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Does Economic Complexity Mitigate Carbon Inequality?

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Abstract

Despite policies to reduce carbon inequality, it remains very high. Yet, the 2023 Climate Inequality Report underlines that the bottom 50% of the world's population that contributes to 12% of carbon emissions is exposed to 75% of income losses that are related to climate change. Whereas the literature has identified a wide range of carbon inequality drivers, this paper stands out from previous works by emphasising the role of economic complexity in explaining carbon inequality through economic development, human capital, income inequality and the intensity of greenhouse gas emissions. Therefore, the main objective of the paper is to analyse the relationship of economic complexity with carbon inequality. To make the assessment, we construct a Gini index of carbon inequality for a world sample and rely on a multidimensional approach of economic complexity measure. Using instrumental variables, we find that technology and trade complexity reduce carbon inequality while research complexity does not have a relationship. Although these results call for measures aimed at the improvement of technology and trade complexity, they are not in line with the objective of climate change mitigation as economic complexity leads to more GHG emissions.

Keywords: *Economic Complexity, Carbon Inequality.*

1. Introduction

Carbon inequality (CI) has received growing attention from both researchers and policymakers in recent decades. Indeed, this issue is at the heart of discussions on the simultaneous achievement of social equity (Sustainable Development Goal – SDG – 10) and climate change mitigation (SDG13) (Rao and Min, 2018). On the one hand, several recent works and reports indicate that greenhouse gas (GHG) emissions are very unevenly distributed between the rich and the poor (Bruckner *et al.*, 2022; Hubacek *et al.,* 2017; Hubacek *et al.*, 2017; OXFAM 2021). Besides, several studies report that income inequality is at the root of CI since the unequal distribution of wealth leads to inequality between poor and rich individuals as well as countries in the size and the type of consumption and therefore, an unequal distribution of personal carbon footprint (Ivanova and Wood 2020; Oswald *et al.*, 2020). Most importantly, a report by OXFAM (2021) reveals that the richest 1% are responsible for twice as much carbon emissions as the poorest half of the world's population. Most important, CI within countries has increased (Chancel, 2022; Zheng *et al.*, 2023). Yet, the Climate Inequality Report (2023) underlines that the bottom 50% of the world population that contributes to 12% of carbon emissions is exposed to 75% of income losses that are linked to climate change. On the other hand, the solutions to this rising CI are hotly debated. Whereas for some authors, reducing carbon inequalities means raising the standard of living of the poor (Zheng *et al.*, 2023), for others this approach compromises the objective of mitigating climate change, and in return requires a reduction in the carbon footprint of the richest to be effective (Hubacek *et al.*, 2017; Oswald *et al.*, 2020). However, some authors have raised the question of whether offering the poor a decent standard of living requires that luxury be restricted elsewhere (Rao and Min, 2018).

Regarding the debate on reducing CI based on the mitigation of income inequality, several studies have sought to identify other explanatory factors for CI. However, there is no investigation into the effect of economic complexity on CI to the best of our knowledge, a gap that this article tries to fill. To date, some studies highlight the relevance of household characteristics as demographic characteristics, household employment burdens and household assets financial plans (Xu *et al.*, 2016). Other contributions suggest that in addition to income inequality, the disparities in industrialisation, income, population share, investment scale, energy usage technical efficiency, potential carbon factor, carbon dioxide (CO_2) emissions and technological change matter for CI (Xu, 2020). Another important driver identified by the literature is human capital, especially education, as it designs individual preferences towards emission-intensive lifestyles (Chancel and Piketty, 2015; Yang and Liu, 2017). On the same note, Chen *et al.* (2019) underline the role of regional disparity. For Wang *et al.* (2019), the most important driving factors of CI are trade openness, technological progress, road density and the secondary industry proportion, while Fan *et al.* (2020) insist on the disparities in government expenditures as the main cause of CI. More recently, Xu *et al.*

(2022) have pointed out the role of energy disparity, while Theine *et al.* (2022) have emphasized the relevance of population density in carbon emissions inequality. Zhang *et al.* (2023), Chancel (2022) and Fremstad and Paul (2019) emphasise carbon tax as a key tool to reduce CI.

Although the literature has not yet examined the influence of economic complexity on carbon inequality (CI), several lines of research motivate our analysis. Economic complexity, defined as the amount of productive knowledge mobilised within an economy (Hausmann *et al.*, 2014), reflects a country's ability to generate and combine knowledge in its productive structure. It is widely recognised as a driver of innovation, productivity, human development, and competitiveness (Hidalgo, 2021), all of which are determinants of greenhouse gas (GHG) emissions and their distribution. However, the environmental implications of economic complexity are not straightforward. While several studies demonstrate a correlation between greater economic complexity and a reduction in CO2 emissions or emission intensity (Romero and Gramkow 2021; Caglar *et al*., 2022), others highlight the potential dependence of these effects on the linkage of emissions to production or consumption (Stojkoski *et al.*, 2023), or on the stage of socioeconomic development (Khezri *et al.*, 2022). Moreover, recent contributions suggest that the relationship between complexity and environmental outcomes may be nonlinear (Agozie *et al.*, 2022; Boleti *et al.*, 2021; Taghvaee *et al.*, 2022), resembling an environmental Kuznets curve (EKC) pattern, whereby the early stages of structural modernisation may increase emissions before cleaner technologies and institutional capacities generate environmental improvements. Therefore, extending this logic to carbon inequality, it is possible that the effect of economic complexity varies according to stages of development. In low-income economies, increased complexity may initially be associated with industrial expansion, skill-enhancing technological change, and unequal access to clean technologies. This could exacerbate emissions disparities. At the same time, it is conceivable that, at more advanced stages, greater technology diffusion, stronger institutions, and greater human capital accumulation could reduce both emissions intensity and income-related carbon disparities. Furthermore, economic complexity influences key determinants of carbon inequality, such as economic development, income distribution, and human capital, suggesting that its effect may operate through multiple mediating channels, with the strength of these effects varying across levels of development.

Building on these discussions, our paper aims to provide a clear empirical answer to whether economic complexity affects CI, as the first study of this kind. Specifically, we build on differences in the economic complexity index (ECI) across countries and over time to explain disparities in CI. Accordingly, this study fills the knowledge gap, on the one hand, in analysing the effect of economic complexity and, on the other hand, in analysing the determinants of

CI. This analysis is even more important because it is difficult to predict whether carbon inequalities will worsen or improve with economic complexity. Economic complexity could, for example, exacerbate income inequality and thus increase CI, or reduce CI through the mitigation of income inequality. Moreover, since COP 21 and more recently COP 27, the reduction of carbon footprints and CI has received renewed interest due to the need to guarantee social justice through environmental policies. Hence, by analysing the relationship of economic complexity, this paper highlights a mechanism to mitigate CI and promote fairness and equity in environmental policies. To make this assessment, we first construct an intra-country Gini index of CI using the data from the World Inequality Database (WID) on the distribution of personal carbon footprint in the population. While many studies point out that it is more difficult to tackle within-country inequalities than between-country inequalities, others argue that tackling within-country inequalities is crucial to gaining political support for greenhouse gas (GHG) mitigation (Chancel and Piketty, 2015). Moreover, it has been shown that within a country, CI is not only spatial (between different regions), as every country has high and low emitters (Chancel and Piketty, 2015).

The second contribution of this article is the use of the multidimensional approach to economic complexity developed by Stojkoski *et al.* (2023), which distinguishes 3 forms of complexity: Trade complexity, technological complexity, and research complexity. Although several studies address economic complexity from the perspective of trade complexity, it should be noted that the latter's data may omit key information on innovative activities, such as patent applications and research publications, which are crucial to understanding this phenomenon. For instance, advances in research and technology could influence production processes, affecting workers' skills and wages, as well as the emissions intensity of industrial activities (Stojkoski *et al.*, 2023). Furthermore, trade-based complexity indicators may systematically underestimate the complexity of economies that are distant from global markets, thereby distorting forecasts of their inclusive green growth. This is particularly true given that economic complexity is not limited to individually held knowledge; it also depends on a society's ability to distribute fragments of knowledge among its members and combine them through complex interaction networks, such as businesses and markets (Hausmann *et al.*, 2014). Moreover, according to Stojkoski *et al.* (2023), while commercial complexity assesses a country's ability to produce and export complex products that require a high level of knowledge and skills, technological complexity goes beyond this concept by considering countries' capacities in terms of institutions, infrastructure, and workforce skills (Hidalgo and Hausmann, 2009). To summarise, the level of technological complexity in a country is indicative of its capacity to produce complex and patentable innovations. Conversely, research complexity measures the complexity of a country's academic research. Ideas based on trade complexity are not as accurate indicators of technological complexity as research complexity.

Furthermore, numerous studies have identified significant discrepancies in the ranking of countries by complexity across dimensions (Stojkoski *et al.*, 2023). Therefore, this multidimensional approach has the advantage of not relying solely on trade data, allowing more accurate estimates of economic complexity (Stojkoski *et al.*, 2023). To do that, we rely on the new dataset from the Observatory of Economic Complexity (OEC), which combines data on international trade, patents, and research articles to construct indicators of trade, technology, and research complexity. Thus, through a multidimensional analysis of the relationships of economic complexity, we can determine which dimension is the most effective instrument for reducing CI.

As the third contribution, the paper addresses endogeneity concerns in economic complexity, since we cannot rule out reverse causality in the relationship, and the omission of variables that affect both economic complexity and CI. Addressing this endogeneity issue is even more important, as several studies suggest that economic complexity is endogenous to macroeconomic outcomes (Boleti *et al.*, 2021; Chu and Hoang, 2020; Romero and Gramkow, 2021; Stojkoski *et al.*, 2023). To address this endogeneity issue, we build on an instrumental variable strategy inspired by Stojkoski *et al.* (2023). It consists of instrumenting economic complexity by the average complexity level of the three economies, with which a country does not share a border (land and maritime), which have the most similar specialisation pattern. This choice builds on the fact that countries with similar specialisation patterns should also intuitively reflect similar complexity to the target country (Stojkoski *et al.*, 2023). Moreover, the complexity of similar economies should not affect the macroeconomic performance of the target country, nor should it be linked to other country-specific characteristics, especially since we exclude neighbouring countries as potentially similar, consistent with the suggestion of Stojkoski *et al.* (2023).

Beyond these contributions, the paper tests the potential transmission channels – that are economic development, income inequality and human capital – building on the discussion on the intended relationship of economic complexity with CI. In this paper, we use a robust mediation analysis developed by Frölich and Huber (2017) to identify the main transmission channels explaining the relationship of economic complexity with CI and to quantify the contribution of each mediating variable.

The study builds on a world sample for the 1995–2019 period. The results show that trade complexity and technology complexity contribute to mitigate CI. These results are robust to the potential exclusion criteria test, the addition of controls and alternative sample specification. Moreover, when using alternative instruments, estimands and data on CI, the results confirm that trade complexity and technology complexity mitigate CI. Interestingly, the results of the transmission mechanisms assessment suggest that technology complexity mitigates CI by

reducing income inequality, improving human capital, and increasing GHG emission intensity. On the same note, trade complexity also narrows CI through improvement in human capital and the rise in GHG emissions intensity. Although these results highlight a redistributive effect of economic complexity, they do not imply that increasing economic complexity is inherently desirable as a climate policy, since trade and technological complexity are also accompanied by higher total greenhouse gas emissions, revealing a fundamental trade-off between distributive equity and environmental economies of scale. Consequently, strategies aimed at increasing complexity must be part of a broader policy framework. Industrial and trade policies that promote greater complexity must be complemented by carbon pricing instruments, emission standards, and targeted support for low-carbon technologies to decouple structural transformation from emissions growth. It is only possible to reconcile gains in carbon equity with overall emissions reduction targets by implementing such a framework.

Further to this introduction, Section 2 presents the methodology. Subsequently, Section 3 presents the baseline results and the sensitivity and robustness analyses, while the last section presents the conclusion and policy recommendations.

2. Economic complexity and carbon inequality: The potential transmission mechanisms

Considering increasing concerns about climate change and persistent global inequality, it is vital to gain a deeper understanding of the intricate relationship between economic development and environmental impact. As highlighted in the introduction, a particularly intriguing aspect of this relationship is the link between economic complexity and carbon inequality. While the existing literature has not extensively explored the relationship between economic complexity and carbon inequality, several findings from previous research suggest that this analysis could be validated through a range of interlinked mechanisms.

First, it is acknowledged that disparities in economic development between nations stem from differences in economic complexity. Specifically, the amount of complexity correlates positively with the level of development. Several studies have found that more complex economies not only generate and embrace new technology but also have a higher innovation potential, allowing them to increase productivity (Hausmann, *et al.*, 2014; Hidalgo and Hausmann, 2009). Meanwhile, Can and Gozgor (2017) demonstrate that technical breakthroughs, productivity gains, and innovation capacity can help reduce carbon disparity in several ways. First, at the firm level, the technological advantage enables frontier firms, particularly those operating in knowledge-intensive sectors, to adopt cleaner, more energy-efficient production processes, either through endogenous innovation or by absorbing imported technologies embedded in capital goods. These dynamics can reduce unit emissions among leading firms and sectors, potentially narrowing the emissions gap between large and small emitters (Ahmed *et al.*, 2022; Can and Gozgor, 2017; Romero and Gramkow, 2021; Wang *et al.*, 2023). As a result, economic complexity may help to reduce CI by promoting technical advancement, productivity gains, and innovation capacity as an economy develops.

Secondly, sectoral reallocation associated with increasing economic complexity – moving away from primary activities towards more sophisticated manufacturing and advanced services – can help reduce average carbon intensity, particularly in countries with strong environmental institutions (Jinapor *et al.*, 2024; Nkemgha *et al.*, 2024). In such contexts, technological modernisation is often accompanied by stricter environmental regulation and carbon pricing, which facilitate the diffusion of clean technologies beyond a small group of export-oriented firms(Bekun et al., 2021; Jinapor et al., 2024). However, in less advanced or middle-income economies, the early stages of complexity modernisation may rely on manufacturing and logistics activities that remain carbon-intensive, resulting in more ambiguous trajectories and potentially increasing carbon inequalities between social groups (Nkemgha et al., 2024). In this sense, the relationship between economic complexity and carbon inequalities is likely to be heterogeneous across countries, depending on income levels and institutional capacities.

Secondly, economic complexity affects carbon inequality through a human capital and skills channel. Indeed, several studies indicate that high-complexity economies foster human capital accumulation by generating demand for skilled labour, accelerating worker training, and promoting learning-by-doing through more sophisticated production processes (Agosin, 2009; Hausmann et al., 2014). Moreover, knowledge creation and human capital formation are well-established drivers of long-term economic growth and development, which, as noted above, may indirectly contribute to reducing carbon inequalities through higher productivity and cleaner technologies.

In the short term, however, this process may accentuate income disparities. Indeed, the skills bias associated with economic complexity may initially increase wage dispersion, as highly skilled workers are better positioned to take advantage of new employment opportunities, while low-skilled workers remain concentrated in low-productivity and potentially more carbon-intensive segments of the economy (Chu and Hoang, 2020; Lee and Wang, 2021). These income gaps translate into differences in consumption patterns, contributing to disparities in individual carbon footprints (Apeti *et al.*, 2025; Chancel, 2022). But over time, when increased complexity is accompanied by inclusive institutions, such as broad access to education, vocational training, and active labour market policies, human capital accumulation becomes more widespread (Vu, 2022). This can reduce income polarisation and facilitate the diffusion of "green skills" within the workforce (Okombi and Lebomoyi, 2025), thereby reducing consumption-related emissions differences between social groups. Furthermore, it has been shown that a more educated population is generally more aware of environmental challenges and more likely to support and adopt sustainable practices, thereby increasing pressure for greener policies and consumption patterns (Ha, 2023). In this way, economic complexity can ultimately help reduce carbon emission inequalities by reducing disparities in both income and environmental behaviour. However, if complexity is concentrated in enclaves tightly integrated into global value chains and coexisting with large informal or low-productivity sectors, labour markets become highly dualised, reinforcing both income and carbon-emission inequalities.

