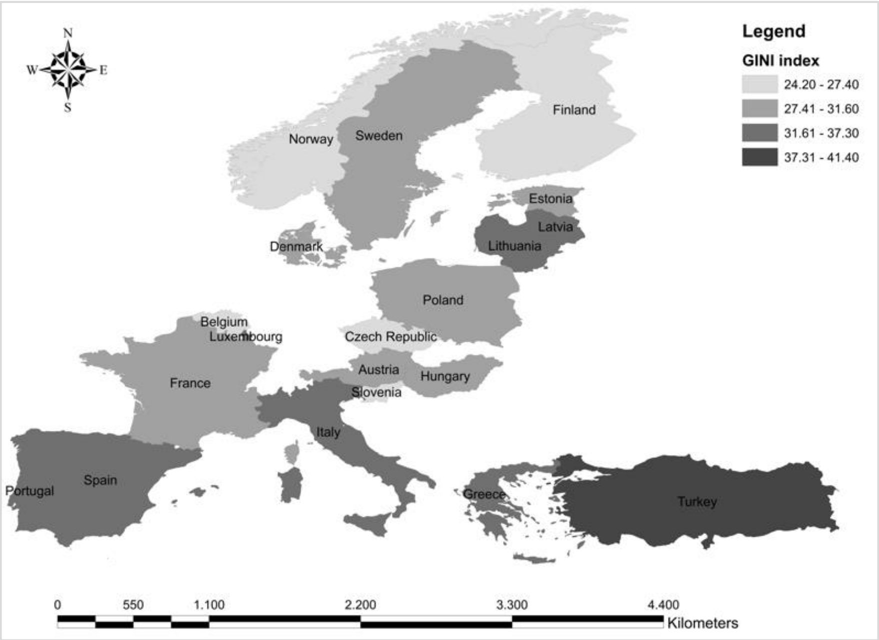

Figure 1. GINI coefficient in OECD countries in 2017
Source: created by the authors based on data from World Bank (2020)

Figure 2 shows the correlation between the Gini coefficient and the other variables of the model. In the first place, a fairly significant negative relation is observed between the level of inequality and the import of technology and the use of the Internet, which indicates that as these last two increase a reduction in the level of income inequality is generated in the 20 OECD countries considered; secondly, concerning the control variables, the Gross Domestic Product per capita shows a negative relation regarding income inequality, showing that as countries generate a higher level of economic growth they will be able to reduce the level of the income gap. On the contrary, a negative relation is identified between income inequality and urban population. As population concentration increases in urban areas, not all people will have the same opportunities, given the specialization and concentration in the labor market, resulting in greater income inequality.

