WIDER Working Paper 2023/9

# Inequality and productive structure

## New evidence at the world level

Verónica Amarante, Bibiana Lanzilotta, and Joaquín Torres*

January 2023

United Nations University World Institute for Development Economics Research

wider.unu.edu

**Abstract:** This paper investigates the evolution of the productive structure around the world and the role it plays in the difference in inequality levels, using panel data for the period from 1995 to 2018. We approximate a country's productive structure through the Economic Complexity Index. Our results indicate that income inequality at the world level is not linearly related to economic complexity. Instead, our results indicate that, when the levels of complexity of the economy are very low, increases in complexity mainly lead to an increase in economic inequality. At higher levels of economic complexity, the effect of economic complexity on income inequality becomes negative. This means that economic complexity becomes equality enhancing after certain thresholds, which seems to reflect the situation in high-income economies.

**Key words:** income inequality, productive structure, economic complexity, panel data

**JEL classification:** O11, O15

---

* Instituto de Economía, Udelar, Montevideo, Uruguay, corresponding author email Veronica.amarante@fcea.edu.uy

This study has been prepared within the UNU-WIDER project World Income Inequality Database (WIID).



Information and requests: publications@wider.unu.edu

ISSN 1798-7237 ISBN 978-92-9267-317-8

https://doi.org/10.35188/UNU-WIDER/2023/317-8

Typescript prepared by Lesley Ellen.

United Nations University World Institute for Development Economics Research provides economic analysis and policy advice with the aim of promoting sustainable and equitable development. The Institute began operations in 1985 in Helsinki, Finland, as the first research and training centre of the United Nations University. Today it is a unique blend of think tank, research institute, and UN agency—providing a range of services from policy advice to governments as well as freely available original research.

The Institute is funded through income from an endowment fund with additional contributions to its work programme from Finland and Sweden, as well as earmarked contributions for specific projects from a variety of donors.

Katajanokanlaituri 6 B, 00160 Helsinki, Finland

## 1 Introduction

Understanding the drivers of income inequality and its links with the productive structure has been a core question in development economics from the seminal work of Kuznets through to the contributions of structuralist economists under the influence of Prebisch. Despite the importance of these connections in theoretical terms, the evidence is not abundant, partly because it is difficult to reflect in a specific measure the multiple dimensions that constitute a productive structure. Moreover, the evolution of income inequality involves a variety of other economic, social, and institutional factors that may also interact with the productive structure, making it more difficult to unravel the link between inequality and the productive structure.

The empirical complexities involved in the structural transformation processes and their links with inequalities have attracted the attention of economic researchers, albeit in a moderate way. For example, Baymul and Sen (2020) present an analysis of the implications of different patterns of sectoral change in terms of inequality. Other attempts to link the sectoral structure of production and inequality can be found in Ciaschi et al. (2021) for Latin America and Martorano and San Filippo (2015) for East Asian countries. Buera et al. (2022) and Andersson and Palacio (2016, 2017) also address the role of productive structures in understanding economic inequality.[1]

With the introduction of the concept of economic complexity and its measurement, renewed interest in the links between income inequality and the productive structure has emerged. Economic complexity aims to reflect the amount of knowledge that is embedded in the productive structure of an economy, and it has helped to provide a deeper understanding of what a country is producing and what is involved in that activity. Based on these notions Hidalgo and Hausmann (2009) developed an index for measuring economic complexity—the Economic Complexity Index (ECI)—which motivated a body of empirical studies that try to disentangle the role of economic complexity in the development process. The evidence has shown that there is a robust and stable relationship between a country's productive structure, as measured by the ECI, and its economic growth (Hausmann et al. 2007).

Another line of research has attempted to understand the link between the complexity of productive structures and income inequality (Chu and Hoang 2020; Hartman et al. 2017; Le Caous and Huarng 2020, among others). The evidence emerging from this literature is still mixed and inconclusive, which is not surprising given the relatively recent nature of this research. Earlier results seemed to point to a negative association, suggesting that economic complexity was a good predictor of lower levels of income inequality. However, more recent studies have challenged this first picture, enriching the analysis of the link between economic complexity and income inequality. The different measures of income inequality, the countries considered, the time periods analysed, the control variables included, and the specification of the models chosen are some of issues that can help us to understand the still inconclusive nature of this evidence. Our paper seeks to contribute to this strand of literature by investigating the evolution of economic complexity around the world and its role in the difference in inequality levels, using panel data for the period from 1995 to 2018.

[1] Another strand of literature considers the expansion of services and its gender inequality implications (Ngai and Petrongolo 2014; Rendall 2013).

## 2 Inequality and economic complexity

### 2.1 The Economic Complexity Index (ECI)

Structural change can be viewed as the process of generating new, more knowledge-intensive activities, which is mainly done through the incorporation of technology. The concept of economic complexity reflects that the amount of knowledge underlying the productive structure of an economy depends on the diversity of all individual knowledge and on the ability of individuals to combine and translate it into knowledge-intensive products and large networks of interaction. Based on this concept Hidalgo and Hausmann (2009) developed an index for measuring economic complexity which motivated a body of empirical studies that try to disentangle the role of economic complexity in the development process.

The characterization of economic structures proposed by Hidalgo and Hausmann (2009) can be formally expressed, following Hausmann et al. (2014), as departing from a matrix $M_{cp}$ in which rows represent different countries and columns represent different products. An element of the matrix equals one if country *c* exports product *p* with revealed comparative advantage (RCA), and zero otherwise.[2] Diversity and ubiquity can be measured by simply summing over the rows of columns of that matrix.

$$Diversity = k_{c,0} = \sum_p M_{cp} \tag{1}$$

$$Ubiquity = k_{p,0} = \sum_c M_{cp} \tag{2}$$

To generate a more accurate measure, both diversity and ubiquity must be corrected using each one to correct the other. The number of a country's capabilities is equal to the average number of capabilities required by its exporting products, whereas the number of capabilities required by a product is the average number of capabilities present in the countries that are exporting it. The method describes an iterative procedure, by recursion, which for a number N of iterations is represented by:

$$k_{c,N} = \frac{1}{k_{c,0}} \sum_p M_{cp} k_{p,N-1} \tag{3}$$

$$k_{p,N} = \frac{1}{k_{p,0}} \sum_c M_{cp} k_{c,N-1} \tag{4}$$

By substituting (4) in (3), following Haussmann et al. (2014), the following equation is obtained:

$$k_{c,N} = \frac{1}{k_{c,0}} \sum_p M_{cp} \frac{1}{k_{p,0}} \sum_{c\prime} M_{c\prime p} k_{c,N-2} \tag{5}$$

$$k_{c,N} = \sum_{c\prime} k_{c',N-2} \sum \frac{M_{cp} M_{c\prime p}}{k_{c,0} k_{p,0}} \tag{6}$$

This equation can be rewritten as:

---

[2] The RCA is the ratio of the share of a country's exports of a certain product in its total export basket to the overall share across countries, following Balassa (1965). If the RCA is equal to or greater than one, a country is classified as a significant exporter of that product. In this way, any trivial correlation with economic size is removed.

$$k_{c,N} = \sum_{c'} \widetilde{M}_{cc'} k_{c',N-2} \tag{7}$$

where:

$$\widetilde{M}_{cc'} = \sum_p \frac{M_{cp} M_{c'p}}{k_{c,0} k_{p,0}} \tag{8}$$

The authors note that equation (7) is satisfied when $k_{c,N} = k_{c,N-2} = 1$. This corresponds to the eigenvector of $\widetilde{M}_{cc'}$ which is associated with the largest eigenvalue. This eigenvector is not very informative, as it corresponds to a vector of ones. They propose, instead, the eigenvector associated with the second largest eigenvalue, as it is the eigenvector that captures the largest amount of variance in a system and it measures economic complexity. So, they define economic complexity as:

$$ECI = \frac{\vec{K} - \langle \vec{K} \rangle}{stdev\ (\overrightarrow{K})}$$

where < > represents an average, *stdev* stands for standard deviation, and $\vec{K}$ is the eigenvector of $\widetilde{M}_{cc'}$ associated with the second largest eigenvalue. This measure allows countries to be ranked in the international market based on their complexity score, assuming a linear relation between the complexity of a product and the complexity of its exporters.