Thirdly, beyond its effects on development and human capital, economic complexity can influence carbon emission inequalities through income distribution. While the empirical relationship between complexity and income inequality remains inconclusive, several studies suggest that more complex economies tend to have lower income inequality. This is because diversified and stable production structures promote the integration of different social groups and the diffusion of skills (Albassam, 2015; Hartmann *et al.*, 2017). In addition, economic complexity has been shown to improve productivity, increase returns to scale, and strengthen the resilience of businesses to shocks, thereby promoting wage stability, employability, and income growth (Barnes *et al.*, 2015; Constantine, 2017; Joya, 2015). However, other studies have shown that economic complexity can exacerbate income inequality by

disproportionately favouring skilled workers. The ability of these workers to adapt to technological change allows them to capture a larger share of the gains from complex production structures (Chu and Hoang, 2020; Lee and Wang, 2021). More recent contributions emphasise that economic complexity can have both favourable and unfavourable effects on inequality, depending on each country's institutional arrangements (Bandeira Morais *et al*., 2021; Nguyen *et al.*, 2023).

At the same time, the literature on carbon emission inequalities consistently identifies income disparities as a fundamental driver of emission inequalities. These disparities translate into disparities in consumption, access to energy-intensive goods, and economic power (Bruckner et al., 2022; Chancel, 2022; Hubacek *et al.*, 2017). High-income individuals tend to consume more energy, travel more frequently, particularly by air, and purchase more carbon-intensive goods, resulting in a significantly larger carbon footprint (Chancel, 2022; Chancel and Piketty, 2015). Furthermore, they are more likely to own or invest in carbon-intensive industries, thereby indirectly contributing to increased emissions (Otto *et al.*, 2019). However, it has also been demonstrated that households engaged in complex activities tend to allocate a greater proportion of their expenditure towards knowledge-intensive services and goods (education, healthcare, digital services), which may be less carbon-intensive than material consumption, provided that the energy system undergoes a gradual decarbonisation process. The equitable distribution of these benefits depends largely on redistribution policies, carbon taxation, and public support for low-carbon housing and transportation. From this perspective, economic complexity, by reducing income inequality, can help mitigate CI. Conversely, if it increases income concentration, it can amplify emission disparities despite technological progress.

Finally, economic complexity can influence carbon inequalities through energy systems, urbanisation patterns, and territorial dynamics. This is particularly due to the fact that complex economic activities are often concentrated in diversified urban centres (Adedoyin *et al.*, 2021; Doğan *et al.*, 2019, 2021). These hubs boast efficient infrastructure, public transportation, and energy-efficient buildings. Consequently, these regions exhibit a lower average carbon intensity (Poggi and Amado, 2024; Poumanyvong and Kaneko, 2010). Concurrently, this spatial concentration can result in significant emission disparities between metropolitan centres and peripheral or rural areas, where households are more reliant on private vehicles, fossil fuels, and energy-intensive housing (Poumanyvong and Kaneko, 2010).

At the national level, complex economies generally have greater technological, financial and institutional capacity to integrate renewable energy on a large scale, deploy smart grids, and internalise carbon prices. However, it is important to note that the distributional consequences of these transitions are not neutral. The benefits of cleaner energy, including lower prices, improved access, and new employment opportunities, depend on several factors. These

include regions connected to new infrastructure, businesses benefiting from innovation incentives, and households protected from transition costs (Poumanyvong and Kaneko, 2010). From this perspective, it is also clear that the political and economic systems of different countries differ significantly: while some countries are steering the modernisation of complexity towards rapid decarbonisation of energy and urban systems, others are prioritising industrial expansion and urban growth, which remain heavily dependent on fossil fuels.

However, it is essential to emphasize that since the relationship between economic complexity and carbon inequality is potentially bidirectional, the productive structure at the origin of emissions can itself influence the accumulation of productive capacities and, consequently, the observed complexity of an economy, as shown in the work of ... This is due in particular to the fact that carbon-intensive sectors—heavy industry, petrochemicals, metallurgy, and extractive activities—generally involve high fixed costs, economies of scale, and sophisticated value chains. They also require advanced technical skills and generate learning effects, technological externalities, and upstream and downstream inter-sectoral linkages. As such, they can contribute to the deepening of national capacities and the sophistication of exports.

In this configuration, if the highest emitters are also those at the technological frontier, the increase in carbon inequality may reflect the concentration of advanced capacities rather than a simple distributional dysfunction. The dispersion of emissions then becomes the product of an unequal distribution of productive capacities: companies, regions, or social groups involved in complex sectors produce and consume more sophisticated goods, which are often energy-intensive. In addition, rents from carbon-intensive activities can finance research, infrastructure, or human capital, further reinforcing complexity and creating trajectories that are dependent on the initial path of industrialisation. However, the persistence of carbon inequality depends on the direction of technical progress. Modernisation biased toward the expansion of energy-intensive activities can amplify both complexity and inequality. Conversely, carbon-efficient technological change—energy efficiency, electrification, green innovation—can gradually reduce emissions dispersion.

3. Methodology

3.1. Data

3.1.1. Economic Complexity

The data on economic complexity is obtained from the Observatory of Economic Complexity (OEC) database which developed a multidimensional approach to the measurement of economic complexity based on Stojkoski *et al.* (2023). This dataset allows us to distinguish three forms of complexity: trade, research and technology complexity and has the advantage of capturing those aspects of economic complexity that are not reflected in international trade data. To construct trade, technology and research complexity, the OEC relies on the complexity metric approach proposed by Hausmann *et al.* (2014). It is based on an algorithm that is based on a binary country-product matrix M with elements M_{cp}, indexed by product p and country c. In matrix M, the elements M_{cp} take the value 1 if the corresponding revealed comparative advantage (RCA) from country c for product p is greater than or equal to 1, and 0 otherwise. It is worthwhile to note that, the RCA from country c of product p is computed using the Balassa index as follows in Equation (2):

$$RCA_{cp} = \frac{x_{cp} \Big/ \sum_p x_{cp}}{\sum_c x_{cp} \Big/ \sum_c \sum_p x_{cp}} \qquad (2)$$

where x_{cp} reflects the value of product *p* manufactured by country *c*.

Hence, the country's diversity and ubiquity indexes are derived by adding the elements across the columns and rows of M, respectively.

$$\begin{cases} Diversity = k_c^{(0)} = \sum_p M_{cp} \\ Ubiquity = k_p^{(0)} = \sum_c M_{cp} \end{cases} \qquad (3)$$

Based on the indicators of ubiquity and diversification in Equation (3) above, Stojkoski *et al.* (2023)use the "reflection method" to construct the economic complexity index (ECI). Specifically, they weight each product in proportion to its ubiquity and derive the ECI by computing the eigenvector K_c of the matrix $\widetilde{M}_{cc'}$ linked to the second-largest eigenvalue.

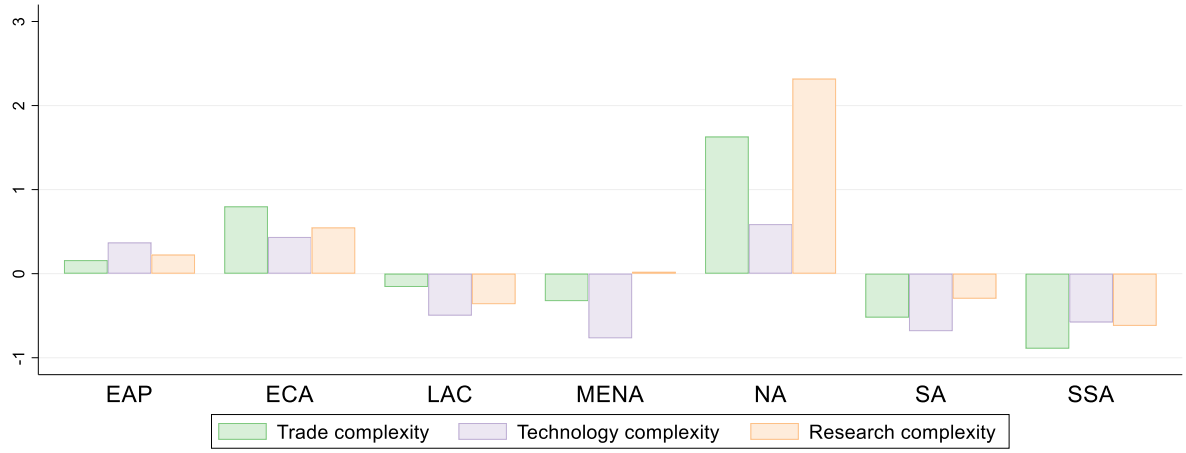
Hence, the ECI is computed as follows in Equation (4):

$$ECI = \frac{K_c - \overline{K}_c}{\sigma(K_c)} \qquad (4)$$

To construct trade complexity (*ECI trade*), technology complexity (*ECI tech*) and research complexity (*ECI res*), Stojkoski *et al.* (2023) use data on exports from the Observatory of Economic Complexity, data on patent applications from the International Patent System of the

World Intellectual Property Organization, and data on published documents from the SCImago Journal & Country Rank portal, in that order.

Figure 2 (and Figures A1–A3 in the Appendix) provides a stylised representation of cross-regional heterogeneity in the composition of economic complexity. Beyond ranking regions, the figure shows that complexity is multidimensional, with regions exhibiting markedly different profiles across trade, technological, and research dimensions. North America consistently displays high complexity across all dimensions, reflecting its diversified productive structure and strong innovation base. In contrast, regions such as Sub-Saharan Africa and the Middle East and North Africa lag behind, albeit along different dimensions, suggesting distinct structural constraints. Importantly, the figure reveals that regions with comparable aggregate complexity may differ substantially in their composition. For instance, Europe and Central Asia, and East Asia and Pacific exhibit relatively strong trade and technological complexity but more moderate research complexity. This heterogeneity is central to our empirical strategy and interpretation, as the subsequent analysis shows that these dimensions have asymmetric nexuses with carbon inequality and emissions. Figure 2 thus motivates our focus on the composition—rather than the level—of economic complexity, providing visual intuition for why different forms of productive upgrading may generate divergent distributional and environmental outcomes.



Note. **EAP**: East Asia and Pacific; **ECA**: Europe and Central Asia; **LAC**: Latin America and Caribbeans; **MENA**: Middle East and North Africa; **NA**: North America; **SA**: South Asia; **SSA**: Sub-Saharan Africa.

Figure 1. Economic complexity index, 1995–2019.

3.1.2. Carbon Inequality

To date, numerous studies have attempted to measure inequalities in the distribution of carbon emissions by adapting traditional tools used to measure income inequality. The first category of studies uses concentration indices, in particular the Gini coefficient (Zheng *et al.*, 2023; Semieniuk and Yakovenko, 2020; Zimm and Nakicenovic, 2020) and the Atkinson index

(Hedenus and Azar, 2005). Other studies use entropy indices of carbon dioxide emissions, such as the Theil index (Xu, 2020; Han *et al.*, 2020; Oswald *et al.*, 2020; Padilla and Serrano, 2006; Hedenus and Azar, 2005), while an alternative approach relies on the use of ratios such as the Palma ratio (Pan *et al.*, 2019). These different measures can be broadly divided into two complementary dimensions: disparities between countries, which provide information on global disparities, and disparities within countries, which reflect differences in emissions between individuals.

In this study, we used a measure of intra-country carbon inequality, as it is more relevant for analysing the role of economic structures, technologies and public policies in the distribution of emissions among individuals. In line with most publications, we used the Gini coefficient, which measures the deviation between the observed distribution and the perfectly equal distribution (Asongu and Odhiambo, 2019a, 2019b). This measure, now widely used in research on carbon inequality, has the advantage of allowing consistent comparisons of the distribution of emissions among population groups, regardless of their size. The measurement of the Gini index of CI is calculated following Xu et al. (2016), according to the following formula in Equation (1):

$$Gini = 1 - \left| \sum_{i=1}^{N} (X_{i+1} - X_i)(Y_{i+1} + Y)_i \right| , \quad (1)$$

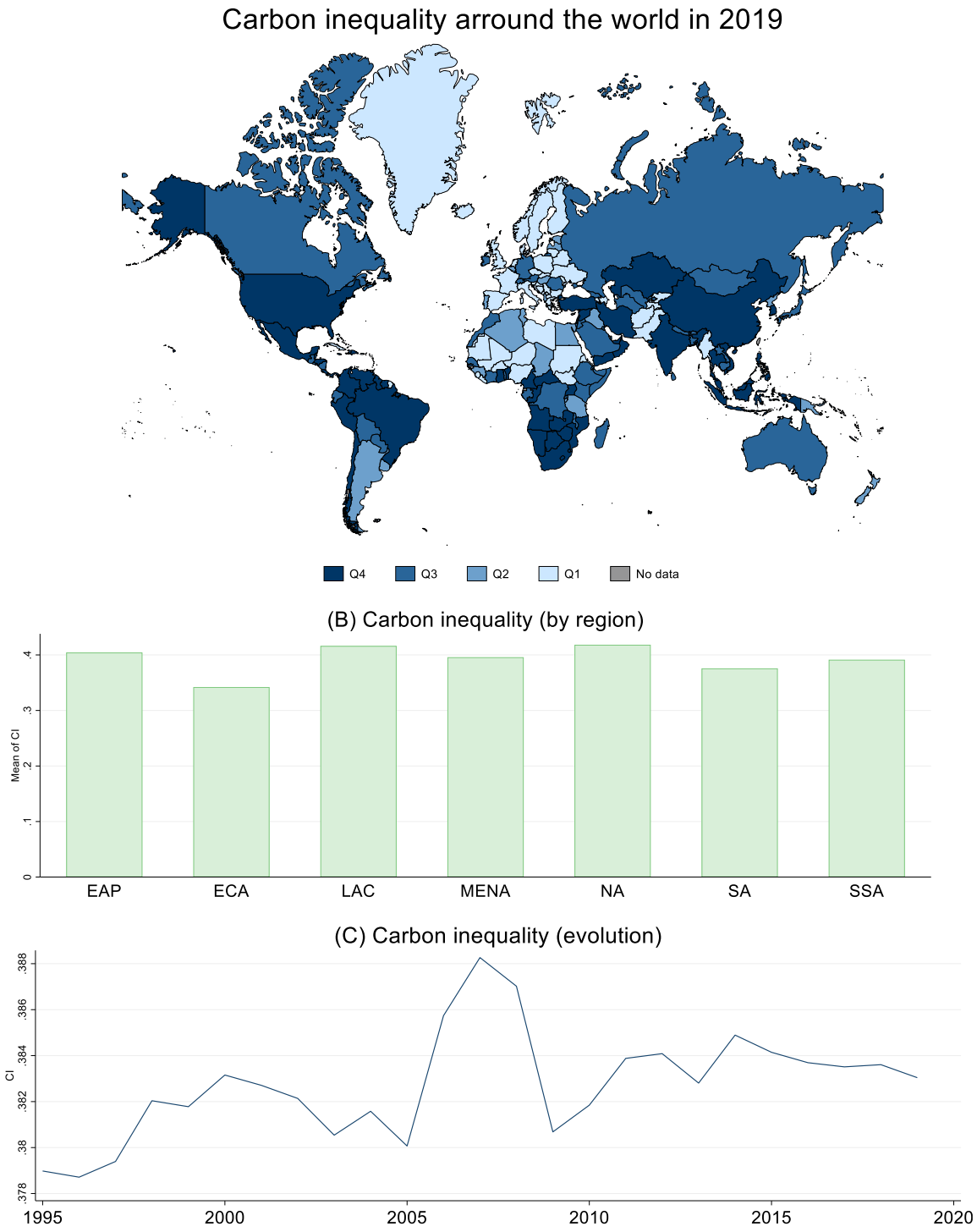
where *N* is the number of population group, X is the cumulative proportion of population and Y is the cumulative personal carbon footprint. X is defined as the number of individuals in population group i divided by the total population, with Xi indexed in terms of non-decreasing order while Y is defined as the quantity of the personal carbon footprint in various dimensions by population groups i divided by total personal carbon footprint, with Yi arranged in increasing order from lowest to the highest.