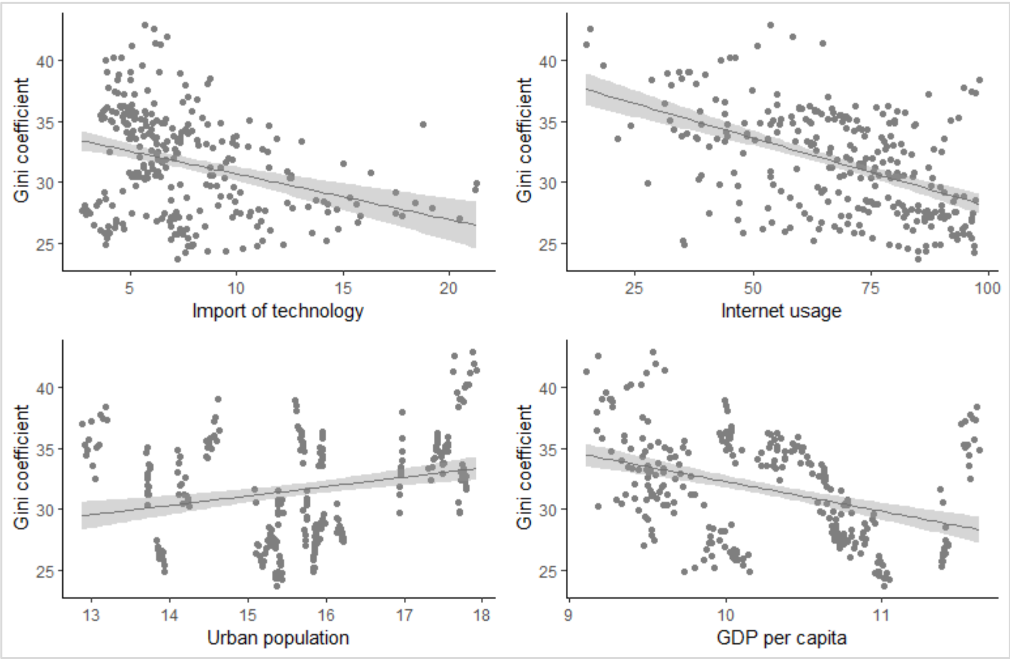

Figure 2. Correlation between the variables of the econometric model
Source: created by the authors based on data from World Bank (2020)

Methodology

In order to demonstrate the impact of technology in the 20 OECD member countries on their income inequality, panel data econometrics is used, which increases the robustness of the estimates, given its flexibility for the inclusion of a greater amount of information. Other advantages of this methodology are that it implicitly considers the heterogeneity of the cross-sectional units and enables the presence of greater degrees of freedom and less collinearity, and, therefore, greater efficiency in the estimation of the results, better identifying the effects of the factors studied (Gujarati & Porter, 2010). First, a model will be estimated with the main study variables. Equation (1) shows this relation:

$$\mathrm{Igini}_{it} = \alpha_{it} + \mathrm{tecnlg}_{it} + \mathrm{usinter}_{it} + \mu_{it} \tag{1}$$

Where Igini_{it} indicates the Gini coefficient, α_{it} is the model constant, tecnlg_{it} refers to ICT imports, $\mathrm{usinter}_{it}$ represents the percentage of the population using the Internet, μ_{it} represents the estimation's error component, caused both by the unobservable and the idiosyncratic fixed effect; i denotes the sample's cross-sectional units, and t is the time series used. The second model includes the logarithm of urban population and GDP per capita as the covariates or control variables. Equation (2) represents this second estimation, intended to provide greater robustness to the model and increase the level of prediction of the coefficients obtained. Among the variables suggested by the corresponding empirical evidence, this study includes lpurb_{it} and lpibpc_{it}, which reflect the effect of the increase in urban population and economic growth on income inequality, expressed in logarithms, as shown in Equation (2):

$$\mathrm{Igini}_{it} = \alpha_{it} + \mathrm{tecnlg}_{it} + \mathrm{usinter}_{it} + \mathrm{lpurb}_{it} + \mathrm{lpibpc}_{it} + \mu_{it} \tag{2}$$

Within the econometric methodology, different types of models are estimated. Firstly and considering that panel data is used, a selection is made between a fixed effects model and a random effects model. The first one is a model in which its main characteristic is that the intercept of each individual is invariant over time, and a certain degree of correlation between the error term and the independent variables is enabled; on the other hand, in the second model there is strict exogeneity between the variables. In addition, their coefficients α_i and the temporal ones ϕ_t are no longer fixed and vary over time and between the different units taken, as defined by Gujarati and Porter (2010). To select the model that best fits the available data, the Hausman (1978) test is used, which enables the analysis of the possible correlation between the α_i and the regressors whose null hypothesis establishes that the model to be estimated should be the random effects model, and the alternative advocates the estimation of the fixed effects model.

After having chosen the best model, some additional tests are applied: the Wooldridge test (1991) to see if the estimated model presents problems of serial autocorrelation, the Wald test modified according to Greene (2000) to determine the presence of heteroscedasticity and the Pesaran test (2004) to detect a possible cross-sectional dependence in the residuals of the model. In all of them, the null

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hypothesis states the non-existence of the problem, and the alternative is the presence of the problem. In the estimations conducted, the first two problems mentioned above were detected, and to finally correct them, the Generalized Least Squares (GLS) model is used, which enables the obtaining of robust, unbiased, and mainly efficient estimators, improving the estimations of the basic Ordinary Least Squares (OLS) model.