Based on this novel measure of economic complexity, a stream of empirical literature has attempted to understand the linkages between economic development and the complexity of productive structures. The underlying idea is that economic complexity reveals information about a country's human capital, technology, and institutions. The increasing influence of this measure of complexity in the growth literature has also led to the emergence of research highlighting potential limitations.

One of the central points in the discussion refers to the exclusion of services in this measure.[3] Empirical results indicate that the growing sophistication in exporting services is a relevant channel for sustained high growth in developing countries (Mishra et al. 2011, among others). Following that line Stojkoski et al. (2016) argue that, due to the lack of disaggregated data on services as opposed to goods, Hidalgo and Haussman (2009) dismissed the inclusion of services. If the complexity indexes for services are higher than those for goods (which is plausible for high technology services), the inclusion of services would result in a tendency to rank countries with a developed service sector higher than countries with an economy centred on the manufacturing of goods. They calculate a complexity index which includes both products and services, although the level of aggregation corresponds to that of services. The addition of services exports in the model increased the complexity of economies with a developed services sector, but this aggregated metric is not as good an explanatory variable of growth as the original Hidalgo and Haussman (2009) index. The aggregation of the information entails extracting less information about the productive capabilities embedded in the goods.

[3] More conceptual critics of the economic complexity approach and its measurement centrality based on data mining techniques can be found in Anderson (2008). Limitations due to the fact that complexity indexes are greatly affected by exogenous changes in international commodity markets, which weakens their link to policy variables, are presented in Salinas (2021).

The proponents of the ECI acknowledge that the lack of services data can bias their measurement if a country's services structure contains different information to that inferred from its trade in goods (Haussman et al. 2014). However, they argue that it is reasonable to expect services data to provide little additional information in a world where countries with a complex goods structure also have a complex services structure. In a similar vein to Stojkoski et al. (2016), they compare an ECI calculated using only goods with one that is calculated with both goods and services (included at a high level of aggregation). They find almost perfect correlation and argue for the validation of an ECI, even without the inclusion of services, reaffirming their idea that, at present, services data is not sufficiently disaggregated to be included in economic complexity calculations.

Another strand of literature proposes alternative measures of economic complexity, based on different methodologies. For example, Cristelli et al. (2013) propose a complexity index based on a non-linear method, whose outcomes differ from the ones derived from the ECI. Other influential proposals aimed at improving the mathematical performance of complexity measures include the fitness and complexity algorithm (Tacchella et al. 2012) and the taxonomy or product progression network (Pugliese et al. 2019; Zaccaria et al. 2018).[4] This strand of literature criticizes the assumption of a linear relationship between the products' and countries' complexities (implicit in the ECI) and argues that the fact that a less competitive country exports a given product should downgrade the product's complexity. Such authors propose to obtain this effect using a non-linear relationship. A different approach is proposed by Sciarra et al. (2020), who reconcile the method of reflections used in the ECI and the fitness and complexity algorithm to provide country and product rankings based on the embedded productive knowledge. Attempts to introduce services in the calculation of these indexes include those by Zaccaria et al. (2018), who find that many countries gain or lose positions in the ranking of economic fitness when services trade is considered. They also verify that complex services tend to cluster with complex manufacturing, suggesting a common capabilities structure.

The fact that different methodologies produce contrasting results fosters the discussion about the advantages of these indexes and undermines their acceptance and application (Sciarra et al. 2020). In sum this is an area of research that is under development, and more sound bases for the economic complexity theory may help to advance specific issues related to measurement.

## 2.2 Economic complexity and income inequality: previous evidence

Several recent studies analyse the link between economic complexity and income inequality (a review can be found in Hartmann and Pinheiro 2022). A very influential paper is the one by Hartmann et al. (2017), who test the relationship between economic complexity, reflected by the ECI, and income inequality, using data from a panel of countries for the period between 1963 and 2008.[5] Both their pooled and fixed effects estimations indicate that economic complexity is a negative and significant predictor of income inequality, even after controlling for other socioeconomic variables such as gross domestic product (GDP), population, education, and different proxies for institutions. They also find that, over time, countries that experience an increase in economic complexity are more likely to experience a decrease in their level of income inequality.

Hartmann et al. (2017) also analyse a measure called the Product Gini Index (PGI), which relates each product to its typical level of income inequality. The PGI is formally defined as the average

[4] These measures are sometimes referred to as the economic fitness approach, to distinguish them from the economic complexity approach.

[5] They use average values of the variables for the time periods 1963–69, 1970–79, 1980–89, 1990–99, and 2000–08.

level of income inequality of a product's exporters weighted by the importance of each product in a country's export basket. Based on that measure, they compare the productive sophistication and structural constraints on income inequality of countries in Latin America and the Caribbean with those of China and other high-performing Asian economies (Hartmann et al. 2016). Their analysis illustrates that Asian economies have managed to diversify into products typically produced by countries with low levels of income inequality, while Latin American countries have remained dependent on products related to high levels of income inequality.

Following the findings of Hartmann et al. (2017), other empirical studies explore the role of economic complexity and inequality.[6] The evidence provided by Lee and Vu (2019) challenges the view of a negative relationship between economic complexity and income inequality. Their ordinary least squares (OLS) and fixed effects estimates are in line with those of Hartmann et al. (2017), as they show that countries whose productive structures are more complex have less income inequality. But the authors argue that those estimates may be biased due to the potential endogeneity of complexity and the persistence of the dependent variable. When they turn to dynamic panel data estimation, their results change, and they find that an increase in economic complexity is associated with higher degrees of inequality in both the short and long runs. This is consistent with the notion that when the economy experiences structural change toward more sophisticated products, the degree of income inequality increases. They also argue that human capital is the key factor that, jointly with economic complexity, affects income distribution. The interaction term between complexity and human capital (especially secondary education) is negative and statistically significant, suggesting that human capital considerably bolsters the negative effect of complexity on income inequality.

Following the same line Chu and Hoang (2020), using panel data from 2002 to 2017, also report a positive association between income inequality and economic complexities under fixed effects two-stage least squares (2SLS) and system generalized method of moments (GMM) estimations. They argue that an increase in economic complexity leads to higher income inequality, not less. They also find that countries with better human capital, efficient public spending, and trade openness can reduce income inequality in the process of increasing their economic complexity, as the coefficients of these variables have moderating impacts on the role of the ECI. They also explore whether the effect of economic complexity on income inequality differs across income levels and find that, although the impact of economic complexity on income inequality is lower in middle-income countries than in high-income countries, it is still not significantly negative. Moreover, the authors state that high-income countries face larger income gaps in the transformation to a knowledge-intensive economy than middle-income countries.

At the country level Bandeira et al. (2021) consider 27 Brazilian states in the period from 2002 to 2014 and point to an inverted U-shaped relationship between economic complexity and inequality, whereas Gao and Zhou (2018) report a negative effect of economic complexity on income inequality at the regional level in China.

Finally, based on the fitness index to reflect economic complexity, Sbardella et al. (2017) uncover an inversed U pattern for economic complexity and wage inequality across countries (OLS and

[6] In a related literature Fawaz and Rahnama-Moghadamm (2019) link income inequality and economic complexity through the trade channel. Another related paper is the one by Le Caous and Huarng (2020), who study the link between economic complexity and human development and find that economic complexity has positive effects on human development but that these effects are mediated by income inequality. Finally, other studies analyse the link between economic complexity and gender wage gaps (Barza et al. 2020; Ben Saad and Assoumou-Ella 2019; Nguyen 2021).

fixed effects). When they study the relationship at the country level for the USA, they find that wage inequality increases with economic complexity.[7]

## 2.3 Arguments linking economic complexity and income inequality

In their discussion about the reasons why higher economic complexity may be negatively linked to lower income inequality, Hartmann et al. (2017) argue that the mix of products that an economy produces constrains the occupational choices, learning opportunities, and even bargaining power of workers and unions. Complex products tend to require a large degree of tacit knowledge and more distributed knowledge than products based on natural resource richness or low labour costs. More distributed knowledge and a large degree of tacit knowledge can enhance the incentives to unionize, boosting wage bargaining and compressing wage inequality. Moreover, this negative relationship between the degree of economic complexity and income inequality may be reinforced by the fact that the quality of institution is likely to co-evolve with the level of economic complexity of an economy. In sum, complex products require the development of a network of skilled workers, related industries, and inclusive institutions for economic growth, all factors that foster more equal societies. On the contrary simple industrial products are mainly associated with natural resource abundance, low labour costs, and routinized activities, all factors that characterize more unequal societies.