Regarding the measurement of individual carbon footprints, the literature generally distinguishes between two approaches: one based on production-related emissions and one based on consumption-related emissions. In this article, we adopt an approach based on individual carbon footprints to measure carbon dioxide emissions resulting directly and indirectly from human consumption throughout supply chains (Clarke et al., 2017). By including emissions embedded in consumed goods and services, this consumption-based approach is particularly well suited to analysing carbon disparities within countries, as it more accurately reflects differences in lifestyles, income levels and consumption habits between individuals. This provides a more comprehensive understanding of the disparities in carbon responsibility between income categories, which are a central theme in this article's discussion of intra-country carbon imbalances.

Data on population groups and individual carbon footprints are drawn from the World Inequality Database (WID), which provides a harmonised international framework linking income, consumption patterns, and individual emissions. These data are constructed using official national emissions inventories and environmentally extended input–output tables, ensuring that the sum of individual emissions matches national totals exactly. While the allocation of emissions across population groups may involve some uncertainty, aggregate consistency is therefore preserved by construction. Compared to other carbon footprint datasets, the WID offers an explicitly distributional approach that is particularly well-suited for computing inequality measures such as the Gini coefficient and for conducting cross-country analyses. We nevertheless address potential measurement error by conducting robustness checks using alternative inequality indices as well as alternative measures of carbon inequality derived from the Global Carbon Atlas and footprint estimates based on EXIOBASE. Finally, as with any global dataset on emissions distribution, WID-based carbon footprints rely on modelling assumptions and imperfect consumption data; however, these limitations are widely acknowledged in the existing literature and do not compromise the internal consistency or cross-country comparability of the measure.

Figure 1 presents the state of CI measured by the Gini index around the world. Graph A highlights substantial cross-country heterogeneity, with carbon inequality ranging from relatively low levels in several small and energy-intensive economies in countries like Liberia (27.7), Slovakia (28.8), Eritrea (30.3), Brunei (30.3) and Malta (30.7) to markedly high levels in countries such as Mexico (50.5), Thailand (49.8), Botswana (49.1), Chile (47.9) and Namibia (46.5). This wide dispersion underscores that carbon inequality is not confined to a specific income group or geographical area, but reflects deep structural differences in production, energy use, and consumption patterns. Interestingly, in Graph (B), we can also observe some regional asymmetries. For instance, North America, Latin America and the Caribbean have the highest average levels of carbon inequality, while Europe and Central Asia have the lowest. These regional contrasts could also suggest that institutional, technological and productive structures, rather than geography alone, play a central role in the distribution of emissions within countries. Importantly, when examining the evolution of CI depicted in graph (C), we observe that carbon inequality has evolved non-linearly over time. While the overall change between 1995 and 2019 is modest, with a slight increase in carbon inequality over the period, a pronounced increase is observed during the pre-2007 period (rising from 0.378 to 0.388), followed by a partial decline thereafter.

(A)



Note. **EAP**: East Asia and Pacific; **ECA**: Europe and Central Asia; **LAC**: Latin America and Caribbeans; **MENA**: Middle East and North Africa; **NA**: North America; **SA**: South Asia; **SSA**: Sub-Saharan Africa.

Figure 2. Carbon inequality

3.1.3. *Controls*

3.2. Econometric Framework

3.2.1. ***Econometric** Model*

To investigate the effect of economic complexity on CI, we estimate the following model in Equation (5):

$$Carbonineq_{i,t} = \beta_0 + \beta_1 ECI^d_{i,t} + \beta_2 X_{i,t} + \eta_i + \mu_t + \xi_{i,t} \quad (5)$$

Where *i* and *t* represent the individual and temporal dimensions, $Carbonineq$ is the CI index, ECI is a proxy of economic complexity. In light of the theoretical background of the study, a negative sign is expected from the ECI coefficient. *X* is the set of controls. η_i and μ_t are respectively the country and the time-specific fixed effects included to isolate the cross-individual and temporal drivers of CI. ξ is the stochastic error term while β denotes coefficients to be estimated.

Concerning the controls variables, we control for some factors that have been identified by previous works as the determinants of CI. The first one is economic development proxied by GDP per capita retrieved from the World Development Indicator (WDI) database. According to Han *et al.* (2020) and Chancel and Piketty (2015), economic development has led to significant carbon inequalities. The second is income inequality provided by the Standardized World Income Inequality Database (SWIID). Oswald *et al.* (2020) and Teixidó-Figueras and Duro (2015) show that economic inequalities translate into inequalities in carbon emissions. The reason for this is that people with differing purchasing power use different goods and services, on the one hand, and on the other, wealthier people, because of their high purchasing power, can acquire more goods than less affluent people. We also control for the corruption proxied by the Corruption index from the Varieties of Democracy dataset. The rationale behind this is that corruption creates permanent distortions in income redistribution by altering the composition of social spending in such a way as to increase the incomes of the richest at the expense of the poorest (Glaeser *et al.*, 2003). Moreover, by facilitating tax evasion and exemptions for the rich, corruption increases the tax burden that falls on the poor who therefore have a reduced purchase power. Another variable that is considered as control is education following Chancel and Piketty (2015) and Yang and Liu (2017) who show that the level of education designs individual preferences towards emission-intensive lifestyles. To proxy education, we rely on the human capital index of Penn World Table which builds on data for the average years of schooling of the population. We also include natural resources as a control variable in order to test the hypothesis of natural resources curse as well as population density following Theine *et al.* (2022). The natural resource rents and the population density are retrieved from WDI.

3.2.2. *Identification Strategy*

In panel data estimates, it is common to rely on the ordinary least squares (OLS), especially when explanatory variables are expected to be correlated with unobserved individual effects. However, they are generally inefficient in the presence of endogeneity. This can arise, on the one hand, when no distinction is made between variable(s) determined by the model and those predetermined (simultaneity problem), and, on the other hand, when an omitted variable affects both the explained variable and one (or more) explanatory variable(s). Moreover, we cannot rule out the possibility of reverse causality in the relationship between economic complexity and CI, nor the omission of variables that affect both ECI and CI. Considering these shortcomings, we avoid OLS estimation.

To address endogeneity, we implement an instrumental variable strategy inspired by the two-stage least squares approach proposed by Stojkoski *et al.* (2023). Specifically, we instrument domestic economic complexity using the average complexity of the three non-neighbouring economies that exhibit the most similar specialisation patterns. The relevance of this instrument rests on the idea that countries with comparable production structures tend to share similar underlying productive capabilities and technological know-how, implying a strong correlation between the complexity levels of structurally similar economies (Stojkoski *et al.*, 2023). The identifying assumption underlying this strategy is that the complexity of non-neighbouring, similarly specialised economies affects domestic carbon inequality mainly through its relationship with domestic economic complexity. While it is impossible to rule out every conceivable channel linking peer-country complexity to domestic carbon inequality, the identification strategy relies on the assumption that such relationships are negligible once domestic economic complexity is controlled for. The economic rationale is that the complexity of geographically distant economies with similar specialisation patterns primarily captures shared long-run capability dynamics, which influence domestic carbon inequality only insofar as they translate into changes in domestic productive structures.

This assumption is economically plausible for several reasons. First, economic complexity reflects deep, slow-moving productive capabilities that evolve through learning, imitation, and technological upgrading among countries with similar specialisation patterns, rather than through short-term shocks. Countries typically accumulate new capabilities by building on existing ones—moving into industries that are close in the knowledge space—rather than by abruptly shifting into unrelated sectors (Hausmann *et al.*, 2014). As a result, complex know-how diffuses primarily among structurally similar economies, making the complexity of non-neighbouring peer countries a source of exogenous long-run variation that captures underlying technological and capability trends. Furthermore, while countries with similar specialisation structures may be connected by global value chains, trade relations, technology diffusion

mechanisms or capital flows, even in the absence of geographical contiguity, these channels only affect carbon inequalities within a country to the extent that they transform domestic productive structures, sectoral composition, skills demand and energy intensity — dimensions that are directly captured by national economic complexity.

For instance, imported intermediate inputs may modify the carbon intensity of domestic production (Zhang, 2015). However, such adjustments typically reflect changes in the composition and technological sophistication of domestic industries—precisely the dimension captured by the economic complexity index. To the extent that imported inputs alter production technologies, their effects operate through transformations in the domestic productive structure rather than through a separate channel. Similarly, trade shocks originating from distant economies could in principle influence relative prices. However, the instrument is constructed from countries that are similar in productive capabilities rather than from major trading partners. As a result, the instrument is unlikely to capture direct trade shocks affecting domestic markets. Moreover, relative price changes mainly affect aggregate emissions, whereas carbon inequality reflects the distribution of emissions across households within a country, which is primarily driven by income distribution and domestic energy policies.

Second, excluding neighbouring economies limits the influence of direct spatial spillovers arising from trade integration, shared energy markets, and common regulatory or institutional environments that could otherwise directly affect domestic carbon inequality. Immediate neighbours are more likely to share such linkages—through cross-border trade, integrated energy infrastructure, or coordinated policies—so that accounting for their complexity could confound the complexity channel with local spillovers (Stojkoski *et al.*, 2023). Focusing instead on geographically distant but similarly specialised economies breaks these direct connections, isolating variation in economic complexity that is independent of short-term shocks or localised policy effects. This approach is consistent with previous studies, which deliberately exclude neighbouring countries to decouple complexity-based instruments from local conditions. Finally, technology diffusion across structurally similar economies represents precisely the mechanism through which productive capabilities spread. Such diffusion contributes to the upgrading and diversification of domestic industries and is therefore embodied in changes in economic complexity itself rather than constituting an independent channel affecting carbon inequality.

Moreover, carbon inequality is primarily driven by within-country distributional mechanisms (Ivanova and Wood 2020; Oswald *et al.*, 2020)—such as income heterogeneity, consumption patterns, energy prices, and domestic policy choices—which are unlikely to be directly affected by the economic complexity of geographically distant economies. Empirical evidence shows that wealthier households account for a disproportionate share of emissions,

making income distribution a central determinant of carbon inequality, while policy instruments such as carbon taxes or energy subsidies shape how emissions are distributed across the population. These internal drivers are not directly influenced by changes in the complexity of non-neighbouring economies with similar specialisation patterns. Accordingly, under our identifying assumption, any effect of the instrument on carbon inequality must operate indirectly through its incidence on domestic economic complexity—for instance by fostering cleaner technologies or higher value-added production—rather than through alternative channels. Finally, common global shocks affecting complexity and emissions are absorbed by time fixed effects, while country fixed effects control for time-invariant unobserved heterogeneity. Together, these features ensure that the instrument captures exogenous variation in domestic economic complexity rather than correlated global or regional trends.

Building on these arguments, they measure the specialisation patterns' similarity between a target country c and a paired country c' using the minimum conditional probability for the countries to be specialised in the same activity as follows in Equation (6):

$$\phi^{d}_{cc'} = \frac{\sum_{p} M^{d}_{c,p} * M^{d}_{c',p}}{\max(M^{d}_{c,p} M^{d}_{c',p})'} \tag{6}$$

Where *d* differentiates between trade, technology, and research. To assess the validity of the strategy of instrumentation, the Hausman exogeneity test is applied. Moreover, Kleibergen and Paap's (2005) weak identification and under-identification tests are employed, since the model is just-identified and the selected instrument may be correlated with other variables in the model. Since, in our baseline specification, domestic economic complexity is instrumented with a single external instrument, the model is exactly identified, and standard overidentification tests, such as the Hansen J-statistic, are not applicable in this setting.

Before turning to the main econometric analysis, we present simple graphical evidence in Figure 3 to anticipate potential results based on the raw data. Specifically, Figure 3 presents simple scatter plots illustrating the relationship between carbon inequality (CI) and the three dimensions of economic complexity: trade, technological, and research. Across all panels, a negative association is evident, indicating that countries with higher complexity tend to have lower carbon inequality. This pattern is not driven by a small number of observations, but reflects a broad dispersion of countries around a downward-sloping fitted line. Notably, the strength and clarity of this negative correlation differ across complexity dimensions, foreshadowing potential heterogeneity in their distributional effects. While trade and technological complexity display relatively pronounced negative associations with carbon inequality, the relationship appears weaker and more dispersed for research complexity. These visual patterns are consistent with the pairwise correlations reported in Table A2.

Importantly, Figure 3 provides only descriptive evidence. The observed correlations do not establish causality and may be affected by reverse causality, omitted variables, or unobserved heterogeneity. Nonetheless, the figure serves as a useful motivation for the econometric strategy developed in the subsequent section, which formally assesses whether these associations persist once endogeneity concerns are addressed.

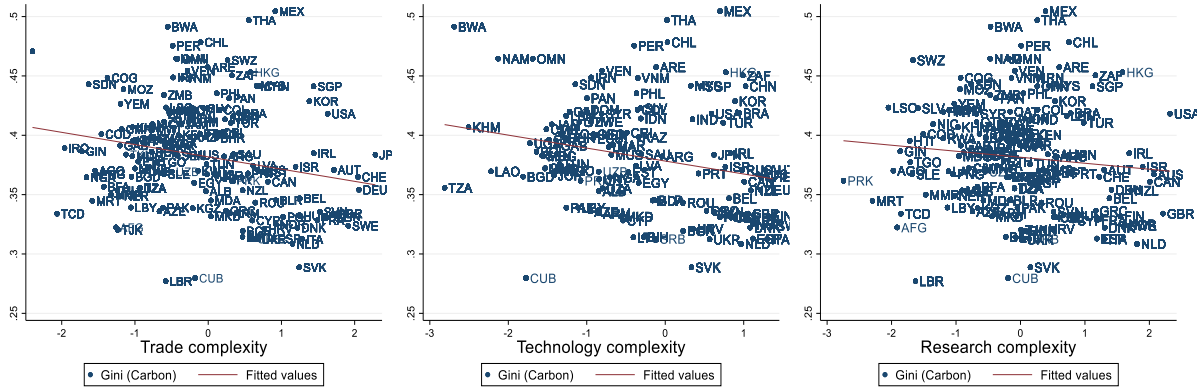


Figure 3. Economic complexity and CI, 1995–2019.

4. Empirical Results

This section presents the results of the basic regression as shown in Equation (1), as well as the results of the robustness and sensitivity analyses. The econometric models are estimated using FE-2SLS.

4.1. Results

IV estimates of the relationship between economic complexity and CI are presented in Table 1. As described earlier, we regress the different proxies of economic complexity dimensions, which are trade, technology and research ECI, on the CI measured by a Gini index. Before analysing the results, a key step is validating the identification strategy. In this regard, the results of the under-identification (UIT) and Hausman exogeneity tests indicate that the instruments are exogenous and that the models are not under-identified. Moreover, the first-stage results suggest that the instruments used are strongly correlated with the different ECI, as they enter positively and significantly, at least at the 1% level, in all regressions. These results are further supported by first-stage graphical evidence. The plots reveal a clear and approximately linear positive relationship between the residualized instruments—constructed from trade, technological, and research similarities—and the endogenous variables. This visual pattern confirms both the relevance and the strength of the instruments. Moreover, the tight clustering of observations around the fitted regression lines indicates that the instruments account for a substantial share of the variation in economic complexity, thereby mitigating concerns related to weak-instrument bias. Most importantly, the Kleibergen-Paap (WIT) F-statistic test of instrument fitness in the first-stage regression confirms a strong correlation (Asongu and Nwachukwu, 2018) and that the instrument is not weak. More interestingly, when we directly introduce our instrument into the second-stage equation (see Table A3 in the appendix), the results remain unchanged. Of greater significance is the finding that the coefficient associated with the instrument becomes statistically insignificant, suggesting that it acts primarily through the national productive structure.