On the other hand, given the dynamic nature of the incidence of the technological component on the level of economic growth and the level of income inequality of nations, this research also proceeds to estimate a Pooled Mean Group (PMG) model, which not only enables measuring the dynamic relation of the relations between the variables analyzed but also the long-term incidence of the explanatory variables on the level of inequality of the countries studied. According to Blackburne and Frank (2007), the MG and PMG estimators assume the specification of an autoregressive distributional lag model (ARDL), where the lags of the dependent variable and the explanatory variables are the determinants of the dynamic relation between the variables in the model. Before going to the model specification, it is important to highlight that PMG estimators enable modeling the long-run relation of non-stationary variables and estimating short-run coefficients and error variances that differ between groups. Nevertheless, they restrict the long-run coefficients to be equal in all groups. Considering contributions such as Alimi and Okunade (2020) and Hafeez et al. (2020), the specifications for estimating the dynamic relation between technology importation, internet use, and income inequality are shown in Equations (3) and (4):

$$\Delta \mathrm{gini}_{it} = \alpha_{ij} + \vartheta_i (\mathrm{ECT})_{t-1} + \sum_{j=1}^{p} \pi^*_{i,j}\, \Delta \mathrm{gini}_{i,t-j} + \sum_{j=1}^{p} \delta^*_{i,j}\, \Delta \mathrm{tecnlg}_{i,t-j} + \sum_{j=1}^{p} \rho^*_{i,j}\, \Delta \mathrm{usinter}_{i,t-j} + \mu_{it} \tag{3}$$

$$\Delta \mathrm{gini}_{it} = \alpha_{ij} + \vartheta_i (\mathrm{ECT})_{t-1} + \sum_{j=1}^{p} \pi^*_{i,j}\, \Delta \mathrm{gini}_{i,t-j} + \sum_{j=1}^{p} \delta^*_{i,j}\, \Delta \mathrm{tecnlg}_{i,t-j} + \sum_{j=1}^{p} \rho^*_{i,j}\, \Delta \mathrm{usinter}_{i,t-j} + \sum_{j=1}^{p} \sigma^*_{i,j}\, X_{i,t-j} + \mu_{it} \tag{4}$$

Where ECT represents the error correction term, which enables the long-run relation to be obtained; ϑ_i is the velocity adjustment between short-run and long-run equilibrium (rate of convergence or divergence); π, δ, ρ, σ are the coefficients that capture the short-run effects of the explanatory variables (including the control variables, lpurb and lpibpc: X); and the subscript t-j refers to the time lags of the explanatory variables of the dynamic model.

Discussion of results

In the first stage, the Hausman test (1978) was applied to determine whether to use fixed effects or random effects; the test produced fixed effects models. To establish if there is autocorrelation in the panels, the Wooldridge test (1991) was used, which determined that all the panels presented autocorrelation problems; in addition, the panels presented heteroscedasticity problems (see Appendix Tables A1, A2, and A3). To correct the econometric problems mentioned above, a Generalized Least Squares (GLS) model was used. Table 4 includes the GLS results, showing the incidence of technology imports and internet use on income inequality, as shown in Equation (1).

The results show that the variables used are statistically significant so that the import of technologies and the use of the Internet have an inverse influence on income inequality, i.e., as ICT imports and the population that uses the Internet increase, income inequality tends to decrease in the member countries of the Organization for Economic Cooperation and Development (OECD). Indeed, as OECD member countries increase the level of ICT imports and the population that has access to the Internet, income inequality will decrease, given that people can enter certain markets that require technological tools. If this is combined with access to the Internet, an even greater effect can be achieved. These aspects are related to the digital economy.

These results are similar to those obtained by Mushtaq and Bruneau (2019) and Canh et al. (2020), who found a negative relation between access to ICT and income inequality and observed that ICT externalities contributed to financial inclusion, accelerating economic growth and reducing inequality. Nevertheless, the effect would be heterogeneous when analyzing different groups of countries. Likewise, Mora-Rivera and García-Mora (2021) and Chahuara and Trelles (2014) show that internet access is a tool that can help reduce the number of poor people, especially in the lower economic strata and that it must also be accompanied by social programs to achieve better results. Wang et al. (2020) and Antonelli and Gehringer (2017) found similar results, highlighting that technology and the use of the Internet can generate positive externalities in terms of employment in the industrial sector, generating better opportunities to obtain a higher salary and even a higher level of productivity.