Increasing economic complexity entails the diversification of the economy and the incorporation of technology. The economy's production changes, the importance of products intensive in natural resources and low-skilled knowledge decreases, and the importance of those that require higher skills and are intensive in technology increases (Hidalgo and Hausman 2009). Understanding the process of economic complexity as a process of skill-biased technological change implies a positive relationship between economic complexity and income inequality, although the literature also proposes that, after a certain threshold of diversification, the relationship begins to be negative. After a certain level of economic complexity is achieved, the supply of highly educated workers may increase and counterbalance the effect of the increasing demand for skilled workers, thus lowering returns to education and income inequality.

Proponents of a positive relationship between economic complexity and income inequality mainly argue that, when economic structures become more complex, demand for qualified workers grows disproportionally. The emergence of new sectors which intensively use skilled workers and the destruction of more traditional sectors which tend to employ unskilled workers implies that economic complexity benefits skilled workers more than unskilled ones, exacerbating the income differentials of the country.

The third possibility, which is less explored in the literature, at least using cross-country approaches, underlines the existence of a non-linear relationship between economic complexity and income inequality. The argument for non-linearity in this link parallels, at least in some sense, the inverted U hypothesis proposed by Kuznets (1955) to link inequality and economic development. The intuition is that, when the levels of complexity of the economy are very low, increases in complexity mainly favour capital owners and highly skilled workers, leading to an increase in economic inequality. At higher levels of economic complexity, other forces such as inclusive institutions, rising job opportunities, and stronger unions may then become more

[7] Le et al. (2020) also provide evidence of an inverted U-shaped relationship between export diversification for a panel of countries.

important, turning the effect of economic complexity on income inequality negative from that threshold on (Bandeira Morais et al. 2021).

Even if the rationale for the relationship between complexity and inequality mainly responds to the skilled–unskilled tension, we must acknowledge that the concept of economic complexity may be also related to, or captures, a number of underlying factors which also influence the levels of income inequality within a country.

# 3 Methodological aspects

## 3.1 Methods

Our empirical strategy is based on the estimation of reduced form equations which try to identify the effects of changes in the productive structure, specifically in economic complexity as reflected by the ECI, on inequality (*Ineq*):

We estimate equation (9) using panel fixed effects regressions to control for time-invariant country characteristics:

$$Ineq_{it} = \alpha + \beta ECI_{it} + C_{it}\prod + \varepsilon_{it} \tag{9}$$

where C is a matrix that includes in its columns a set of control variables. The estimation of the causal effect of the productive structure on inequality (the coefficient β) would require an exogenous source of variation for each of the variables that are included in the regression, as all these factors are arguably endogenous to income inequality, as discussed earlier. This means that we will not be able to make any statement about causality, and our results should be interpreted as associations. In other words causality may be running from income inequality to economic complexity.

If the error term ε has a constant component by country that is correlated with inequality, typically unobservable features of the countries, simple OLS estimations would introduce omitted variable bias in the estimation. To handle this problem ε can be written as $\varepsilon_{it} = \eta_i + u_{it}$ and therefore the model can be rewritten as:

$$Ineq_{it} = \alpha_i + \beta PS_{it} + C_{it}\prod + \gamma_t + u_{it} \tag{10}$$

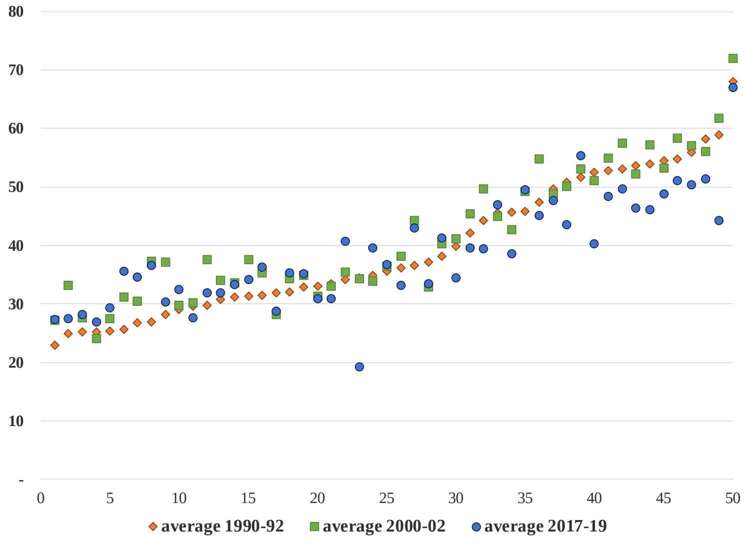
where $\alpha_i = \eta_i + \alpha$ and $u_{it} = \varepsilon_{it} - \eta_i$. This estimation strategy will yield consistent estimates of the coefficients of the model if there are no time-varying omitted variables that are correlated with both the explanatory variables and the dependent variable. We also explore the relevance of dynamic panel data estimations.

### 3.2 Data

To estimate equation (10) this paper combines data from different datasets to construct a macro panel for world countries in the period from 1995 to 2018. Data for income inequality comes from the World Income Inequality Database (WIID) of the United Nations University World Institute for Development Economics Research (UNU-WIDER 2021).[8] This dataset is based on an integrated inequality series which enables more consistent comparisons over time and across countries. It should be noted that this dataset has a wider coverage than others, with a richer representation of low-income countries and from regions with poorer data. Our main income inequality variable considers net per capita Gini, that is, the level of income inequality in the country net of taxes and transfers. For an alternative approach to the dynamics of the income distribution, we also consider the income share of the bottom 5 per cent and top 5 per cent of the population, also included in the WIID database. Finally, to test whether the results are sensitive to the use of different inequality data, we also considered Gini coefficient estimates from the Estimated Household Income Inequality Data Set (EHII), taken from UTIP-UNIDO.[9]

Inequality data from the WIID shows a general pattern of an increase in national inequality levels around the world between the 1995s and the 2000s, although the results are mixed in the last decade (Figure 1). Countries with a higher level of inequality at the beginning of the period tend to show a decrease in inequality levels, at least as reflected by these Gini coefficients, whereas for lower inequality countries more recent Gini coefficients are above those at the beginning of the period.

Figure 1: Evolution of Gini coefficient around the world, 1995–2019




Source: authors' compilation based on data from the WIID companion dataset (UNU-WIDER 2021).

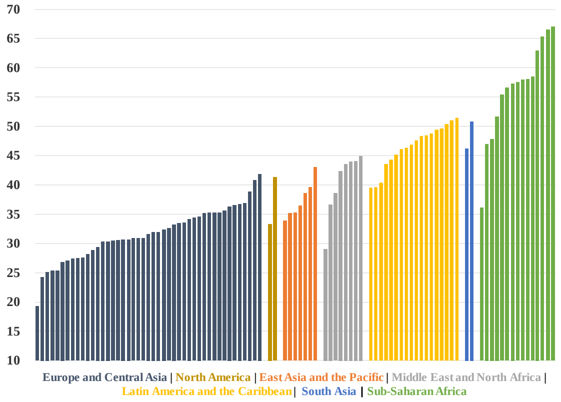
Other relevant patterns when considering WIID inequality data are the important heterogeneities by region and the presence of certain homogeneity within regions when considering national levels of inequality (Figure 2). The most recent available data indicates that countries from Europe and

[8] The WIID was first launched in 2000, giving continuity to one of the first, most successful initiatives to collect cross-country information of inequality by Deininger and Squire (1996) (Gradín and Oppel 2021). The most recent version is from June 2022. We use the May 2021 version of the companion dataset: https://doi.org/10.35188/UNU-WIDER/WIIDcomp-310521.

[9] See UTIP (n.d.).

Central Asia show lower levels of inequality, whereas countries from sub-Saharan Africa, followed by Latin American countries, present the highest levels of inequality.