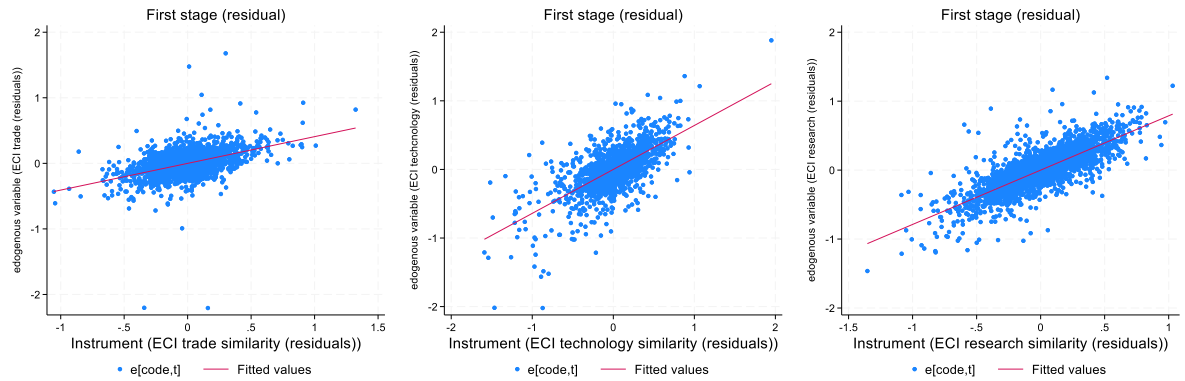


Figure 4. First stage plots.

Regarding the results of the second stage, they show that trade complexification mitigates CI as trade ECI enters the regressions positively and significantly at the 1% level. Similarly, they also indicate that technology complexity reduces CI. However, research technology does not affect CI given that its associated parameter is not meaningful at least at the 1% level. This suggests that only trade complexity and technology complexity effectively contribute to the reduction of CI. As Constantine (2017) suggests, economic (technology) complexification leads to higher productivity and increasing returns to scale, thereby boosting workers' incomes. Moreover, technology and trade complexity may improve the diffusion of skills and knowledge through extensive social class consciousness (Constantine, 2017; Hartmann *et al.*, 2017; Emeka *et al.*, 2024), which in turn can contribute to the reduction of income inequality as well as a greater preference for a lower emission-intensive lifestyle.

Table 1. Economic complexity and CI, FE-2SLS estimates

	(1)	(2)	(3)
	Second stage		
Trade ECI	-0.013***		
	(0.003)		
Technology ECI		-0.007***	
		(0.002)	
Research ECI			0.001
			(0.001)
Natural resources	0.002*	0.001	0.001
	(0.001)	(0.001)	(0.001)
GDP per capita (in log)	0.029***	0.024***	0.021***
	(0.003)	(0.006)	(0.004)
Corruption	0.014**	0.037***	0.027***
	(0.006)	(0.007)	(0.005)
Population (in log)	0.019***	0.042***	0.024***
	(0.005)	(0.012)	(0.004)
Education	-0.024***	-0.002	-0.040***
	(0.008)	(0.012)	(0.006)
Income inequality	0.447***	0.582***	0.458***
	(0.023)	(0.027)	(0.022)
	First stage		
Instrument	0.406***	0.643***	0.786***
	(0.016)	(0.029)	(0.017)
Observations	2,198	1,803	2,339
R-squared	0.171	0.216	0.199
Countries	134	100	135
Wald test	0.000	0.000	0.000
WIT	634.7***	500.0***	2212***
UIT	486.7***	151.0***	481.9***
Endogeneity test	0.000	0.003	0.006

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Turning to controls, the results also provide some interesting evidence. They suggest that the per capita GDP is associated with the increase in CI. The results also indicate that as income inequality rises, CI increases given that the uneven distribution of wealth leads to inequality

between poor and rich in the size and the type of consumption and therefore an unequal distribution of personal carbon footprint (Ivanova and Wood, 2020; Oswald *et al.*, 2020). In the same line, Table 2 suggests that the increase in corruption, population and natural resource rents contributes to the worsening of CI. The detrimental effect of corruption as underlined earlier is due to the distortions that it creates in income redistribution by altering the composition of social spending in such a way as to increase the income of the richest at the expense of the poorest (Glaeser *et al.*, 2003). As suggested by the literature, our results also indicate that education has a beneficial effect on CI as it mitigates it. This result is in line with the findings of Chancel and Piketty (2015) and Yang and Liu (2017), who argue that more educated people easily recognise the principles of environmental protection and the risks of increasing carbon emissions. Therefore, they are more inclined to conserve energy or consume energy with a large carbon footprint.

4.2. Sensitivity and Robustness Analyses

4.2.1. Potential Exclusion Criteria

Although the identification strategy adopted here appears relevant, we cannot rule out the possibility of the weak exogeneity of the average complexity level of the three economies with which a country does not share a border as an instrument. For robustness purposes, we examine the sensitivity of the result to the potential violations from the exclusion restriction. We rely precisely on Conley *et al.*'s (2012) union of confidence intervals (UCI) approach to the plausible exogeneity test. This test allows the identification of the upper and lower bounds of the incidence of economic complexity on CI when our instrument deviates from a scenario of perfect exogeneity. In other words, in the presence of a direct nexus between the instrument and the CI. When both the upper and lower bounds of the confidence interval are either above or below zero, as we would expect with ECI trade and ECI technology, the test effects are conclusive.

The computed bounds for the 95% confidence intervals of the UCI technique by Conley et al. (2012) are displayed in Table 2. They show that none of the confidence intervals of the trade complexity and technology complexity contain zero and thus provide substantial evidence in favour of the statistically significant robust relationship of trade complexity with technology complexity. On the same note, the results robustly indicate that research complexity does not affect CI.

Table 2. Plausible exogenous bound test results

	(1)	(2)	(3)
	ECI trade	ECI tech	ECI res
Trade ECI	-0.013***		
	(0.003)		
Technology ECI		-0.007***	
		(0.002)	
Research ECI			0.001
			(0.001)
UCI [Lower-bound; Upper-bound]	**[-0.284; -0.006]**	**[-0.176; -0.003]**	**[-0.132; 0.003]**
Observations	2,200	1,810	2,342
Controls	Yes	Yes	Yes
Fixed effect	Yes	Yes	Yes
Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1			

On the same note, we evaluate the robustness of our estimates through a formal sensitivity analysis that allows for potential violations of the exclusion restriction, following Kiviet (2020). This approach has the advantage of addressing this concern by explicitly allowing for mild violations of the exclusion restriction and by providing a formal sensitivity analysis of IV estimates. Rather than treating instrument validity as a binary condition, the Kiviet framework models potential violations as direct effects of the instrument on the outcome. This makes it possible to quantify how large such violations would need to be to materially affect the estimated robust relationship.

The results from this test, presented in Figure 5, indicate that across the three dimensions of economic complexity—trade, technology, and research—the estimated coefficients remain close to zero and statistically indistinguishable from zero over a broad, economically plausible range of assumed endogeneity. Moreover, the IV and Kinky Least Squares (KLS) estimates are highly consistent throughout this range, suggesting that the findings are not driven by weak identification or minor departures from instrument exogeneity. Only under extreme, economically implausible endogeneity assumptions do the estimates exhibit instability, leading to a substantial widening of the confidence intervals. Overall, this sensitivity analysis reinforces the credibility of our identification strategy and confirms that the absence of a statistically significant effect is robust to moderate violations of the exclusion restriction.

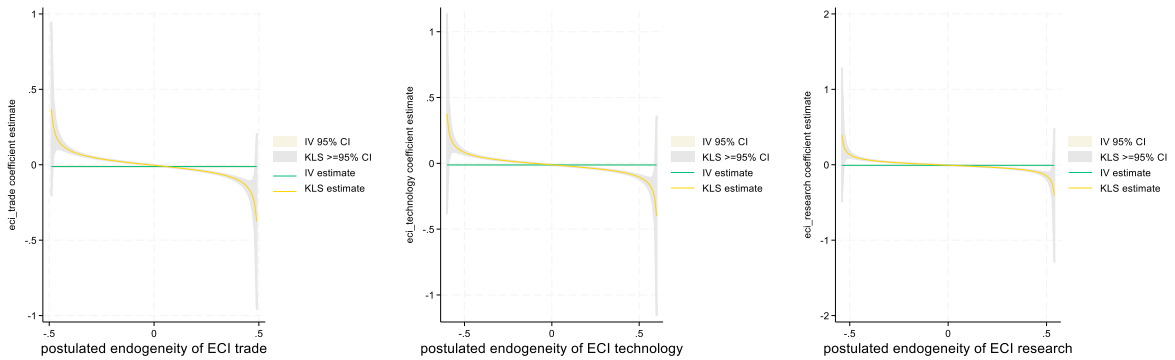


Figure 5. First stage plots.

4.2.2. *Falsification test*

In line with previous tests, this section uses placebo tests to assess the robustness of our results. To this end, we use three complementary approaches. The first is based on a placebo test using randomisation of the instrumental variable. The underlying idea is that if the results obtained so far were due to unobserved factors or a spurious relationship between the instrument and the endogenous variable, a randomly reconfigured version of the instrument could also produce statistically significant relationships. In concrete terms, this test consists of deliberately breaking the theoretical link between the instrument and the endogenous variable by randomly reassigning the values of the instrument among the observations. We thus construct a falsified instrumental variable from random draws of the observed values of the initial instrument, then estimate equation (5) by instrumenting economic complexity using this placebo instrument. The related results are reported in columns (1) – (3) of Table 3. As the results indicate, our fake instrument has no statistically significant impact on our endogenous variables (the various dimensions of economic complexity). Furthermore, the results demonstrate that economic complexity does not affect carbon inequality, thereby refuting the hypothesis of unobservables or a misleading trend that could influence our results.

The second approach involves maintaining the original instruments while adjusting the dependent variable. In this regard, we rely on media bias (retrieved from the Variety of Democracy Database) as the output variable. The underlying principle of this placebo test is as follows: if the instrument also explained media bias, this would suggest that it primarily captures institutional or 'democratic quality' dimensions, rather than productive capacities. Indeed, the issue of media bias is closely linked to questions of press freedom and political power structures, while CI are primarily determined by technological and energy-related factors. Once again, the results presented in columns (4) – (6) show that by changing the dependent variable and maintaining our initial instrumentation strategy, economic complexity has no relationship with carbon inequality. This absence of a significant effect of the instrument on this placebo variable reinforces thus our main findings.

The last and third approach involves maintaining the original instruments while replacing our interest independent variable (economic complexity) by a governance indicator, precisely a governance index constructed as the average of the six governance indicartors of the World Governance Indicators. The rationale behind this test is based on the premise that if similar specialisation patterns reflect institutional characteristics associated with both economic complexity and emissions inequality, then the instrument would contravene the exclusion restriction. Conversely, the absence of such a link would reinforce the credibility of our instrumentation strategy. The results of this test, presented in column (7) of Table (3), highlight two main findings. Firstly, regarding the results of the first stage, it appears that the parameter associated with our instrument is not significant. This indicates that the average complexity of the three non-neighbouring economies with the most similar specialisation patterns does not reflect similar institutional characteristics in our study. It is important to note that the results of the second step demonstrate that, according to our identification strategy, governance does not have a significant nexus with carbon inequalities. Consequently, our instrument does not affect carbon inequalities via similar institutional characteristics.

Table 3. Plausible exogenous bound test results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: Carbon inequality			Dependent variable: Bias Media			
	Second stage						
Trade ECI	-0.002			-0.004			
	(0.004)			(0.003)			
Technology ECI		-0.003			-0.006		
		(0.005)			(0.005)		
Research ECI			-0.001			-0.000	
			(0.005)			(0.004)	
Governance indicator							0.517
							(1.267)
	First stage						
Fake instrument	0.006	0.014	0.018				
	(0.185)	(0.172)	(0.159)				
Good instrument				0.406***	0.643***	0.786***	1.236
				(0.016)	(0.029)	(0.017)	(1.111)
Observations	2,198	1,803	2,339	2,174	1,905	2,425	1,917
R-squared	0.078	0.069	0.115	0.167	0.184	0.201	0.088
Countries	134	100	135	134	100	135	134
Wald test	0.000	0.000	0.000	0.000	0.000	0.000	0.000
WIT	17.125***	24.174***	22.178***	323.8***	489.0***	1241***	87.212***
UIT	21.258***	22.824***	21.111***	298.6***	136.1***	317.5***	98.241***
Endogeneity test	0.021	0.003	0.006	0.000	0.003	0.006	0.071

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4.2.3. *Additional Controls*

As part of the second robustness assessment, additional specification results are provided, with other relevant drivers of CI included in the conditioning information set. The successive inclusion of the additional control variables prevents strong correlations among them. We first include a proxy for urbanisation following Xu et al. (2016), who show that the gap between the poor and the rich in urban areas is intrinsically related to CI in China. Secondly, we consider energy consumption in light of Xu (2020), who suggests that it contributes to the increase in CI. We measure it using the electricity demand (in the log) from the Ember-Climate database. In the same dataset, we use low-carbon electricity consumption, as the literature suggests that decarbonising the energy supply contributes to the reduction of CI (Zheng *et al.*, 2023). We also include the size of trade openness, following Wang et al. (2019), who argue that it exacerbates CI. Finally, we include a dummy variable for inflation targeting, as recent studies (Mbassi et al., 2025) find that it does not affect renewable energy consumption. We rely on information from Bambe (2023) to construct our inflation-targeting dummy. The new results are retrieved in Table 3. As it is apparent, the addition of those controls does not alter our baseline findings. Interestingly, the results suggest that trade openness and urbanisation may increase CI. By contrast, low-carbon electricity demand and inflation targeting contribute to the reduction of CI. Ultimately, the inclusion of additional controls does not alter the baseline findings.