Nevertheless, the results did not match those found by Ali et al. (2019), who mention that when ICT affordability is high, income inequality is also high, given that it is positively associated with people's socioeconomic position. Noh and Yoo (2008), Martin (2018), and Vargas and Guerrero-Riofrío (2019) also obtain opposite results, which highlight that the existing digital divide prevents the use of technology from contributing positively to improving workers' productivity, so it becomes a social problem and those who benefit the most are people with higher incomes and those who manage to make more efficient use of the available technologies.

Table 4
GLS regression between income inequality, technology, and Internet use

	GLS
Import of technology	-0.162*
	(-2.50)
Internet usage	-0.058***
	(-4.88)
Constant	36.35***
	(36.04)
Observations	280

T-statistic in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: created by the authors

In order to better estimate the effects of the main explanatory variables, the control variables urban population and GDP per capita were incorporated. The econometric formalization is shown in Equation (2). Table 5 shows the results corresponding to Equation (2). As can be demonstrated, the import of technological goods at 1% and the population using the Internet at 5% are still relevant variables, maintaining the negative relation and statistically significant with income inequality shown in Table 4, corroborating their contribution to the increase in the standard of living and the reduction of income inequality. The effect of the urban population is positive and statistically significant at 1%, so income inequality tends to increase as the population in the urban sector increases. In contrast, GDP per capita shows an inverse relation regarding income inequality, i.e., as economic growth is generated in OECD member countries, income inequality tends to decrease, with a statistical significance level of 1%, with all other factors remaining constant.

Regarding the urban population, the increase in inequality may be due to the fact that in this sector the goods and services offered by the state are better than those offered in the rural sector, which is why there is rural-urban migration, increasing the inequality gap in health services, education, drinking water, etcetera, results that coincide with Sulemana et al. (2019) in their study for Sub-Saharan Africa, where a greater concentration of people in the urban sector is related to greater income inequality. This may occur, according to Kuznets (1955), because economic growth causes economies to move away from agriculture to subsequently industrialize and urbanize and because rural people, who are generally less educated and skilled than their urban counterparts, are trapped in persistent poverty due to the limited economic opportunities and other barriers they encounter when migrating to cities.

On the other hand, concerning economic growth, the fact that the population has a higher per capita income enables access to a wide range of goods and services, which decreases the gap between rich and poor, in addition to the fact that the state in this scenario may obtain higher tax revenues and may implement welfare programs for the most vulnerable groups, results similar to those found in Lazo Dioses

(2018) for the different regions of Peru. Similarly, Diaz and Mayorga (2009) indicate that the level of the economic growth path affects the behavior of inequality in Latin America. This result implies that the higher the level of GDP per capita, the lower the degree of inequality would be, at least on average (perhaps excluding Brazil). Given the results presented in Tables 4 and 5, it is possible to corroborate the hypothesis posed about the negative and statistically significant effect that the importation of technological goods and the use of the Internet has on income inequality, demonstrating the importance of technological progress in the enhancement of productive capacities and the improvement of individuals' labor income. The positive effect of technology in reducing income inequality is a result that coincides with the findings of works such as Canh et al. (2020), Asongu et al. (2019), Mora-Rivera and Garcia-Mora (2021), Chahuara and Trelles (2014), Hafeez et al. (2020), Ahmad et al. (2022), Antonelli and Gehringer (2017), and Mushtaq and Bruneau (2019).