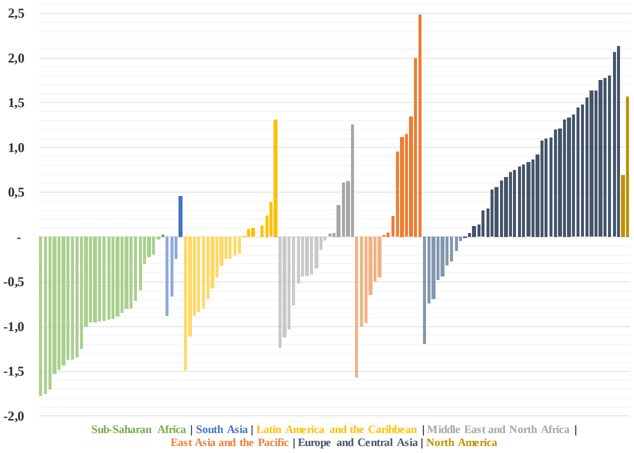
Figure 2: Gini coefficients by region




Source: authors' compilation based on data from the WIID companion dataset (UNU-WIDER 2021).

Our other main variable is the ECI, described in the previous section, which reflects the sophistication of a country's productive structure, that is, economic complexity. The data used in this study is taken from the Atlas of Economic Complexity, elaborated by the Growth Lab at Harvard University (n.d.). As discussed, the measure combines information on the diversity of a country (the number of products it exports) and the ubiquity of its products (the number of countries that export that product). More sophisticated economies are diverse and export products that, on average, have low ubiquity because only a few countries can make these sophisticated products. As Figure 3 shows, economies from sub-Saharan Africa, South Asia, and a major part of Latin America exhibit lower levels of economic complexity. More complex economies (whose index reaches 1.5 or more) belong to East Asia and the Pacific, as well as some European countries and the USA.

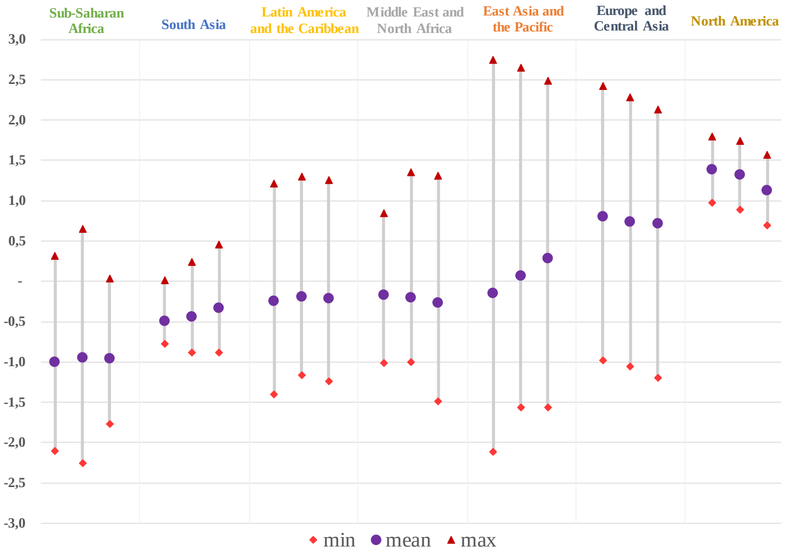
Figure 3: Economic Complexity Index by country-region, 2019




Source: authors' compilation based on data from the Growth Lab at Harvard University (n.d.).

Additionally, most relevant increases in the ECI in the last decades took place in East Asia and the Pacific, as well as South Asia. In sub-Saharan Africa, Latin America, Europe, and Central Asia, the ECI showed important stability, and North America showed a decline in the index (Figure 4).

Figure 4: Changes in the Economic Complexity Index by region (1995, 2005, 2019)



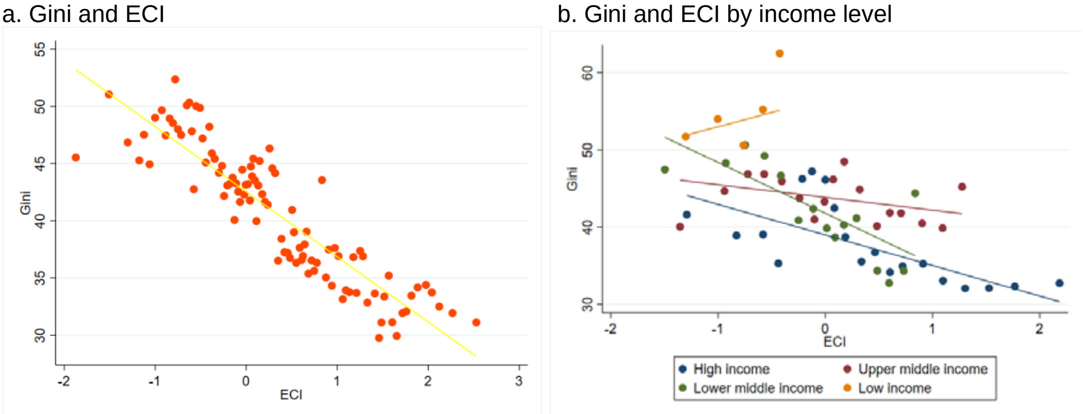

Source: authors' compilation based on data from the Growth Lab at Harvard University (n.d.).

A first descriptive analysis of the link between economic complexity and income inequality is presented in the scatterplots in Figure 5. Panel a. shows a strong relative correlation between the Gini index and the ECI, considering aggregated cross-sectional data. However, when the linkage is analysed by region (panel b.), it emerges that in low-income countries the correlation appears to be positive. This first descriptive evidence is suggestive of heterogeneous patterns at the global level and motivates our econometric analysis.

Figure 5: Gini index and ECI

a. Gini and ECI

b. Gini and ECI by income level




Source: authors' compilation based on data from the WIID companion dataset (UNU-WIDER 2021) and the Growth Lab at Harvard University (n.d.).

Following the related literature, the control variables in our econometric analysis include per capita GDP and other macroeconomic and socioeconomic conditions such as population, school enrolment at the tertiary level, terms of trade, informality, and government consumption.[10] We also include a set of institutional factors contained in the World Bank's Worldwide Governance

[10] We also considered the share of informal employment in total employment as reported by the International Labour Organization among the control variables. But the limited availability of data led to the loss of numerous observations, weakening the econometric approach.

Indicators. These factors cover voice and accountability, political stability and absence of violence/terrorism, government effectiveness, regulatory quality, rule of law, and control of corruption. Details for our main variables are presented in Table A1 in the Appendix.

## 4 Results

In this section we present the results, exploring whether changes in a country's level of economic complexity are linked to changes in its income inequality, in the framework of country fixed effects panel regressions. Several versions of the results from the estimation of equation (10), which differ by the variables included as controls, are presented in Table 1. Our basic model (column 1) shows a positive and statistically significant influence of economic complexity and a negative effect of GDP on inequality. This result suggests that a more complex economic structure increases income inequality, contrary to the results obtained by Hartmann et al. (2017) but in line with those in Chu and Hoang (2020) and in Lee and Vu (2019) (under different estimation techniques).

Columns (2–5) of Table 1 show the results when a set of control variables are successively added. When the set of control variables used by Hartmann et al. (2017) are added (see column 2), the magnitude of the coefficient of complexity index moderates but maintains its significance and positive effect on inequality. This result substantively differs from the negative link found by Hartmann and co-authors between the ECI and income inequality. Moreover, in contrast to the results of Hartmann et al. (2017), GDP per capita is not significant, population influence is negative, and the corruption control variable is significant (at a 10 per cent significance level), with the expected negative sign. The different set of countries used by Hartmann et al. (2017) and the fact that they average the values of the Gini index by decade may explain our contrasting results. These results also warn us about the sensitivity of the estimations to the periods, variables, and countries considered, and underscore the importance of generating evidence to better understand the link between the productive structure and inequality.

Column 3 of Table 1 presents the estimate of our base equation adding the control variables used by Chu and Hoang (2020). In this estimation the complexity indicator loses its significance in explaining inequality. Neither GDP per capita nor its square is significant, contrary to the results reported by these authors. The control variables that are significant in our estimation are institutions (the aggregate measure of governance indicators, see Table A1) and trade as a percentage of GDP. Both variables have a positive influence on income inequality, a result also found by Chu and Hoang (2020).