Table 4. Results including additional controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Trade ECI	-0.014**	-0.014**	-0.016**	-0.014**	-0.015**	-0.014**												
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)												
Technology ECI							-0.007**	-0.008**	-0.008**	-0.007**	-0.007**	-0.007**						
							(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)						
Research ECI													0.001	0.001	0.001	0.001	0.002	0.001
													(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Urbanisation	0.045*	0.045*	0.062*	0.063*	0.067*	0.066*	-0.037	-0.044	-0.039	-0.033	-0.038	-0.039	0.044*	0.036*	0.039*	0.047*	0.047*	0.048*
	(0.026)	(0.027)	(0.029)	(0.028)	(0.028)	(0.028)	(0.030)	(0.032)	(0.034)	(0.034)	(0.034)	(0.034)	(0.020)	(0.021)	(0.023)	(0.023)	(0.023)	(0.023)
Electricity per capita		0.001	0.001	0.003	0.002	0.002		0.002	0.003	0.004	0.005	0.004		0.001	0.001	0.003*	0.003*	0.003*
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)		(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Low-carbon electricity			-0.001	-0.001	-0.001	-0.001			-0.001	-0.000	-0.001	-0.001			-0.001	-0.001	-0.000	-0.000
			(0.001)	(0.001)	(0.001)	(0.001)			(0.001)	(0.001)	(0.001)	(0.001)			(0.001)	(0.001)	(0.001)	(0.001)
Shadow economy				0.002**	0.003**	0.004**				0.003**	0.003**	0.004**				0.002**	0.002**	0.003**
				(0.000)	(0.000)	(0.000)				(0.001)	(0.001)	(0.001)				(0.000)	(0.000)	(0.000)
Inflation targeting					-0.017**	-0.018**					-0.025**	-0.024**					-0.020**	-0.021**
					(0.005)	(0.005)					(0.004)	(0.004)					(0.006)	(0.006)
World Bank						-						-						-

Governance Index						0.024**						0.038**						0.016**
						(0.004)						(0.004)						(0.004)
Observations	2178	2147	2068	1958	1958	1958	1788	1759	1727	1643	1643	0.005	2319	2269	2170	2056	2056	2056
Countries	133	133	128	123	123	123	99	99	98	95	95	(0.003)	134	134	129	124	124	124
Previous Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	-0.001	Yes	Yes	Yes	Yes	Yes	Yes
Countries fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	(0.001)	Yes	Yes	Yes	Yes	Yes	Yes
WIT	463.784	427.924	400.797	485.590	501.231	512.237	476.204	455.699	452.960	450.036	467.954	0.003**	2185.2	2118.8	2055.3	1841.3	1947.2	1954.4
UIT	208.541	195.418	188.168	196.746	198.124	199.846	147.200	137.683	136.581	130.017	142.645	(0.001)	497.661	480.713	461.901	442.505	431.784	426.356
Endogeneity test	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.004	0.005	0.003	0.004	-0.025**	0.006	0.007	0.005	0.012	0.007	0.005

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4.2.4. *Alternative Country Samples*

As a third proof, we assess the robustness of the results to different subsamples to examine whether our findings differ with the level of development or depend on the region. We first distinguish between developed and developing countries, following the 2019 WDI classification, especially as the literature suggests, on the one hand, that CI reflects the differences between the level of development (Chancel, 2022), and, on the other hand, that most developing countries are less complex than developed ones (Hartmann et al., 2017; Hidalgo & Hausmann, 2009; Stojkoski et al., 2023). To make this assessment, we amend Equation (3) to include the interaction of the ECI with a dummy that takes 1 in the case of a developed country and 0 in the case of a developing country. We then use the marginal relationship of ECI to compare developed and developing nations. Considering the regional difference in economic complexity and CI, we also use the same approach to assess the incidence of economic complexity in the different regions. The results of the marginal incidence that are presented in Figure 4 indicate that trade complexity reduces CI in both economies. However, the relationship is quite important in developing countries. Concerning technology complexity, they suggest that CI gets reduced only in developing countries while in developed ones it is not affected by technology complexity, as the marginal incidence is not significant at least at the 10% level. On the same note, research complexity appears to not affect CI in both developed and developing countries.

The greater relationships of trade and technological complexity on carbon inequalities in developing countries can be explained by the combined dynamics of structural transformation and technological catch-up. Increased trade complexity is generally associated with productive diversification, a gradual shift away from carbon-intensive extractive industries, and greater integration into international value chains (Qayyum *et al.*, 2021). This process promotes both the expansion of formal employment and the diffusion of more efficient technologies, thereby helping to reduce emissions disparities through combined nexuses on the productive structure and income distribution. Concurrently, the rise in technological complexity in economies with initially limited capacity is indicative of a process of catch-up. By improving skills, infrastructure, and innovation capacity, technology complexity can encourage the wider adoption of lower-carbon production processes and reduce the gap between modern sectors and traditional, high-emission activities. Conversely, in advanced economies, where productive structures are already diversified and close to the technological frontier, additional gains in complexity are more marginal and often concentrated in skill-intensive segments. In these contexts, emissions inequalities are more closely related to consumption patterns than to sectoral characteristics, which limits the additional distributional nexus of trade or technological complexity.

When dealing with the effect of regions, the results indicate that trade complexity contributes to mitigating CI in all the regions. Interestingly, this relationship is larger in Sub-Saharan Africa. This suggest that suggests that the trade complexity equalising nexus operates through relatively universal structural mechanisms. By promoting productive diversification, reducing dependence on carbon-intensive primary sectors, and fostering integration into global value chains, trade complexity tends to broaden formal employment and diffuse cleaner production practices. These transformations mitigate both income concentration and production-based emission disparities, resulting in a consistent reduction in carbon inequality across heterogeneous regions. Turning to technology complexity, the results show that it only reduces CI in EAP, ECA, LAC, MENA and NA regions. The absence of a substantial equalising nexus due to technological complexity in SA and SSA may indicate limited absorption capacity and entrenched structural dualism. In these regions, technological modernisation is often concentrated in specific urban or export-oriented areas, without spreading sufficiently across sectors and households to affect the distribution of carbon emissions. Conversely, in regions with a more advanced industrial infrastructure and a robust institutional framework, greater technological complexity is more likely to lead to the wider adoption of cleaner production processes and more inclusive structural transformation, thereby reducing disparities in carbon emissions. As with the level of development, we also find that research complexity does not influence CI no matter the region.

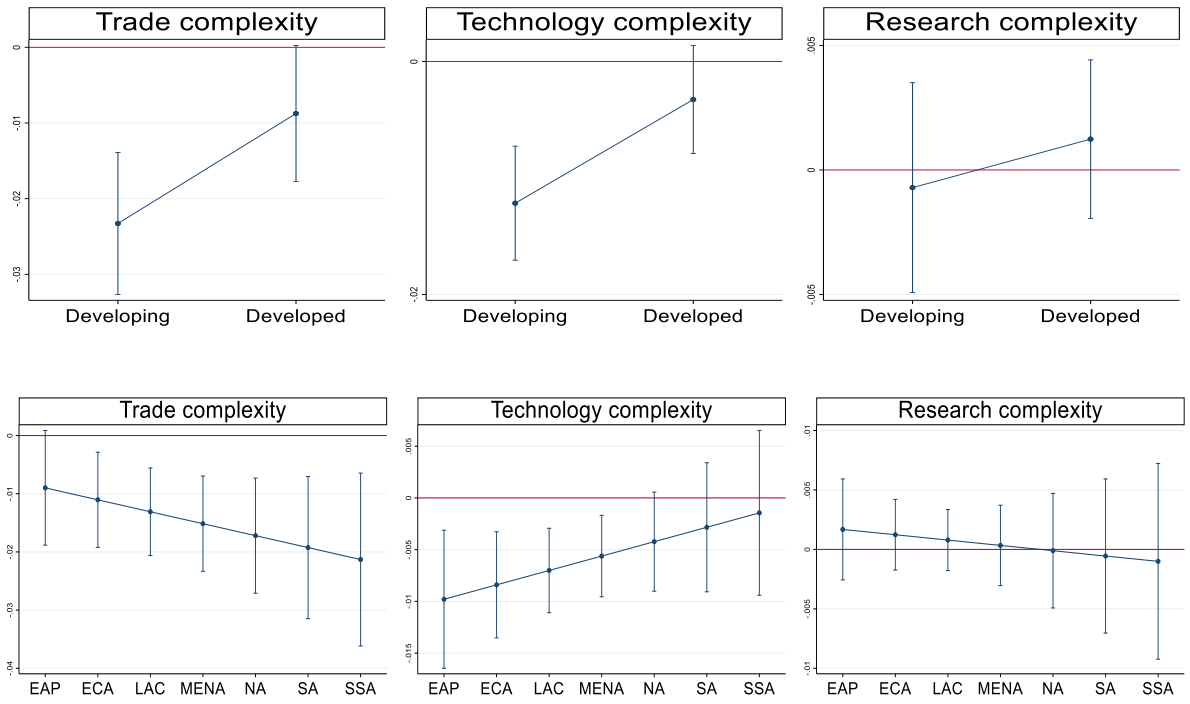


Figure 6. The marginal relationship of economic complexity

4.2.5. *Dealing with the moderating relationship of institution*

Because institutions simultaneously shape productive coordination and the distribution of environmental and income outcomes, they are not merely confounding variables but structural conditioning factors. The distributional consequences of economic complexity are therefore unlikely to be homogeneous across institutional environments. To address this issue, we analyse the moderating nexus of institutions on the economic complexity-CI nexus. To do that, we have amended equation (5) to incorporate the interaction between our indicators of economic complexity and indicators of institutional quality. Our primary focus is on the rule of law and egalitarian democracy, as derived from the Vdem database. The results of this analysis are presented in Figures 7 and 8.

When examining the moderating role of the rule of law (see Figure 7), the results show that the marginal nexus of trade complexity decreases as institutional quality improves. Specifically, in environments with weak rule of law, trade complexity tends to increase carbon inequalities. However, in institutionally strong contexts, it can help to reduce these inequalities. This phenomenon can be attributed to the absence of a robust legal framework, which results in the rent being generated by export upgrades being concentrated in energy-intensive sectors that are often dominated by politically connected firms. Weak enforcement of environmental standards and unequal access to clean technologies then allow for the externalisation of carbon costs, reinforcing the concentration of emissions. Conversely, robust rule of law promotes regulatory enforcement, the diffusion of clean technologies and increased competitive discipline, which reduces the dispersion of emissions among agents. In terms of technological complexity, a contrary pattern emerges: carbon inequalities increase in environments with strong rule of law, but decrease when it is weak. In fact CI may rise under a strong rule of law because secure property rights, financial depth, and contract enforcement enable large-scale expansion of capital- and energy-intensive sectors. These high-productivity activities often concentrate emissions among a limited number of firms or high-income groups, increasing dispersion. Moreover, stronger institutions improve monitoring and reporting, which can reveal underlying concentration in emissions. In contrast, weak rule-of-law environments constrain large-scale industrial growth due to limited finance and institutional uncertainty. Economic activity remains more fragmented and informal, with emissions spread across smaller, low-productivity actors, reducing measured carbon inequality despite weaker overall environmental performance. Finally, research complexity does not appear to have a significant effect on carbon inequalities, regardless of the level of rule of law.

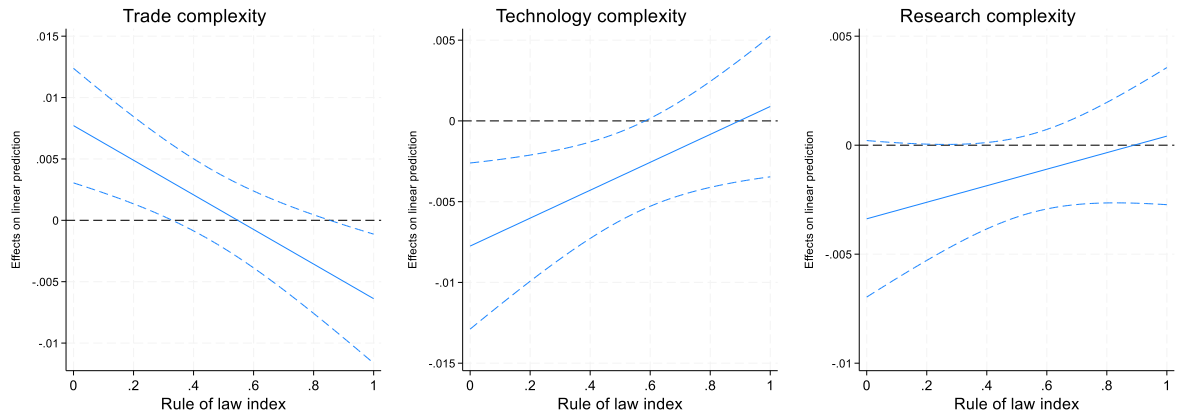


Figure 7. The marginal nexus of economic complexity

Similarly, regarding the moderating role of democracy (see Figure 8), the results highlight significant heterogeneity. On the one hand, the results show that the linkage of trade complexity decreases monotonically with democracy. The findings indicate that when democratic levels are low, the correlation is positive and statistically significant. However, as democratic accountability increases, the correlation gradually diminishes until it reaches zero, or even becomes negative. Conversely, technological complexity exhibits a distinct dynamic; its nexus is negative at low levels of democracy but gradually becomes less negative — even slightly positive — as democracy strengthens. This result indicates that the structural and distributional consequences of technological progress depend heavily on the degree of institutional inclusiveness. In fragile institutional environments, advanced technologies may remain concentrated in a few capital-intensive sectors, limiting their diffusion and accentuating structural imbalances. Conversely, in more democratic regimes, enhanced protection of property rights, augmented investment in human capital and more competitive markets facilitate a more widespread dissemination of technological benefits. Finally, the complexity of research shows a clear upward trend, although the marginal relationships are statistically insignificant.

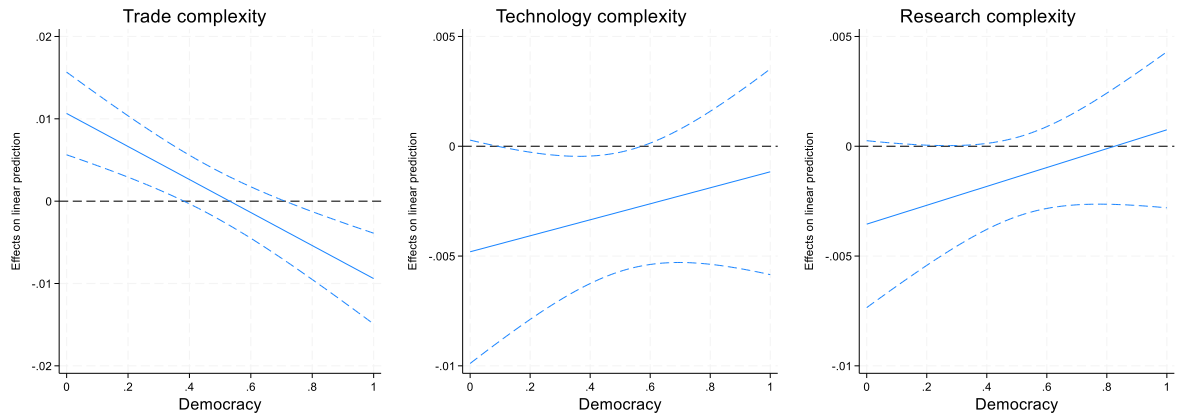


Figure 8. The marginal relationship of economic complexity

4.2.6. *Alternative Measures of Carbon Inequality*

The results obtained so far indicate that trade and technology complexity are strongly associated with the decline of the CI, while research complexity does not influence it. As a reminder, these results are obtained using a Gini index to measure the CI. However, even though the Gini index allows direct comparison between two populations regardless of their size, several studies suggest that it is not easily decomposable. Moreover, very different carbon distributions can present the same Gini coefficient. Given the debate on the measurement of inequality, we test the sensitivity of our findings using alternative measures of inequality. Precisely, we rely first on the Atkinson index of CI which presents the percentage of total carbon emission that a given society would have to forgo to have a more equal distribution of carbon emission between its citizens. This index also considers the degree of society's aversion to inequality. We compute Atkinson1, Atkinson2, and Atkinson3 indices corresponding to inequality aversion parameters respectively equal to 0.5, 1 and 2.[1] We also rely on the Theil index of CI which has the advantage to quantify how much inequality is due to the difference between individuals within and between groups. The results using these alternative measures are reported in Table 4. Results with the Atkinson indices that are exhibited in Columns (1) – (9) are in line with the baseline one, comforting that trade and technology complexity reduce the CI while research complexity does not. When dealing with the Theil index, we obtain comparable results with trade and technology complexity. However, the parameter associated with research complexity becomes significant, indicating that research complexity may increase CI.

[1] The more positive is the inequality aversion parameter, the more sensitive Atkinson index is to income differences at the bottom of the distribution, i.e., the more is society concerned with the income inequality.