Table 5
GLS regression with control variables (urban population and GDP per capita)

	GLS
Import of technology	-0.223***
	(-3.65)
Internet usage	-0.0287*
	(-2.38)
lpurb	1.054***
	(4.51)
lpibpc	-3.025***
	(-5.86)
Constant	49.45***
	(7.80)
Observations	280

T-statistic in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: created by the authors

It is important to emphasize that although Tables 4 and 5 establish the relation between the variables of interest, these results correspond to a "static" type of estimation. Consequently, this study also proposes the estimation of a model that considers the possible long-term dynamic incidence of the explanatory variables on inequality, specifically, a Pooled Mean Group (PMG) model, a methodology validated by the corresponding Hausman Test, as is done in Alimi and Okunade (2020) and Hafeez et al. (2020). Finally, it is important to mention that prior to the estimation of such model, first-generation unit root tests were conducted (given the existence of cross-sectional independence detected earlier), finding that all variables used in the estimation exhibit a unit root problem (not being able to reject the null hypothesis of the existence of unit roots, given the p-values of such tests), as stated in Appendix Table A5; in other words, to become stationary they must be "differenced" at least once; justifying the estimation of the relation between the variables analyzed and econometric methods that consider the long-run equilibrium.

Table 6
Long-run estimation of the relation between inequality and the import of technologies and internet use, using a PMG estimation

	PMG1	PMG2
Ec		
Import of technology	0.0221	0.141^{***}
	(0.96)	(3.38)
Internet usage	-0.0519^{***}	-0.0655^{***}
	(-7.33)	(-4.50)
lpurb		19.52^{***}
		(13.25)
lpibpc		4.699^{***}
		(3.87)
Observations	260	260

T-statistic in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: created by the authors

In Table 6, considering the dynamic and long-term effect of technology in improving productivity and increasing production, it can be observed that technology imports are no longer a determining variable for reducing inequality, probably due to the high level of accumulation of such equipment in the countries analyzed and the significant gap in terms of digital skills. The increase in technological imports widens the existing income gap in these territories. These results are consistent with those found in Neal (2013), Adams and Klobodu (2019), and Igwegbe and Amaka (2021), where the contribution in the reduction of income inequality by the explanatory variables ceases to be statistically significant in the long run. The use of the Internet as a proxy variable for the use of Information and Communication Technologies (ICTs) continues to be statistically meaningful in the long run, denoting the positive dynamic effect of the use of technology on the growth of the countries analyzed and on their inequality reduction processes, as demonstrated by Tang et al. (2022), Hafeez et al. (2020), Ahmad et al. (2022), and Alimi and Okunade (2020). Finally, regarding the control variables, it is evident that the increase in urban population and per capita output causes an increase in the level of income inequality in OECD countries, confirming the difficulty of reducing such inequality, even in the case of more developed countries, and coinciding with Adams and Klobodu (2019), Mishra and Agarwal (2019), Bahmani-Oskooee and Ardakani (2020), and Hailemariam et al. (2021).

Conclusions

This research paper reviews the relation between the import of technological goods, people with internet access, and income inequality for the countries comprising the Organization for Economic Cooperation and Development (OECD) in the period 2004-2017 using panel data, generalized least squares (GLS), and PMG estimators. The results of the GLS model show that the hypothesis posed does hold for this group of countries, i.e., that the import of technology and the population's internet use decrease the income inequality gap, being statistically meaningful. This implies that a greater acquisition of Information and Communication Technologies (ICTs) in sectors such as education, health, and finance will increase productivity and efficiency since these countries have high rates of ICT imports, which are reflected in the different social sectors, increasing their scope, generating economic growth and development, and partly reducing the existing inequality between the public and private sectors.

Moreover, if the population combines ICTs with Internet access, this generates an even greater effect since it can generate new skills in what is known as the digital economy. This combination's productivity, reach, and efficiency enable them to enter the new era of digital globalization, increasing their human capital and the likelihood of accessing the labor market. In this context, technology transforms people's daily lives. In very few cases, the increase in technology combined with access to the Internet means that not all work is productive; in the vast majority, the appropriate use of technology generates innovation in business and entrepreneurship, enabling even the level of environmental degradation to be reduced.