The last two columns of Table 1 show the basic equation when informality (measured by the informal output as a percentage of GDP) is included (column 4), and when institutions and trade are also added as control variables (column 5). In both estimations economic complexity keeps the positive and significant effect on inequality found in our base model (column 1). The negative influence (reducing effect) of GDP per capita growth on inequality is also maintained. Informality, measured through its weight in GDP, is significant and presents the expected positive sign in both equations (at the 10 per cent or 5 per cent level of significance, respectively). Moreover, the control variables related to institutions and trade (included in the estimation in column 5) are also significant, as found by Chu and Hoang (2020).

Table 1: Fixed effects estimation results

| VARIABLES | (1) Basic | (2) Hartmann controls | (3) Chu & Hoang controls | (4) Informality | (5) Complete |
|---|---|---|---|---|---|
| ECI | 1.909 | 1.610 | 0.641 | 2.131 | 1.806 |
| | [0.745]** | [0.649]** | [0.710] | [0.732]*** | [0.685]*** |
| GDP (per capita, log) | -3.864 | 9.127 | 11.21 | -2.045 | -3.000 |
| | [1.029]*** | [9.603] | [14.07] | [1.374] | [1.558]* |
| GDP2 | | -0.681 | -0.793 | | |
| | | [0.502] | [0.735] | | |
| Population(log) | | -7.593 | | | |
| | | [2.399]*** | | | |
| Rule of law | | 2.361 | | | |
| | | [1.392]* | | | |
| Control of corruption | | -0.152 | | | |
| | | [0.907] | | | |
| Government effectiveness | | -0.819 | | | |
| | | [0.905] | | | |
| Political stability & absence of violence/terrorism | | -0.551 | | | |
| | | [0.530] | | | |
| Regulatory quality | | 0.121 | | | |
| | | [0.776] | | | |
| Voice & accountability | | 0.637 | | | |
| | | [1.054] | | | |
| Institutions | | | 2.301 | | 2.147 |
| | | | [1.082]** | | [0.935]** |
| Institutions2 | | | -0.374 | | |
| | | | [0.682] | | |
| School enrolment, tertiary (% gross) | | | -0.0140 | | |
| | | | [0.0168] | | |
| Government consumption (% of GDP) | | | -0.115 | | |
| | | | [0.0874] | | |
| Trade (% of GDP) | | | 0.0208 | | 0.0197 |
| | | | [0.0103]** | | [0.0106]* |
| Informality (%GDP) | | | | 0.272 | 0.307 |
| | | | | [0.147]* | [0.152]** |
| Constant | 77.11 | 140.8 | 5.745 | 51.49 | 57.50 |
| | [9.860]*** | [54.05]** | [67.05] | [16.67]*** | [18.36]*** |
| Observations | 1,306 | 1,125 | 852 | 1,306 | 1,102 |
| R-squared | 0.127 | 0.219 | 0.132 | 0.149 | 0.206 |
| Number of countries | 126 | 126 | 111 | 126 | 123 |
| Log likelihood | 1 | 9 | 7 | 2 | 4 |

Note: robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Source: authors' estimations.

We further explore this positive link between inequality and economic complexity, considering whether the ECI has differential effects at the top and at the bottom of the distribution of income. Instead of considering the Gini as the independent variable, we consider the share of income captured by the bottom 5 per cent of the population (according to the prevailing income distribution in that country) and the share of income captured by the top 5 per cent of the population. Increases in economic complexity have a negative impact on the share of income that goes to the population at the bottom of the income distribution, whereas, as the ECI increases, the share of income captured by the top 5 per cent of the population also increases (Table A2 in the Appendix). These results help us to understand the inequality enhancing effect of increases in the ECI at the global level through the impact on the upper and lower parts of the distribution.

While the evidence presented in Table 1 suggests that having a more complex production structure makes the economy more unequal, the disaggregated estimates evidence differences between high-income and non-high-income countries (Table 2).

For high-income economies neither complexity nor GDP presents significant coefficients, except for the estimate that includes the Hartmann et al. (2017) control variables (column 2). It is worth noting that for the set of estimations for high-income countries the coefficients of the complexity indicator are always negative, showing that higher levels of complexity are associated with lower levels of inequality (similarly to Hartmann's findings). For this set of countries informality plays a key role in explaining inequality rises (columns 4–5).

In contrast, for non-high-income countries, both the ECI and GDP growth have a significant effect in most estimations, as in the overall estimate. Increases in complexity are associated with increases in inequality and increases in GDP reduce inequality (columns 6 to 10). This pattern is predominant for the aggregated estimations presented earlier (Table 1). In turn, for this group of countries, informality loses significance in explaining inequality (columns 9–10).

Finally, for both high- and non-high-income countries, institutions exhibit a significant and positive coefficient, as in the joint estimation (of Table 1). In sum, desegregated estimations suggest that our overall results are strongly influenced by those found for non-high-income countries and that for high-income countries.

Table 2: Fixed effects estimation results, high-income countries and non-high-income countries

| | (1) Basic | (2) Hartmann controls | (3) Chu & Hoang controls | (4) Informality | (5) Complete | (6) Basic | (7) Hartmann controls | (8) Chu & Hoang controls | (9) Informality | (10) Complete |
|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | High-income countries | | | | | Non-high-income countries | | | | |
| ECI | -0.906 | -1.441 | -1.280 | -0.391 | -0.287 | 2.567 | 2.171 | 0.580 | 2.730 | 2.328 |
| | [1.143] | [0.789]* | [1.201] | [0.989] | [0.896] | [0.910]*** | [0.872]** | [0.883] | [0.905]*** | [0.909]** |
| GDP (per capita, log) | -0.475 | 2.092 | 47.99 | 1.981 | -0.598 | -4.701 | 30.55 | 28.69 | -3.209 | -3.554 |
| | [1.696] | [34.09] | [31.94] | [1.896] | [2.461] | [1.225]*** | [12.95]** | [22.85] | [1.593]** | [1.840]* |
| GDP2 | | -0.192 | -2.554 | | | | -1.891 | -1.714 | | |
| | | [1.645] | [1.529] | | | | [0.718]** | [1.256] | | |
| Population(log) | | -8.678 | | | | | -9.253 | | | |
| | | [2.644]*** | | | | | [3.278]*** | | | |
| Rule of law | | 2.632 | | | | | 1.805 | | | |
| | | [1.181]** | | | | | [1.901] | | | |
| Control of corruption | | -1.020 | | | | | 0.476 | | | |
| | | [0.815] | | | | | [1.260] | | | |
| Government effectiveness | | 0.0841 | | | | | -0.488 | | | |
| | | [1.145] | | | | | [1.222] | | | |
| Political stability & absence of violence/terrorism | | -0.115 | | | | | -0.493 | | | |
| | | [0.384] | | | | | [0.638] | | | |
| Regulatory quality | | 0.858 | | | | | -0.370 | | | |
| | | [1.098] | | | | | [0.969] | | | |
| Voice & accountability | | -0.156 | | | | | 0.399 | | | |
| | | [1.169] | | | | | [1.183] | | | |
| Institutions | | | 7.461 | | 2.469 | | | 1.328 | | 2.175 |
| | | | [2.224]*** | | [1.158]** | | | [1.637] | | [1.172]* |
| Institutions2 | | | -2.585 | | | | | -0.936 | | |
| | | | [1.178]** | | | | | [1.450] | | |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| School enrolment, tertiary (% gross) | | | 0.0119 | | | | | -0.0588 | | |
| | | | [0.0170] | | | | | [0.0318]* | | |
| Government consumption (% of GDP) | | | -0.111 | | | | | -0.121 | | |
| | | | [0.117] | | | | | [0.107] | | |
| Trade (% of GDP) | | | 0.0179 | | 0.0137 | | | 0.00956 | | 0.0163 |
| | | | [0.0113] | | [0.0125] | | | [0.0175] | | [0.0163] |
| Informality (%GDP) | | | | 0.417 | 0.351 | | | | 0.216 | 0.279 |
| | | | | [0.184]** | [0.191]* | | | | [0.164] | [0.178] |
| Constant | 40.71 | 173.3 | -191.0 | 5.602 | 29.99 | 87.42 | 79.62 | -71.17 | 66.35 | 66.63 |
| | [18.05]** | [196.8] | [165.6] | [22.83] | [28.38] | [10.97]*** | [68.27] | [103.1] | [18.73]*** | [21.42]*** |
| Observations | 522 | 457 | 396 | 522 | 457 | 784 | 668 | 456 | 784 | 645 |
| R-squared | 0.013 | 0.171 | 0.141 | 0.068 | 0.118 | 0.189 | 0.277 | 0.210 | 0.203 | 0.242 |
| Number of countries | 45 | 45 | 41 | 45 | 45 | 81 | 81 | 70 | 81 | 78 |
| Log likelihood | 1 | 9 | 7 | 2 | 4 | 1 | 9 | 7 | 2 | 4 |

Note: robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Source: authors' estimations.