Table 5. Results using alternative measures of CI

	Atkinson1			Atkinson2			Atkinson3			Theil		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Trade complexity	-0.012***			-0.012***			-0.012***			-0.059***		
	(0.003)			(0.003)			(0.003)			(0.011)		
Technology complexity		-0.006***			-0.006***			-0.006***			-0.035***	
		(0.002)			(0.002)			(0.002)			(0.007)	
Research complexity			0.001			0.001			0.001			0.008**
			(0.001)			(0.001)			(0.001)			(0.004)
Observations	2350	1845	2508	2350	1845	2508	2350	1845	2508	2350	1845	2508
R-squared	0.167	0.219	0.198	0.167	0.219	0.198	0.167	0.219	0.198	0.162	0.232	0.189
Countries	134	100	135	134	100	135	134	100	135	134	100	135
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
WIT	473.51	500.02	2212.2	473.51	500.02	2212.2	473.51	500.02	2212.2	473.51	500.02	2212.2
UIT	202.62	150.95	481.85	202.62	150.95	481.85	202.62	150.95	481.85	202.62	150.95	481.85
Endogeneity test	0.000	0.001	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.000	0.000	0.000

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4.2.6. *Dealing with alternative data of carbon inequality*

Following the implementation of alternative measures of inequality, we are currently assessing the sensitivity of our results to individual carbon footprint data. To achieve this, we are using alternative carbon footprint data from the EXIOBASE database following Hubacek et al. (2017). This approach has the advantage of relying on a detailed multi-regional input-output matrix, which allows us to accurately track embedded carbon emissions throughout global value chains across 200 sectors in 43 economies (mainly advanced) and 5 regions on . This structure provides a consistent and detailed measurement of consumption carbon footprints, regardless of assumptions about income distribution. In contrast to WID data, which focuses on individual inequality, EXIOBASE's sectoral granularity captures indirect emissions embedded in global value chains.

The new results obtained with the new data and presented in Table 6 indicate that trade and technology complexity reduce CI. Conversely, the incidence of research complexity on CI is found to be non-significant. These results once again demonstrate that our conclusions are not influenced by the nature of the data used to measure carbon footprints.

Table 6. Plausible exogenous bound test results

	(1)	(2)	(3)
	EXIOBASE		
	Second stage		
Trade ECI	-0.035***		
	(0.004)		
Technology ECI		-0.028***	
		(0.006)	
Research ECI			-0.010
			(0.009)
	First stage		
Instrument	0.518***	0.614***	0.741***
	(0.185)	(0.172)	(0.159)
Observations	1038	1012	1054
R-squared	0.427	0.586	0.431
Countries	43	43	43
Wald test	0.000	0.000	0.000
WIT	138.14***	215.25***	213.17***
UIT	93.214***	194.87***	201.41***
Endogeneity test	0.001	0.003	0.006
Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1			

4.2.7. *Alternative instruments and alternative estimands*

In our baseline IV specifications, domestic economic complexity is instrumented using the average complexity of the three non-neighbouring economies with the most similar

specialisation patterns. While placebo and sensitivity tests support the validity of this approach, one cannot entirely rule out the possibility that these structurally similar economies may still share indirect links—such as participation in global value chains, technology diffusion, trade relationships, or comparable regulatory and institutional frameworks—that could themselves influence the domestic distribution of carbon emissions. Similar specialisation patterns may also reflect common structural or institutional features, including governance quality or education systems, which could be correlated with both economic complexity and carbon inequality. Moreover, even in the absence of direct geographic proximity, maritime or land connections may generate spillovers in production, capital flows, or technology that affect emissions inequality.

To address these concerns and further strengthen the credibility of our identification strategy, we, first, conduct robustness checks using alternative instruments for economic complexity based on national innovation outputs, following Boleti *et al.* (2021). Specifically, we use country-level numbers of patents and scientific publications as instruments for economic complexity. This choice is theoretically well-grounded, as economic complexity indices are designed to capture the stock of productive knowledge embedded in an economy, while patents and publications provide direct, observable signals of innovative activity, technological capabilities, and knowledge creation. Economies that generate more patents and scientific output tend to engage in more sophisticated, knowledge-intensive production processes, which are central to the notion of economic complexity. Empirically, the relevance of these instruments is well supported in the literature. Higher patenting activity is strongly associated with higher levels of economic complexity; for example, Mishra *et al.* (2020) show that resident patent counts have a positive and statistically significant effect on the Economic Complexity Index. Recent studies further combine trade data with patent and publication indicators to construct more predictive and robust measures of productive sophistication.

Regarding the exclusion restriction, we argue that patents and scientific publications do not directly affect carbon inequality outside the economic complexity channel. Carbon inequality reflects the unequal distribution of emissions across income or demographic groups and is primarily driven by within-country factors such as income distribution, consumption patterns, energy prices, and national energy and climate policies. Empirical evidence consistently shows that high-income households account for a disproportionate share of emissions; for instance, Chancel (2022) documents that the top 10 per cent of the global population is responsible for roughly half of total emissions. This highlights that carbon inequality is fundamentally shaped by patterns of resource use and consumption rather than by knowledge production per se. Patents and publication volumes do not directly determine who consumes energy or how emissions are distributed across households; any effect they have on emissions inequality must

therefore operate indirectly through structural changes in the economy associated with greater economic complexity, such as shifts toward higher-value-added or cleaner production technologies.

We also use the instrumental approach proposed by Lewbel (2012), which is based on the use of internal instruments constructed from the heteroscedasticity of errors, combined with lags of the variable suspected of endogeneity. More specifically, economic complexity is instrumented using its lags.

The results using these alternative instruments are presented in **Table 6**. Consistent with our baseline instrumentation strategy results, the new results confirm that trade and technology complexity significantly reduce carbon inequality, as the related coefficients are negative and statistically significant. Meanwhile, these new results also confirm that research complexity does not affect carbon inequality. Interestingly, the results of the under-identification (UIT) and Hausman exogeneity tests indicate that the instruments are exogenous and that the models are not under-identified. Moreover, the first-stage results suggest that the instruments used are strongly correlated with the different ECI, as they enter positively and significantly, at least at the 5% level, and the Hansen J overidentification test is non-significant in all regressions. Most importantly, the Cragg-Donald (WIT) F-statistic test of instrument fitness in the first-stage regression confirms a strong correlation.

Table 7. Economic complexity and CI, FE-2SLS estimates with alternative instruments

	(1)	(2)	(3)	(4)	(5)	(6)
	Second stage					
Trade ECI	-0.025**			0.030***		
	(0.009)			(0.010)		
Technology ECI		-0.013***			0.015***	
		(0.005)			(0.004)	
Research ECI			0.124			0.115
			(0.382)			(0.104)
	First stage					
Patents (in log)	0.141***	0.343***	0.038**	--	--	--
	(0.017)	(0.032)	(0.016)	--	--	--
Number of articles published				--	--	--
(in log)	0.787***	0.270***	0.248***			
	(0.223)	(0.051)	(0.064)	--	--	--
Observations	1476	1494	1494	2,198	1,803	2,339
R-squared	0.348	0.257	0.211	0.171	0.216	0.199
Countries	110	90	89	134	100	135
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Wald test	0.000	0.000	0.000	0.000	0.000	0.000
WIT	60.03***	56.90***	91.17***	63.51***	98.00***	89.12***
UIT	71.93***	74.99***	152.4***	147.3***	286.7***	312.6***
Hansen j-test	0.564	0.219	0.398	0.378	0.579	0.615
Endogeneity test	0.000	0.000	0.000	0.000	0.000	0.000
Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1						

Having confirmed the stability of our baseline findings using alternative instruments, we further assess robustness by turning to the system generalised method of moments (SYS-GMM). This assessment is even more important given that we cannot rule out the potential endogeneity of our control variables (education, inequality, GDP per capita). Furthermore, as highlighted by Chancel (2024) and Chancel and Piketty (2024), carbon inequalities within countries appear to persist over time. Based on these observations, we amend equation (5) by including carbon inequalities delayed by one period and use the SYS-GMM estimator. The results of these estimations are presented in **Table 6.** As can be observed, our conclusions do not differ from those obtained so far. They confirm that CI decreases with trade and technology complexities. Therefore, considering the potential endogeneity of our control variables does not alter our conclusions derived from the estimation of the basic model using instrumental variables. Interestingly, the different diagnostic tests (the Hansen's *J* overidentification, Arellano and Bond's (1991) residual autocorrelation tests and the Hansen C test of exogeneity of iv-style instruments) do not invalidate the quality of the instrumentation within the system-GMM framework. Most importantly, the parameter of the lagged dependent variable is positive, significant at the 1% level and around [0.847 0.887], corroborating the strong inertia of CI.

Table 8. Economic complexity and CI, System GMM estimates

	(1)	(2)	(3)
Trade ECI	-0.017***		
	(0.004)		
Technology ECI		-0.012***	
		(0.002)	
Research ECI			0.047
			(0.031)
Lagged carbon inequality index	0.874***	0.887***	0.847***
	(0.010)	(0.011)	(0.010)
Constant	-0.012*	-0.016	-0.007
	(0.007)	(0.021)	(0.010)
Observations	2124	1815	2219
Countries	134	100	135
Controls	Yes	Yes	Yes
Instruments	35	35	35
Wald test	0.000	0.000	0.000
AR (1)	0.005	0.011	0.009
AR (2)	0.795	0.843	0.826
Hansen J-test	0.756	0.814	0.913
Hansen C-test	0.954	0.786	0.874
Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1			

4.2.8. Assessing Transmission Channels

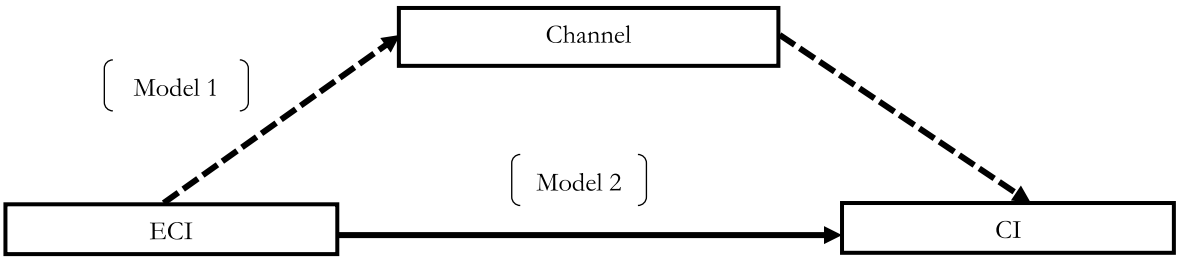
As the core idea of this paper is that the relationship between economic complexity and military spending is mediated by economic development, income inequality, and human capital, the final robustness analysis examines the mediation relationship of the transmission channel. To do that, the approach considered relies on robust mediation analysis with

instrumental variables developed by Frölich and Huber (2017). Specifically, it involves estimating two regression equations, as illustrated in Figure 9. In the first regression, we estimate the incidence of economic complexity (β_1) on the mediators. In the second regression, we assess the effect of the mediators (β_3) on CI while controlling for the direct effect of economic complexity (β_2). Based on these results, the indirect effect is given by the product of (β_1) and (β_3). This term also reflects the size of the average causal mediation effect (ACME), which essentially depends on the level at which economic complexity influences the mediator (β_1) and the extent to which the mediator affects CI (β_3). In every regression, ECI is instrumented by the average complexity level of the three economies, with which a country does not share a border (land and maritime), which have the most similar specialisation pattern.

Since this identification strategy requires that the instrument affects carbon inequality and the mediators only through domestic economic complexity, we argue that the use of non-neighbouring countries is intended to minimise direct spillovers through trade, policy coordination, or geographic proximity. Given the lack of direct economic or institutional linkages, it is unlikely that the complexity of distant but structurally similar countries directly influences domestic carbon inequality or mediators such as GDP, income inequality, human capital, or emissions. Moreover, conditional on domestic economic complexity, a rich set of time-varying controls, and country fixed effects, we assume that the mediators are not systematically confounded with the outcome.

Although the sequential ignorability assumption is inherently demanding, several elements mitigate this concern in our empirical setting. First, we control for a comprehensive set of time-varying covariates capturing the main structural determinants of both the mediators and carbon inequality. These include natural resource rents (affecting production structure and emissions intensity), GDP per capita (level of development), population size (scale effects), human capital (technological absorption and consumption patterns), and institutional quality (corruption). These factors are consistently identified in the literature as key drivers of inequality and emissions dynamics. Second, country fixed effects absorb all time-invariant heterogeneity—such as geography, colonial legacy, deep institutional traits, and persistent cultural characteristics—that could jointly influence mediators and carbon inequality. Time fixed effects further capture global shocks, technological waves, and international policy dynamics. Third, the mediators considered are macro-structural variables that evolve gradually over time. Conditional on economic complexity and structural controls, large short-term omitted confounders simultaneously affecting mediators and carbon inequality become less plausible. However, importantly, it should be noted that identification does not require the absence of all unobserved heterogeneity, but only the absence of residual confounders correlated with both the mediator and the outcome.

To assess the validity of the strategy of instrumentation, we report the corresponding first-stage regressions F-statistics (Fstat1 and Fstat2).



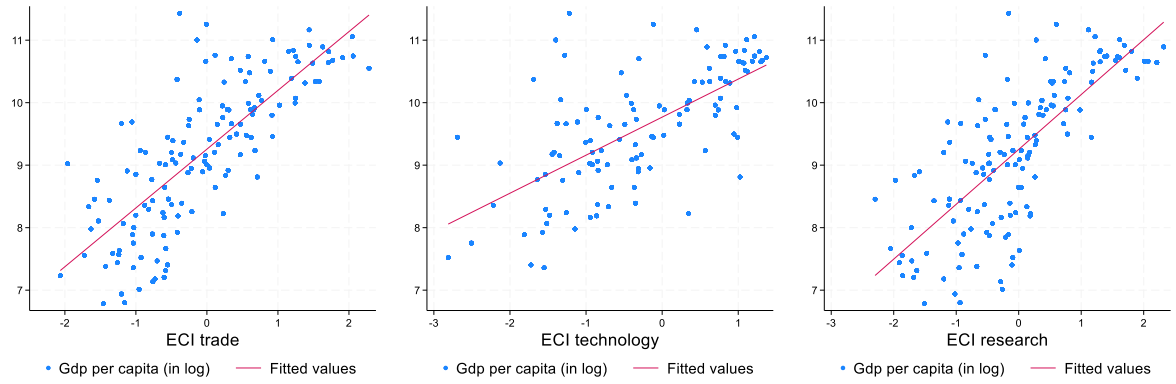
Note. In Model 1: $channel_{i,t} = \alpha_1 + \beta_1 ECI_{i,t} + \upsilon_{i,t}$

In Model 2: $Gini_{i,t} = \alpha_2 + \beta_2 channel_{i,t} + \beta_3 ECI_{i,t} + \nu_{i,t}$

Thus, Direct nexus = total nexus = β_3; indirect nexus= $\beta_1 * \beta_2$ and total nexus = $\beta_1 * \beta_2 + \beta_3$

Figure 9. Transmission mechanisms

Before running the mediation analysis, we first provide graphical evidence on the relationship between economic complexity and the mediators on the one hand, and between the mediators and CI on the other hand (see Figures 10 and 11). As can be observed, economic complexity is positively correlated with GDP per capita, human capital and GHG. Conversely, economic complexity is negatively correlated with income inequality, suggesting that inequality may decrease as an economy becomes more complex. Concerning the relationship between the mediators and CI, Figure 10 shows that GDP per capita is weakly and positively correlated with CI, while strongly and positively correlated with income inequality and GHG emission are positively correlated with CI as underlined in Section 2. Conversely, Human capital is negatively correlated with CI.