Therefore, economic growth has a positive effect on the reduction of income inequality, given that the increase in the income of the inhabitants of the different OECD countries enables them to have greater purchasing power and access to certain goods or services that increase their well-being, reducing in part the existing gap between rich and poor. In addition, it was found that the increase in the urban population generates an increase in income inequality, given that the goods and services provided in the urban sector are much better than those provided in the rural sector, increasing the gap between the quality of life in the urban and rural sectors. Furthermore, in terms of health, education, social security, etcetera, the urban population benefits from a large part of the policies implemented by the state, and given that the concentration of wealth remains in this sector, the rural zone is marginalized, and the assistance it receives is limited, causing rural-urban migration. In addition, people who migrate are generally employed in less qualified jobs, mainly in the informal sector, earning lower salaries.

Although the above corroborates the importance of the acquisition and accumulation of technology and digital skills in economic growth and the reduction of inequality, it is necessary to qualify these results, highlighting that if dynamic econometric methodologies, such as PMG estimators, are used to estimate the relation between the variables analyzed, it can be demonstrated that the contribution of variables such as technology imports and the increase in urban population and GDP per capita to the reduction of income inequality is no longer statistically significant in the long term. This shows that in order to obtain a positive effect of technological progress on economic growth and the improvement of living conditions, it is necessary to reduce the digital divide that prevents the efficient use of existing technology and the implementation of policies aimed at the transformation of the productive infrastructure of the countries.

Given the favorable results found in the GLS model, some policy implications arise. One of them would be to increase the level of ICT coverage, prioritizing access to education since this will increase human capital due to the positive externalities generated, increasing employment in the different sectors (industrial, agricultural, financial, etcetera). More flexible tariff levels could be managed in the countries to make obtaining or importing technological capital equipment easier. As for the use of the Internet, governments should increase digital coverage so that it reaches all corners of their countries and implement subsidy programs to make its cost more accessible. On the other hand, the creation of adequate and sustainable jobs would help to avoid, to a certain extent, migration from the rural to the urban sector, in addition to improving basic services such as water, electricity, and sewerage to increase the welfare of people in this sector, properly identifying the sectors most in need of state intervention.

Finally, implementing policies to increase both internal and external investment, focusing on strategic sectors such as the technology industry, can contribute to the economic growth of this group of countries, which in turn would improve labor market conditions, thereby reducing income inequality. The present research could not aggregate all countries due to a lack of data and the need to refine the econometric model better. Future research should analyze the effect on developing countries, also considering factors such as foreign direct investment and industrialization processes.

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Annex

Table A1
Hausman test (1978)

Models	Prob>chi2
Basic	0.0001
With control variables	0.0023

Note: Decision at 95% confidence level
Source: created by the authors

Table A2
Fixed effects models without applying the corrections to the data

	Basic	With control variables
Import of technology	0.0778	0.153*
	(1.37)	(2.59)
Internet usage	0.00774	0.0138
	(1.09)	(1.60)
lpurb		4.445*
		(2.22)
lpibpc		-3.112**
		(-2.81)
Constant	30.49***	-8.152
	(40.37)	(-0.24)
N	280	280
r2	0.00883	0.0622
r2_o	0.250	0.0868
r2_w	0.00883	0.0622
sigma_u	4.352	6.648

sigma_e	1.295	1.265
rho	0.919	0.965

T-statistic in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: created by the authors

Table A3
Diagnostic test

Models	Autocorrelation	Heteroscedasticity	Cross-sectional dependence
Basic	0.0006	0.0000	0.4154
With control variables	0.0006	0.0000	0.7047
Existing problem	Yes	Yes	No

Note: p-values are shown, and decision is made with a confidence level of 95%
Source: created by the authors

Table A4
OECD member countries

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

Source: created by the authors, with information from the World Bank (2020)

Table A5
Results of unit root tests (p-values) applied to the variables of the estimated model

Variables		Breitung (with tendency)	Harris-Tzavalis (with tendency)
Gini coefficient	In levels	0.2537	0.0055
	In first differences	0.0001	0.0000
Import of technology	In levels	0.3514	0.7612
	In first differences	0.0000	0.0000
Internet usage	In levels	0.9977	0.9978
	In first differences	0.0000	0.0000
lpurb	In levels	1.0000	1.0000
	In first differences	0.0000	0.0000
lpibpc	In levels	0.1387	0.4714
	In first differences	0.0000	0.0507

Source: created by the authors, with information from the World Bank (2020)