## 4.1 On the non-linear effect of complexity on inequality

To test the hypothesis of non-linearity in the relationship between the complexity of the production structure and inequality in countries, we propose two approaches that attempt to capture these effects.

First, we include the quadratic term of the complexity indicator (Table 3). The negative sign of the estimated coefficient for the quadratic term of ECI (in the base model column 1), significant for estimations (1) and (4), suggests that, while the influence of increases in complexity on inequality is positive, this positive effect disappears as levels of complexity reach a certain threshold. This resembles the inverted U pattern of the link between inequality and development proposed by Kuznets. In our case these results indicate that, for lower levels of economic complexity, increases in ECI are inequality enhancing. This happens up to a certain point: once economies reach a certain level of economic complexity, subsequent increases in complexity lead to lower inequality. In the base model, the influence of GDP growth remains positive and significant. The same is not valid for the equation which includes informality that is significant and positive. In this estimation, the quadratic term is significant (at 10 per cent) but GDP growth is not. In the remaining estimates the quadratic term is not significant.

Table 3: Fixed effects estimation results, non-linear estimations

| VARIABLES | (1) Basic | (2) Hartmann controls | (3) Chu & Hoang controls | (4) Informality | (5) Complete |
|---|---|---|---|---|---|
| ECI | 2.005 | 1.673 | 0.495 | 2.233 | 1.867 |
| | [0.745]*** | [0.685]** | [0.708] | [0.724]*** | [0.697]*** |
| ECI2 | -0.569 | -0.319 | 0.291 | -0.587 | -0.263 |
| | [0.318]* | [0.321] | [0.337] | [0.304]* | [0.290] |
| GDP (per capita, log) | -3.707 | 9.243 | 11.00 | -1.866 | -2.906 |
| | [1.020]*** | [9.668] | [13.90] | [1.422] | [1.593]* |
| GDP2 | | -0.680 | -0.787 | | |
| | | [0.506] | [0.728] | | |
| Population(log) | | -7.802 | | | |
| | | [2.432]*** | | | |
| Rule of law | | 2.240 | | | |
| | | [1.382] | | | |
| Control of corruption | | -0.105 | | | |
| | | [0.911] | | | |
| Government effectiveness | | -0.764 | | | |
| | | [0.899] | | | |
| Political stability & absence of violence/terrorism | | -0.528 | | | |
| | | [0.530] | | | |
| Regulatory quality | | 0.0724 | | | |
| | | [0.784] | | | |
| Voice & accountability | | 0.548 | | | |
| | | [1.061] | | | |
| Institutions | | | 2.337 | | 2.076 |
| | | | [1.081]** | | [0.929]** |
| Institutions2 | | | -0.492 | | |
| | | | [0.711] | | |
| School enrolment, tertiary (% gross) | | | -0.0139 | | |

| | | | | | |
|---|---|---|---|---|---|
| | | | [0.0168] | | |
| Government consumption (% of GDP) | | | -0.119 | | |
| | | | [0.0873] | | |
| Trade (% of GDP) | | | 0.0209 | | 0.0193 |
| | | | [0.0102]** | | [0.0107]* |
| Informality (%GDP) | | | | 0.274 | 0.307 |
| | | | | [0.146]* | [0.152]** |
| Constant | 76.12 | 143.4 | 7.221 | 50.22 | 56.88 |
| | [9.847]*** | [54.71]*** | [66.13] | [17.12]*** | [18.67]*** |
| Observations | 1,306 | 1,125 | 852 | 1,306 | 1,102 |
| R-squared | 0.133 | 0.221 | 0.133 | 0.156 | 0.207 |
| Number of countries | 126 | 126 | 111 | 126 | 123 |
| Log likelihood | 2 | 10 | 8 | 3 | 5 |

Note: robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Source: authors' estimations.

We are aware that some explanatory variables in the estimated models may not be exogenous or predetermined. To solve the possible endogeneity problem, we take the first lags of the regressors (instead of considering them contemporaneously).

The first set of results in Table 4 (columns 1–3) correspond to the estimation of three linear models (with differences in their control variables). The second set of results (columns 4–6) incorporate the quadratic term of the ECI (in each of the above specifications) to capture the non-linear effect of complexity on inequality.

The results (for the linear models) are similar to those found when regressors are considered contemporaneously. Once again a positive effect of complexity on inequality levels and a negative effect of economic growth can be noted.

In turn informality loses significance while the control variables trade and institutions preserve it. The quadratic term of the ECI is not significant in any of the equations, ruling out this form of non-linearity when considering these specifications (which seek to avoid contemporary reverse causality). It is important to note that the introduction of lags implies a significant decrease in the sample size, which could affect the power of the estimates. The exploration of the endogeneity between economic complexity and income inequality is open for future research.

Table 4: Fixed effects estimation results with lagged regressors

| VARIABLES | (1) Basic | (2) Informality | (3) Complete | (4) Basic | (5) Informality | (6) Complete |
|---|---|---|---|---|---|---|
| ECI = L, | 2.193 | 2.354 | 1.812 | 2.247 | 2.405 | 1.767 |
| | [1.028]** | [1.025]** | [0.902]** | [1.064]** | [1.053]** | [0.895]* |
| Informality = L, | | 0.238 | 0.262 | | 0.237 | 0.263 |
| | | [0.242] | [0.225] | | [0.240] | [0.225] |
| GDP Log = L, | -3.733 | -2.319 | -3.411 | -3.670 | -2.264 | -3.473 |
| | [1.400]*** | [1.844] | [1.828]* | [1.382]*** | [1.889] | [1.846]* |
| Institutions= L, | | | 2.680 | | | 2.714 |
| | | | [1.505]* | | | [1.501]* |
| Trade (% of GDP) = L, | | | 0.0194 | | | 0.0198 |
| | | | [0.0142] | | | [0.0146] |

| | | | | | | |
|---|---|---|---|---|---|---|
| ECI2 = L | | | | -0.187 | -0.175 | 0.166 |
| | | | | [0.534] | [0.507] | [0.431] |
| Constant | 74.38 | 53.45 | 61.15 | 73.92 | 53.06 | 61.56 |
| | [13.69]*** | [23.68]** | [22.44]*** | [13.56]*** | [24.05]** | [22.53]*** |
| Observations | 760 | 760 | 677 | 760 | 760 | 677 |
| R-squared | 0.127 | 0.141 | 0.192 | 0.127 | 0.142 | 0.192 |
| Number of countries | 74 | 74 | 72 | 74 | 74 | 72 |
| Log likelihood | 1 | 2 | 4 | 2 | 3 | 5 |

Note: robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Source: authors' estimations.

## 5 Final comments

This paper argues that the relationship between economic complexity and income inequality is not homogenous across countries. Contrary to previous evidence, we find that the general pattern suggests a positive link, meaning that increases in economic complexity are globally inequality enhancing.

Previous evidence which indicated that economic complexity was a good predictor of lower income inequality seems to have been driven by a group of high-income countries or countries which had already reached a certain stage of complexity in their economies. From a certain point on, higher complexity is associated with lower income inequality. But on the way to this threshold of high economic complexity, the process of generating sophisticated economic structures is accompanied by increases in income inequality.

The reasons behind this link are difficult to disentangle and remain a challenge for future research, but simplistic explanations based on blind trust in the incorporation of technology do not help us to understand the real determinants of inequality. Exploration of the association between an increase in economic complexity and the demand for higher skills could be a fruitful future research direction to understand the links between inequality and complexity. The role of services in this process, which is blurred due to data weaknesses, should also be further explored to help with understanding how the productive knowledge embedded in a country's economy affects its levels of inequality.