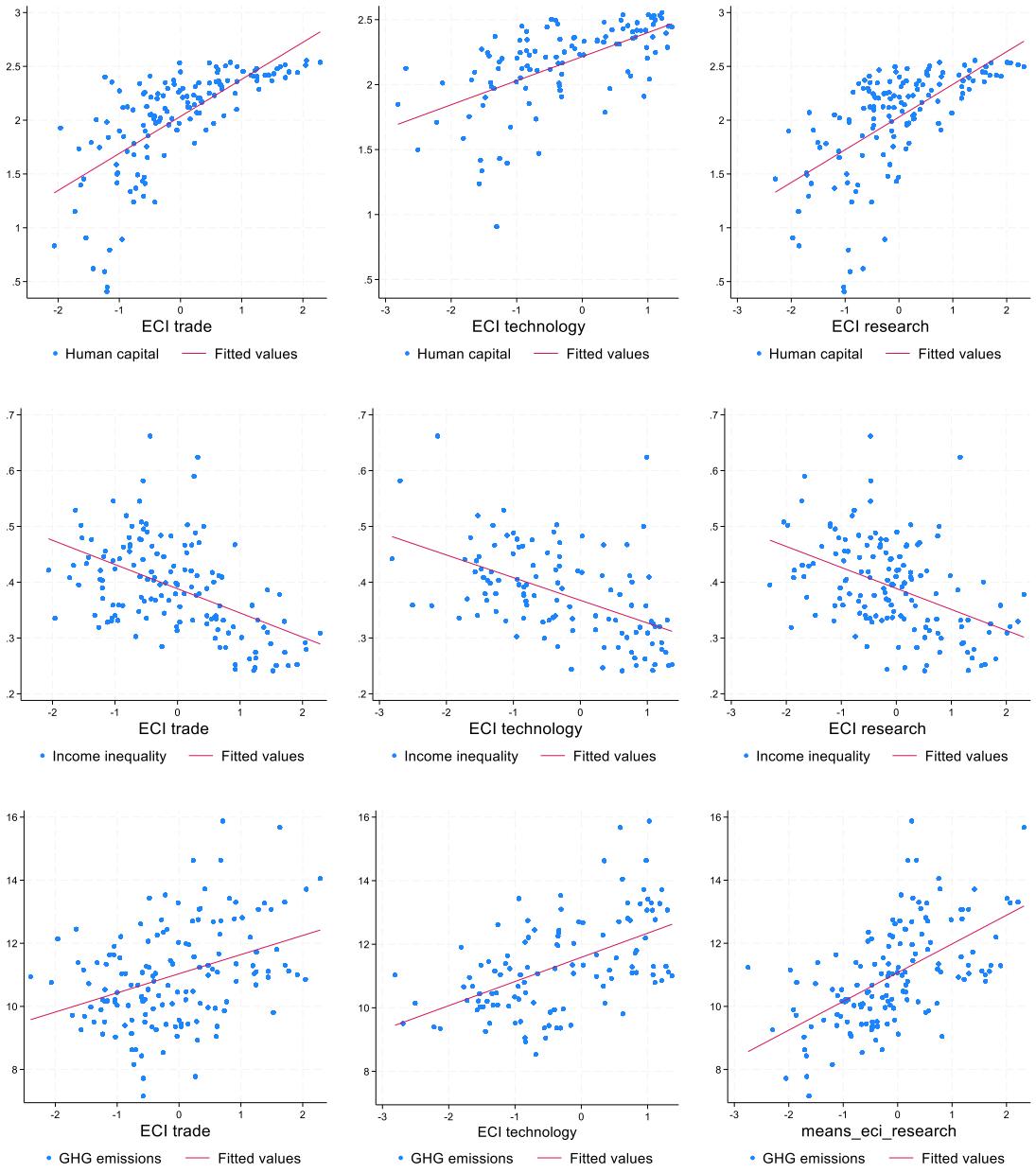


Figure 10. Graphical evidence of the Transmission mechanisms

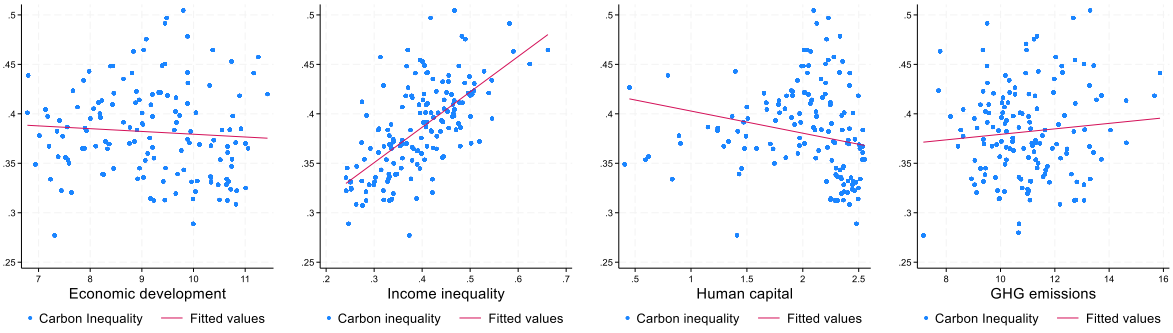


Figure 11. Graphical evidence of the Transmission mechanisms

The estimation results reported in Table 8 shed light on the economic mechanisms through which economic complexity shapes carbon inequality. The first part of the table (Model 1) examines how different dimensions of economic complexity affect the proposed mediators, while the second part (Model 2) evaluates how these mediators, in turn, influence carbon inequality. The results indicate that both trade and technological complexity foster economic development (coefficients of 0.097 and 0.043) and significantly enhance human capital accumulation (0.045 and 0.031). This suggests that more sophisticated and diversified production structures expand learning opportunities, stimulate skill formation, and facilitate structural upgrading. In line with Stojkoski et al. (2023), complexity thus appears as a driver of productive capability accumulation and long-term growth. Importantly, the technological dimension also acts as a redistributive force, significantly reducing income inequality. This finding supports the view that innovation-intensive structures may generate more inclusive labor demand by broadening access to higher-skilled occupations. However, the expansion of trade and technological complexity simultaneously increases GHG emissions, reflecting scale effects and higher energy use associated with structural transformation. Complexity therefore generates both upgrading and environmental pressure. The credibility of these relationships is reinforced by the strength of the instruments. The first-stage F-statistics (Fstat1) range from 148.3 to 3458, well above conventional thresholds, indicating that the exogenous component of economic complexity is precisely identified. For instance, in the income inequality channel, the F-statistic reaches 1530, ruling out weak instrument concerns and strengthening the possible causal interpretation of the technological effect.

Turning to the second stage (Model 2), the results clarify how the identified mediators translate into variations in CI. Income inequality significantly increases carbon inequality, indicating that unequal income distributions are associated with a more unequal distribution of carbon emissions. Economically, this reflects the fact that higher-income groups typically account for a disproportionate share of consumption-based emissions, thereby amplifying disparities in carbon footprints. In contrast, human capital, economic development, and GHG emissions are found to reduce carbon inequality. The negative linkage of human capital suggests that better-educated societies may adopt cleaner technologies more broadly and exhibit more homogeneous consumption patterns, thereby compressing the distribution of emissions. Similarly, higher levels of economic development appear to mitigate carbon inequality, possibly through improved access to energy-efficient infrastructure and more inclusive growth dynamics. Interestingly, higher aggregate GHG emissions are associated with lower carbon inequality. This result likely reflects a scale effect: as emissions rise due to broader industrialization or mass consumption, carbon-intensive activities become less concentrated among top income groups and more diffused across the population. Interestingly, the Fstat2 values (ranging from 45.65 to 247.8) confirm the robustness of the identification. The systematic

significance at the 1% threshold of these F statistics proves that the identified channels (development, inequality, human capital, GHG) transmit the incidence of complexity in a statistically reliable manner.

Taken together, these findings indicate that economic complexity may influence carbon inequality through multiple and partly offsetting channels—particularly via income distribution, human capital accumulation, and structural development—highlighting the multidimensional nature of the transmission mechanisms.

Considering the results of the mediation analyses presented in Table 6, the null hypothesis of no mediation is not rejected at the 10% significance level for economic development across trade, technology, and research complexity. Regarding the channel of income inequality, the mediation relationship is not rejected for only the technology complexity, as the ACME (-0.010) is significant at the 1% level. Regarding the human capital channel, the mediation relationship is not rejected only for trade and technology complexity. For trade complexity, ACME is -0.023 and is significant at the 1% level, while for technology complexity, it is around -0.015 and significant at the 5% level. The corresponding results suggest that the hypothesis that economic development serves as a channel through which economic complexity affects CI is not supported. Most importantly, the results show that technological complexity mitigates CI by reducing income inequality, improving human capital, and increasing GHG emission intensity. On the same note, trade complexity also narrows CI through human capital and the rise in GHG emissions intensity.

Table 9. Robust mediation analyses

	Economic development			Income inequality			Human capital			GHG emissions		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Model 1. Dependent variable: the Chanel												
Trade complexity	0.097***			-0.001			0.045***			0.114***		
	(0.003)			(0.003)			(0.010)			(0.022)		
Technology complexity		0.043***			-0.006***			0.031***			0.121***	
		(0.012)			(0.001)			(0.003)			(0.011)	
Research complexity			0.014*			-0.000			0.004***			0.010
			(0.009)			(0.001)			(0.001)			(0.008)
Fstat1	729.8***	148.3***	355.6***	617.3***	1530***	456.7***	655.8***	1590***	353.3***	634.34***	1483***	3458
Model 2. Dependent variable: the ECI												
Channel	-0.927	-0.229***	-0.064	8.149	1.555***	4.615	-0.474**	-0.545***	20.38	-0.266**	-0.078***	-0.071*
	(1.273)	(0.090)	(0.051)	(10.29)	(0.364)	(8.882)	(0.191)	(0.178)	(14.26)	(0.134)	(0.022)	(0.042)
Trade complexity	0.080			-0.015			0.014***			0.024**		
	(0.106)			(0.027)			(0.005)			(0.010)		
Technology complexity		0.001			-0.001			-0.010**			0.002	
		(0.003)			(0.001)			(0.004)			(0.002)	
Research complexity			0.001			-0.001			-0.082			0.000
			(0.002)			(0.004)			(5.698)			0.001
Fstat2	90.257***	151.3***	247.8***	78.752***	178.99***	173.8***	174.4***	80.291***	78.245***	240.4***	225.3***	45.65***
Composition relationships												
ACME	0.089	-0.010**	-0.001	0.007	-0.007***	0.002	-0.021**	-0.017***	0.082	-0.030*	-0.009***	0.001
	(0.124)	(0.004)	(0.001)	(0.022)	(0.002)	(0.006)	(0.010)	(0.006)	(0.001)	(0.016)	(0.003)	(0.001)
Direct nexus	-0.080	0.001	0.001	-0.015	-0.001	-0.001	0.014***	0.010**	-0.082	0.024	0.002	-0.000
	(0.106)	(0.003)	(0.002)	(0.027)	(0.001)	(0.004)	(0.005)	(0.004)	(34.38)	(0.010)	(0.002)	(0.001)
Total nexus	-0.009***	-0.009***	0.000	-0.007	-0.007***	0.001	-0.007**	-0.008***	0.000	-0.006**	-0.007***	0.001
	(0.003)	(0.002)	(0.001)	(0.022	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)
% of total effect mediated	--	109.00%	--	--	87.02%	--	276.0%	224.6%	--	457.9%	128.0%	--
Observations	2200	1810	2342	2200	1810	2342	2200	1810	2342	2200	1810	2342
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Fstat1 is F statistic for the excluded instruments in first stage one (T on Z), Fstat2 is F statistic for the excluded instruments in first stage two (M on Z|T). M refers to mediator, T to treatment, Z to dependent variable. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5. Conclusion, implications and future directions

This study aimed to assess the relationship between economic complexity and CI using a sample of developed and developing countries over the 1995–2019 period. It has contributed to the existing literature by underlining how economic complexity matters in CI. To make the assessment, we have constructed a Gini index of CI and relied on a multidimensional measure of economic complexity. Moreover, this study has relied on the instrumental variable approach to address endogeneity issues that may arise from the assessment of the nexus of economic complexity. Precisely, the study has employed the average complexity level of the three economies which have the most similar specialisation pattern as an instrument to identify the robust linkage between economic complexity and CI. We also dealt with the potential violations from the exclusion restriction, the development level and regional specificities, alternative measures of inequality as well as the assessment of the transmission channels to ensure robustness.

The main finding of the study is that trade and technology complexity contribute to the mitigation of CI, whereas research inequality appears to influence CI. This result is robust to potential violations from the exclusion restriction, the inclusion of additional controls and alternative measures of CI. Interestingly, the results indicate that the incidence of economic complexity is greater in developing countries. On the same note, we find that trade complexity is more effective in reducing CI in SSA, while technology complexity has a greater linkage in the ECA region. Moreover, the assessment of the transmission mechanisms suggests that the incidence of technology complexity passes through income inequality, GHG emission intensity, and human capital, whereas the linkage of trade complexity passes only through human capital. Although these results call for measures to improve technology and trade complexity to achieve social equity, they compromise the objective of climate change mitigation, as economic complexity leads to higher GHG emissions.

Overall, our results indicate that the distributional linkages of economic complexity depend more on its composition than on its aggregate level. While trade and technological complexity are associated with reductions in carbon inequality, research complexity does not exert a statistically significant relationships. These findings suggest that productive upgrading should be strategically directed toward skill-intensive and low-carbon sectors. Meanwhile, the positive relationship between economic complexity and total emissions underscores that complexity-enhancing strategies cannot substitute for climate policy. Instead, they must be complemented by explicit environmental instruments—such as carbon pricing, emission standards, and energy-efficiency regulations—to offset scale effects. Moreover, the identified transmission channels further highlight the central role of human capital and income

distribution. Policies that support education, vocational training, and skill upgrading, particularly in green technologies, can therefore strengthen equity gains while facilitating cleaner production. In this regard, the development of complex low-carbon industries requires targeted apprenticeship and vocational programmes, alongside increased public support for clean-technology research and tax incentives for private R&D. These efforts could be reinforced through green financing instruments, including green bonds and other sustainable financial tools, as well as a strengthened regulatory framework. Finally, enhanced international trade and cooperation—especially with developing countries—can foster technology transfer and promote exports of complex, low-carbon products.

The findings in this study leave room for future research, especially regarding how the established findings withstand empirical scrutiny when viewed through country-specific lenses using relevant, robust country-oriented time-series econometrics techniques. Moreover, understanding how the findings and corresponding interactions are relevant to the United Nations' 2030 Sustainable Development Goals (SDGs) is worthwhile. Future research could also further investigate the mechanisms linking economic complexity to carbon inequality. While this study emphasizes structural channels such as human capital, income inequality, and emission intensity, additional pathways may also be relevant. In particular, future work could examine how economic complexity influences household consumption patterns, which shape the distribution of carbon footprints across income groups. Another promising avenue concerns energy pricing mechanisms, as structural transformation may alter energy demand, market structures, and the accessibility of low-carbon technologies. Finally, exploring the interaction between economic complexity and environmental policies—such as carbon pricing or regulatory frameworks—could provide deeper insights into the political economy of structural transformation and its distributional environmental consequences.

While the additional robustness checks and alternative instruments have been introduced, the identification strategy ultimately relies on the assumption that economic complexity in structurally similar countries affects domestic carbon inequality only through its impact on domestic complexity. Given the possibility that structurally similar economies may also share technological diffusion channels, trade integration, or exposure to global value chains, this exclusion restriction may not hold perfectly. Hence, the instrumental variable estimates should be interpreted as providing suggestive evidence on the relationship between economic complexity and carbon inequality rather than definitive causal effects. Thus, future studies should employ the relevant robust empirical strategies in order to establish if the established findings withstand empirical causal scrutiny.

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Appendixes

Table A1. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Gini (carbon)	4200	0.383	0.050	0.116	0.678
Theil (carbon)	4200	0.368	0.137	0.032	1.212
Atkinson1 (carbon)	4200	0.134	0.036	0.017	0.402
Atkinson2 (carbon)	4200	0.223	0.049	0.036	0.624
Atkinson3x (carbon)	4200	0.349	0.057	0.073	0.854
Trade complexity	2773	0.000	0.997	-4.299	2.409
Technology complexity	2096	0.000	0.994	-3.162	1.569
Research complexity	2899	0.004	0.998	-2.746	3.044
Natural resources	3531	22.602	1.979	16.233	27.002
GDP per capita in log	3414	9.204	1.186	6.227	11.563
Egalitarian democracy	4530	0.397	0.241	0.028	0.876
Population (in log)	3576	16.373	1.397	13.154	21.065
Informal sector	3776	33.34	12.648	8.065	69.346
Education	3432	2.017	0.484	-0.598	2.595

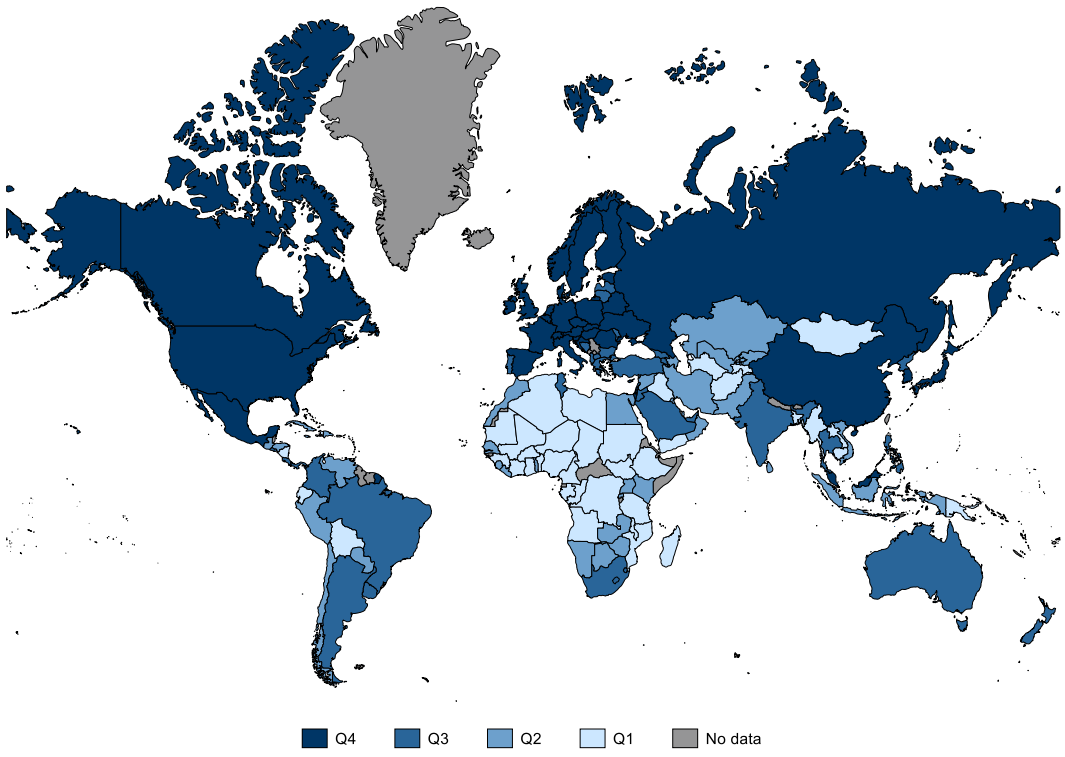


Figure A1. Trade complexity around the world

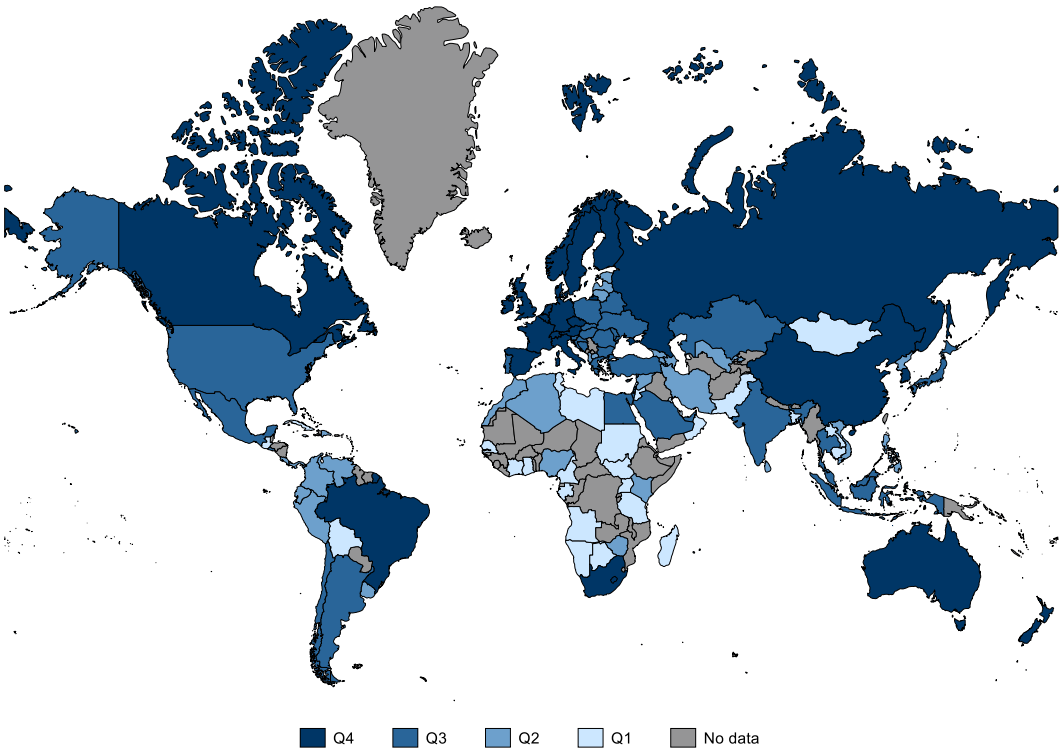


Figure A2. Technology complexity around the world

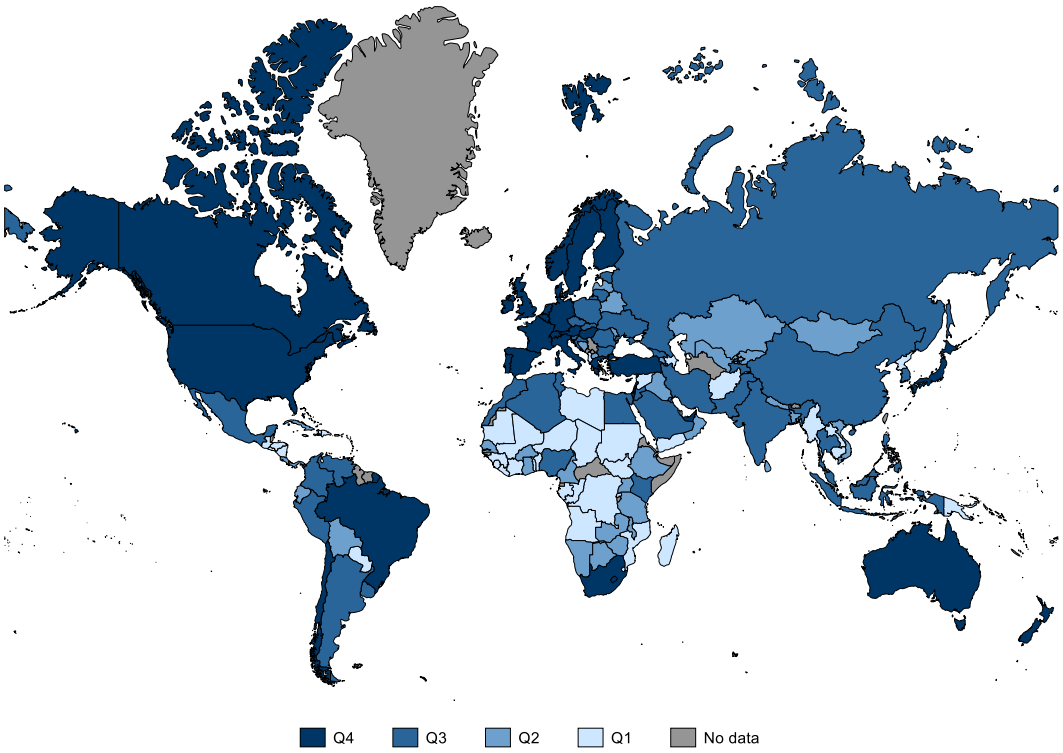


Figure A.3 Research complexity around the world

Table A2. Pairwise correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) Gini	1.000													
(2) Theil	0.896***	1.000												
(3) Atkinson1	0.979***	0.962***	1.000											
(4) Atkinson2	0.995***	0.916***	0.988***	1.000										
(5) Atkinson3	0.960***	0.810***	0.920***	0.966***	1.000									
(6) Trade complexity	-0.194***	0.003	-0.111***	-0.160***	-0.195***	1.000								
(7) Technology complexity	-0.161***	0.013	-0.087***	-0.136***	-0.184***	0.726***	1.000							
(8) Research complexity	-0.122***	0.072***	-0.042**	-0.100***	-0.160***	0.711***	0.674***	1.000						
(9) natural research	0.111	0.318***	0.202***	0.138***	0.059***	0.503***	0.620	0.643***	1.000					
(10) GDP per capita	-0.060***	0.129***	0.023	-0.032*	-0.092***	0.733***	0.574***	0.684***	0.706***	1.000				
(11) Egalitarian democracy	-0.268***	-0.152***	-0.221***	-0.250***	-0.260***	0.678***	0.572***	0.613***	0.379***	0.575***	1.000			
(12) Population	0.119***	0.185***	0.146***	0.135***	0.138***	0.047**	0.202***	0.198***	0.437***	-0.151***	-0.088***	1.000		
(13) Informal sector	0.092***	-0.035**	0.035**	0.075***	0.121***	-0.569***	-0.461***	-0.583***	-0.532***	-0.623***	-0.477***	-0.075***	1.000	
(14) Education	-0.092***	0.060***	-0.026	-0.061***	-0.078***	0.686***	0.507***	0.565***	0.520***	0.753***	0.489***	-0.110***	-0.385***	1.000

Table A3. Economic complexity and CI, FE-2SLS, assessment of the instrument robustness

	(1)	(2)	(3)
	Second stage		
Trade ECI	-0.014***		
	(0.003)		
Technology ECI		-0.007***	
		(0.002)	
Research ECI			0.001
			(0.002)
Natural resources	0.002*	0.001	0.001
	(0.001)	(0.001)	(0.001)
GDP per capita (in log)	0.028***	0.024***	0.021***
	(0.003)	(0.006)	(0.004)
Corruption	0.014**	0.038***	0.030***
	(0.006)	(0.007)	(0.005)
Population (in log)	0.019***	0.042***	0.024***
	(0.005)	(0.012)	(0.004)
Education	-0.024***	-0.002	-0.040***
	(0.008)	(0.012)	(0.006)
Income inequality	0.447***	0.582***	0.458***
	(0.023)	(0.027)	(0.022)
Instrument	0.101	0.100	0.105
	(0403)	(0.400)	(0.408)
	First stage		
Instrument	0.406***	0.643***	0.786***
	(0.016)	(0.029)	(0.017)
Observations	2,198	1,803	2,339
R-squared	0.171	0.216	0.199
Countries	134	100	135
Wald test	0.000	0.000	0.000
WIT	634.7***	500.0***	2212***
UIT	486.7***	151.0***	481.9***
Endogeneity test	0.000	0.003	0.006
Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1			

Table A4. Robustness test to additional variables

	(1)	(2)	(3)	(7)	(8)	(9)	(13)	(14)	(15)
Trade ECI	-0.014***	-0.014***	-0.014***						
	(0.005)	(0.005)	(0.005)						
Technology ECI				-0.007***	-0.007***	-0.007***			
				(0.002)	(0.002)	(0.002)			
Research ECI							0.001	0.001	0.001
							(0.002)	(0.002)	(0.002)
Urbanisation	0.068**	0.076***	0.067**	-0.035	-0.037	-0.039	0.049**	0.050**	0.049**
	(0.028)	(0.028)	(0.028)	(0.034)	(0.034)	(0.034)	(0.023)	(0.023)	(0.023)

Electricity per capita	0.002	0.002	0.002	0.003	0.003	0.003	0.004**	0.003*	0.004**
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Low-carbon electricity	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Shadow economy	0.005***	0.004***	0.004***	0.003***	0.003***	0.005***	0.003**	0.003**	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Inflation targeting	0.018***	0.019***	0.018***	0.023***	0.024***	0.024***	0.021***	0.021***	0.021***
	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.004)	(0.006)	(0.006)	(0.006)
World Bank Governance Index	0.020***	0.021***	0.018***	0.035***	0.035***	0.031***	0.018***	0.017***	0.016***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Trade openness	0.006**	0.007***	0.006**	0.004	0.006**	0.005*	0.005***	0.004**	0.005***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Foreign direct investment net inflows		0.005***	0.005***		0.004***	0.005***		0.005***	0.005***
		(0.002)	(0.002)		(0.002)	(0.002)		(0.002)	(0.002)
Environmental Performance Index			-0.010***			-0.009***			-0.008***
			(0.002)			(0.002)			(0.002)
Observations	2178	2147	2068	1788	1759	1727	2319	2269	2170
Countries	133	133	128	99	99	98	134	134	129
Previous Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Countries fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
WIT	485.215	454.342	402.100	476.204	435.147	450.968	2192.4	2113.1	2064.1
UIT	213.631	198.001	199.621	148.206	139.357	137.004	497.003	478.780	463.124
Endogeneity test	0.000	0.000	0.000	0.002	0.004	0.005	0.006	0.007	0.005

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A6. Result by the level of development

	(1)	(2)	(3)
Trade complexity	-0.023***		
	(0.005)		
Technology complexity		-0.012***	
		(0.002)	
Research complexity			-0.001
			(0.002)
Trade complexity * developed (dummy)	0.015**		
	(0.006)		

Technology complexity * developed (dummy)		0.009***	
		(0.003)	
Research complexity * developed (dummy)			0.002
			(0.003)
Developing countries	-0.023***	-0.012***	-0.023***
	(0.005)	(0.002)	(0.005)
Developed countries	-0.009*	-0.003	-0.009*
	(0.005)	(0.002)	(0.005)
Observations	1691	1589	2230
Countries	134.000	100.000	135.000
Controls	Yes	Yes	Yes
WIT	236.851	248.009	312.265
UIT	203.093	151.089	181.622
Endogeneity test	0.000	0.001	0.025
Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1			

Table A7. Results by region

	(1)	(2)	(3)
Trade complexity	-0.007		
	(0.006)		
Technology complexity		-0.011***	
		(0.004)	
Research complexity			0.002
			(0.003)
Trade complexity * region	-0.002		
	(0.002)		
Technology complexity * region		0.001	
		(0.001)	
Research complexity * region			-0.000
			(0.001)
EAP	-0.009*	-0.010***	0.002
	(0.005)	(0.003)	(0.002)
ECA	-0.011***	-0.008***	0.001
	(0.004)	(0.003)	(0.002)
LAC	-0.013***	-0.007***	0.001
	(0.004)	(0.002)	(0.001)
MENA	-0.015***	-0.006***	0.000
	(0.004)	(0.002)	(0.002)
NA	-0.017***	-0.004*	-0.000
	(0.005)	(0.002)	(0.002)
SA	-0.019***	-0.003	-0.001
	(0.006)	(0.003)	(0.003)
SSA	-0.021***	-0.001	-0.001
	(0.008)	(0.004)	(0.004)
Observations	2198	1803	2339
Countries	134.000	100.000	135.000
Controls	Yes	Yes	Yes
WIT	427.006	401.8	1728
UIT	171.497	116.80	446.5
Endogeneity test	0.000	0.000	0.061
Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1			