## References

Anderson, C. (2008). 'The End of Theory: The Data Deluge Makes the Scientific Method Obsolete'. *Wired Magazine*, 16(7): 16–07.

Andersson, M., and A. Palacio (2016). 'Structural Change and Income Inequality: Agricultural Development and Inter-sectoral Dualism in the Developing World, 1960-2010'. *Oasis*, (23): 99–122.

Andersson, M., and A. Palacio (2017). 'Structural Change and the Fall of Income Inequality in Latin America: Agricultural Development, Inter-sectoral Duality and the Kuznetz Curve'. In L. Bértola and J. Williamson (eds), *Has Latin American Inequality Changed Direction? Looking Over the Long Run*. Cham: Springer Nature. https://doi.org/10.1007/978-3-319-44621-9_15

Balassa, B. (1965). 'Trade Liberalization and "Revealed" Comparative Advantage'. *The Manchester School*, 33(2): 99–123. https://doi.org/10.1111/j.1467-9957.1965.tb00050.x

Bandeira Morais, M., J. Swart, and J.A. Jordaan (2021). 'Economic Complexity and Inequality: Does Regional Productive Structure Affect Income Inequality in Brazilian States?'. *Sustainability*, 13(2): 1006. https://doi.org/10.3390/su13021006

Barza, R., C. Jara-Figueroa, C. Hidalgo, and M. Viarengo (2020). 'Knowledge Intensity and Gender Wage Gaps: Evidence from Linked Employer-Employee Data'. CESifo Working Paper 8543. Munich: CESifo. https://doi.org/10.2139/ssrn.3689464

Baymul, C., and K. Sen (2020). 'Was Kuznets Right? New Evidence on the Relationship between Structural Transformation and Inequality'. *The Journal of Development Studies*, 56(9): 1643–62. https://doi.org/10.1080/00220388.2019.1702161

Ben Saâd, M., and G. Assoumou-Ella (2019). 'Economic Complexity and Gender Inequality in Education: An Empirical Study'. *Economics Bulletin*, 39: 321–34.

Buera, F., J. Kaboski, R. Rogerson, and J. Vizcaino (2022). 'Skill Biased Structural Change'. *The Review of Economic Studies*, 89(2): 592–625. https://doi.org/10.1093/restud/rdab035

Chu, L.K., and D.P. Hoang (2020). 'How Does Economic Complexity Influence Income Inequality? New Evidence from International Data'. *Economic Analysis and Policy*, 68: 44–57. https://doi.org/10.1016/j.eap.2020.08.004

Ciaschi, M., L. Galeano, and L. Gasparini (2021). 'Estructura productiva y desigualdad salarial: evidencia para América Latina'. *El Trimestre Económico*, LXXXVIII (1)349: 77–106. https://doi.org/10.20430/ete.v88i349.1078

Cristelli, M., A. Gabrielli, A. Tacchella, G. Caldarelli, and L. Pietronero (2013). 'Measuring the Intangibles: A Metrics for the Economic Complexity of Countries and Products'. *PloS ONE*, 8(8): e70726. https://doi.org/10.1371/journal.pone.0070726

Deininger, K., and L. Squire (1996). 'A New Data Set Measuring Income Inequality'. *The World Bank Economic Review*, 10(3): 565–91. https://doi.org/10.1093/wber/10.3.565

Elgin, C., M. Kose, F. Ohnsorge, and S. Yu (eds) (2021). 'DP16497 Understanding Informality'. CEPR Press Discussion Paper. 16497. Available at: https://cepr.org/publications/dp16497 (accessed 19 January 2023).

Fawaz, F., and M. Rahnama-Moghadamm (2019). 'Spatial Dependence of Global Income Inequality: The Role of Economic Complexity'. *The International Trade Journal*, 33(6): 542–54. https://doi.org/10.1080/08853908.2018.1535336

Gao, J., and T. Zhou (2018). 'Quantifying China's Regional Economic Complexity'. *Physica A: Statistical Mechanics and its Applications*, 492: 1591–603. https://doi.org/10.1016/j.physa.2017.11.084

Gradín, C., and A. Oppel (2021). 'Trends in Inequality Within Countries Using a Novel Dataset'. WIDER Working Paper 2021/139. Helsinki: UNU-WIDER. https://doi.org/10.35188/UNU-WIDER/2021/079-5

Growth Lab at Harvard University (n.d.). 'The Atlas of Economic Complexity'. Cambridge, MA: Growth Lab at Harvard University. Available at: https://atlas.cid.harvard.edu/ (accessed June 2022).

Hartmann, D., M.R. Guevara, C. Jara-Figueroa, M. Aristarán, and C. Hidalgo (2017). 'Linking Economic Complexity, Institutions, and Income Inequality'. *World Development*, 93: 75–93. https://doi.org/10.1016/j.worlddev.2016.12.020

Hartmann, D., C. Jara-Figueroa, M. Guevara, A. Simoes, and C. Hidalgo (2016). 'The Structural Constraints of Income Inequality in Latin America'. *Integration and Trade Journal*, 40: 70–85.

Hartmann, D, and F. Pinheiro (2022). 'Economic Complexity and Inequality at the National and Regional Level'. Paper prepared as a chapter for *The Handbook of Complexity Economics*, edited by P. Chen, W. Elsner, and A. Pyka. Available at: https://arxiv.org/ftp/arxiv/papers/2206/2206.00818.pdf (accessed 3 January 2023).

Hausmann, R., C.A. Hidalgo, S. Bustos, M. Coscia, A. Simoes, and M.A. Yildirim (2014). *The Atlas of Economic Complexity: Mapping Paths to Prosperity*. Cambridge, MA: MIT Press. https://doi.org/10.7551/mitpress/9647.001.0001

Hausmann, R., J. Hwang, and D. Rodrik (2007). 'What You Export Matters'. *Journal of Economic Growth*, 12(1): 1–25. https://doi.org/10.1007/s10887-006-9009-4

Hidalgo, C.A., and R. Hausmann (2009). 'The Building Blocks of Economic Complexity'. *Proceedings of the National Academy of Sciences*, 106(26): 10570–75. https://doi.org/10.1073/pnas.0900943106

Kuznets, S. (1955). 'Economic Growth and Income Inequality'. *American Economic Review*, 45: 1–28.

Le, T.H, C. Nguyen, T. Su, and B. Tran-Nam (2020). 'The Kuznets Curve for Export Diversification and Income Inequality: Evidence from a Global Sample'. *Economic Analysis and Policy*, 65: 21–39. https://doi.org/10.1016/j.eap.2019.11.004

Le Caous, E., and F. Huarng (2020). 'Economic Complexity and the Mediating Effects of Income Inequality: Reaching Sustainable Development in Developing Countries'. *Sustainability*, 12(5): 2089. https://doi.org/10.3390/su12052089

Lee, K.-K., and T.V. Vu (2019). 'Economic Complexity, Human Capital and Income Inequality: A Cross-country Analysis'. *Japan Economic Review*, 71: 695–718. https://doi.org/10.1007/s42973-019-00026-7

Martorano, B., and M. Sanfilippo (2015). 'Structural Change and Wage Inequality in the Manufacturing Sector: Long Run Evidence from East Asia'. *Oxford Development Studies*, 43(2): 212–31. https://doi.org/10.1080/13600818.2015.1028914

Mishra, S., S. Lundström, and R. Anand (2011). 'Service Export Sophistication and Economic Growth'. World Bank Policy Research Working Paper 5606. Washington, DC: World Bank. https://doi.org/10.1596/1813-9450-5606

Ngai, R., and B. Petrongolo (2014). 'Gender Gaps and the Rise of the Service Economy'. *American Economic Journal: Macroeconomics*, 9(4): 1–44.

Nguyen, C.P. (2021). 'Gender Equality and Economic Complexity'. *Economic Systems*, 45(4). https://doi.org/10.1016/j.ecosys.2021.100921

Pugliese, E., G. Cimini, A. Patelli, A. Zaccaria, L. Pietronero, and A. Gabrielli (2019). 'Unfolding the Innovation System for the Development of Countries: Coevolution of Science, Technology and Production'. *Scientific Reports*, 9(1): 1–12. https://doi.org/10.1038/s41598-019-52767-5

Rendall, W. (2013). 'Structural Change in Developing Countries: Has It Decreased Gender Inequality?'. *World Development*, 45: 1–16. https://doi.org/10.1016/j.worlddev.2012.10.005

Salinas, G. (2021). 'Proximity and Horizontal Policies: The Backbone of Export Diversification and Complexity'. IMF Working Paper WP/21/64. Washington, DC: International Monetary Fund. https://doi.org/10.5089/9781513571614.001

Sbardella, A., E. Pugliese, and L. Pietronero (2017). 'Economic Development and Wage Inequality: A Complex System Analysis'. *PloS ONE*, 12(9): e0182774. https://doi.org/10.1371/journal.pone.0182774

Sciarra, C., G. Chiarotti, L. Ridolfi, and F. Laio (2020). 'Reconciling Contrasting Views on Economic Complexity'. *Nature Communications*, 11(1): 1–10. https://doi.org/10.1038/s41467-020-16992-1

Stojkoski, V., Z. Utkovski, and L. Kocarev (2016). 'The Impact of Services on Economic Complexity: Service Sophistication as Route for Economic Growth'. *PloS ONE*, 11(8): e0161633. https://doi.org/10.1371/journal.pone.0161633

Tacchella, A., M. Cristelli, G. Caldarelli, A. Gabrielli, and L. Pietronero (2012). 'A New Metrics for Countries' Fitness and Products' Complexity'. *Scientific Reports*, 2(1): 1–7. https://doi.org/10.1038/srep00723

UNU-WIDER (2021). 'World Income Inequality Database (WIID) Companion dataset (wiidcountry and/or wiidglobal)'. Version 31 May 2021. Helsinki: UNU-WIDER. https://doi.org/10.35188/UNU-WIDER/WIIDcomp-310521

UTIP (n.d.). 'Estimated Household Income Inequality Data Set (EHII)'. Austin, TX: University of Texas Inequality Project. Available at: https://utip.gov.utexas.edu/datasets.html (accessed 6 January 2023).

Zaccaria, A., S. Mishra, M.Z. Cader, and L. Pietronero (2018). 'Integrating Services in the Economic Fitness Approach'. World Bank Policy Research Working Paper 8485. Washington, DC: World Bank.

## Appendix

Table A1: Variables included in the estimations

| Variable name | Description | Source | # Countries | # Observations |
|---|---|---|---|---|
| Gini | Standardized series of the per capita net income distribution | UNU-WIDER | 195 | 1,580 |
| ECI | Economic Complexity Index | The Growth Lab at Harvard University. The Atlas of Economic Complexity | | |
| GDP | Per capita mean income (gross domestic product); 2017 purchasing power parity USD | UNU-WIDER | 190 | 1,555 |
| Population | Total population | UNU-WIDER | 195 | 1,580 |
| Bottom 5 | Income share of the bottom 5% (between percentiles 1 and 5) | UNU-WIDER | 186 | 1,501 |
| Top 5 | Income share of the top 5% (between percentiles 96 and 100) | UNU-WIDER | 186 | 1,501 |
| Informality (% GDP) | Includes both model-based (dynamic general equilibrium model) and survey-based estimates of informal output (% of official GDP). | Elgin et al. (2021) World Bank | 156 | 3,704 |
| Worldwide Governance Indicators | Aggregate (Inst) and individual governance indicators for six dimensions: voice and accountability; political stability and absence of violence/terrorism; government effectiveness; regulatory quality; rule of law; control of corruption | World Bank | 214 | 4,185 |
| School enrolment, tertiary (% gross) | Ratio of total enrolment, regardless of age, to the population of the age group that officially corresponds to tertiary education. | World Bank | 192 | 2,911 |
| Trade (% GDP) | Sum of exports and imports of goods and services measured as a share of gross domestic product. | World Bank | 195 | 4,271 |
| General government final consumption expenditure (% GDP) | All government current expenditures for purchases of goods and services (including compensation of employees) | World Bank | 186 | 4,046 |

Source: authors' own elaboration.

Table A2: Fixed effects estimation results, income share of lower and upper ventiles

| | Income share bottom 5% | | | | | Income share top 5% | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| VARIABLES | Basic | Hartmann | Chu & Hoang | Informality | Complete | Basic | Hartmann | Chu & Hoang | Informality | Complete |
| ECI | -0.351 | -0.307 | 0.0194 | -0.360 | -0.237 | 0.503 | 0.407 | -0.210 | 0.612 | 0.415 |
| | [0.172]** | [0.167]* | [0.180] | [0.185]* | [0.167] | [0.261]* | [0.268] | [0.314] | [0.266]** | [0.264] |
| GDP (per capita, log) | 1.041 | -1.773 | -0.0120 | 0.987 | 1.437 | -1.780 | 0.623 | -3.460 | -1.077 | -1.631 |
| | [0.305]*** | [2.622] | [4.146] | [0.412]** | [0.434]*** | [0.457]*** | [3.971] | [6.122] | [0.685] | [0.716]** |
| GDP2 | | 0.150 | 0.0636 | | | | -0.127 | 0.0819 | | |
| | | [0.137] | [0.216] | | | | [0.207] | [0.320] | | |
| Population(log) | | 1.116 | | | | | -2.204 | | | |
| | | [0.709] | | | | | [1.110]** | | | |
| Rule of law | | -0.531 | | | | | 0.837 | | | |
| | | [0.261]** | | | | | [0.514] | | | |
| Control of corruption | | -0.00879 | | | | | 0.309 | | | |
| | | [0.230] | | | | | [0.355] | | | |
| Government effectiveness | | 0.148 | | | | | -0.328 | | | |
| | | [0.192] | | | | | [0.346] | | | |
| Political stability & absence of violence/terrorism | | 0.0596 | | | | | -0.0107 | | | |
| | | [0.131] | | | | | [0.197] | | | |
| Regulatory quality | | 0.0831 | | | | | -0.162 | | | |
| | | [0.237] | | | | | [0.329] | | | |
| Voice & accountability | | -0.107 | | | | | 0.156 | | | |
| | | [0.275] | | | | | [0.393] | | | |
| Institutions | | | -0.575 | | -0.525 | | | 1.293 | | 1.081 |
| | | | [0.308]* | | [0.261]** | | | [0.463]*** | | [0.384]*** |
| Institutions2 | | | 0.194 | | | | | -0.201 | | |
| | | | [0.212] | | | | | [0.330] | | |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| School enrolment, tertiary (% gross) | | | 0.00231 | | | | | -0.00530 | | |
| | | | [0.00428] | | | | | [0.00686] | | |
| Government consumption (% of GDP) | | | 0.0261 | | | | | -0.0329 | | |
| | | | [0.0254] | | | | | [0.0360] | | |
| Trade (% of GDP) | | | -0.00497 | | -0.00603 | | | 0.00470 | | 0.00629 |
| | | | [0.00362] | | [0.00349]* | | | [0.00463] | | [0.00492] |
| Informality (%GDP) | | | | -0.00762 | 0.00190 | | | | 0.0986 | 0.102 |
| | | | | [0.0436] | [0.0428] | | | | [0.0623] | [0.0620] |
| Constant | -4.251 | -9.480 | 0.0490 | -3.498 | -7.480 | 55.62 | 80.53 | 63.89 | 45.87 | 50.31 |
| | [2.933] | [15.05] | [19.76] | [4.945] | [5.137] | [4.406]*** | [23.76]*** | [29.24]** | [8.155]*** | [8.403]*** |
| Observations | 1,256 | 1,087 | 824 | 1,256 | 1,064 | 1,256 | 1,087 | 824 | 1,256 | 1,064 |
| R-squared | 0.147 | 0.198 | 0.138 | 0.148 | 0.206 | 0.164 | 0.227 | 0.154 | 0.183 | 0.231 |
| Number of countries | 123 | 123 | 107 | 123 | 120 | 123 | 123 | 107 | 123 | 120 |
| Log likelihood | 2 | 10 | 8 | 3 | 5 | 2 | 10 | 8 | 3 | 5 |

Note: robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Source: authors' estimations.