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Economic diversification: its relationship with inequality and ensuing policy options

Abstract

This paper empirically explores the relationship between export diversification and income inequality. Using a sample of 182 countries from 1998 to 2018, the study employs a fixed effects model to examine the interaction between diversification and inequality. The results show a statistically significant linear positive association between export diversification and income inequality. The study also finds heterogeneity in the association across income and commodity-dependence groups, with the result holding in the subsamples comprising low-income, and commodity-dependent developing countries. The results remain significant to a series of robustness checks. This suggests that while export diversification is associated with rising income, it may initially benefit specific groups, leading to higher inequality. The paper emphasizes the importance of inclusive policies to ensure that the benefits of diversification extend to vulnerable groups from an early stage; it proposes recommendations for governments to promote inclusive diversification efforts.

Key words

Export diversification, income inequality, commodity dependence, inclusiveness

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1. Introduction

UNCTAD defines an economy as commodity-dependent when over 60 per cent of its total merchandise export revenues stem from primary commodities, such as food and agricultural raw materials, fuels, and minerals. Under this definition, about 101 countries were commodity-dependent[1] in 2019-2021, of which 95 were developing countries and 34 were Least Developed Countries (UNCTAD, 2023a). Commodity dependence poses developmental challenges, as the volatility of commodity prices increases countries' vulnerability to exogenous shocks. Commodity dependence is associated with slow growth, low productivity, low human development, political instability, and illicit financial flows (UNCTAD, 2021). These factors create a challenging socioeconomic environment in Commodity-Dependent Developing Countries (CDDCs), retarding their development.

Volatility in commodity prices affects the foreign exchange earnings of CDDCs, which can create macroeconomic instability and impede long-term planning and investments for growth and development (UNCTAD, 2018a). Contests over the control of resource rents can cause political instability (Nkurunziza, 2021) while Dutch disease may result in currency appreciation and a decline in the competitiveness of traditional export sectors (UNCTAD, 2021). In addition, low productivity growth and the impending depletion of finite natural resources hinder sustainable economic development in CDDCs.

Recent global events, including the coronavirus pandemic that erupted in late 2019, the war in Ukraine that started in early 2022, climate change, and the decarbonization agenda, accentuate the economic vulnerabilities of countries that over-rely on commodities. For net commodity exporters, commodity dependence implies volatile export revenues, which can hamper CDDCs' development planning. For net commodity importers, overreliance on a single commodity or trading partner may lead to crises in cases of supply shocks from suppliers or in interconnected and generally long supply chains. The case of net food and fuel importers is particularly salient, especially in the aftermath of the energy and food crises triggered by the war in Ukraine. These crises have posed significant threats to food and energy security in developed and developing countries (UNCTAD, 2022a, 2022b). Altogether, this highlights the need for diversification to reduce overreliance on a few exports or a limited number of trading partners.

Diversification is particularly important for CDDCs. Export diversification refers to the degree to which an economy exports products across various sectors or trading partners (UNCTAD, 2018c). This brings significant advantages: beyond stabilizing export earnings and building resilience to external shocks, diversification can foster job creation and economic growth. Some scholars have indeed argued that countries become wealthier by learning to produce a more diverse range of technologically dynamic and sophisticated goods and services instead of increasing production of the same (Hausmann et al., 2007). Empirical studies (Al-Marhubi, 2000; Hausmann et al., 2007) suggest that export diversification can prompt long-term growth, showing positive and significant correlations between per capita income and export diversification. The examples of Costa Rica, Mauritius, and Malaysia have been cited as successful cases.

Nonetheless, export diversification may have unintended consequences on income distribution, a subject of significant discussion among academics and policymakers. Central to this debate is the Kuznets curve hypothesis, which posits an inverted U-shaped relationship between economic growth and income inequality (Kuznets, 1955). Based on Kuznets' hypothesis and the seemingly positive association between export diversification and growth (Al-Marhubi, 2000; Hausmann et al., 2007), some studies (e.g., Lee et al., 2007; Blancheton and Chhorn, 2019) find that despite increasing income in the long-run, increased diversification fuels inequality. However, other studies offer different perspectives. Le et al. (2020) find an inverted U-shape relationship between export diversification and income inequality. Gupta et al. (2002) find a positive relationship between inequality and export concentration, and Lee et al. (2022) highlight that export diversification can exacerbate inequality for countries with low- and medium levels of inequality.

Previous work provides insight into the potential factors explaining the link between diversification and inequality. However, differences in the direction of the effect and sample size lead to mixed findings and create uncertainty about the true association. This motivates this paper to empirically examine the relationship between export

[1] An economy can also be deemed import commodity dependent. This study focuses on export commodity dependence, and thus this is the definition used throughout unless otherwise stated.

diversification and income inequality, accounting for per capita income and other controls, to unveil the socioeconomic implications of diversification. This study offers various contributions. First, it uses a larger sample of countries over a more extended period for more accurate and reliable results. Second, it uses different measures of inequality to ensure that results are not variable-specific. Third, the study provides guidance for policymakers in CDDCs to adopt much-needed diversification strategies that are inclusive and account for the potential deleterious effects on vulnerable groups.[2]

The study examines the relationship between diversification and inequality using a fixed effects model on a panel of 182 countries from 1998 to 2018, using three-year period averages. A fixed effects methodology accounts for time-invariant factors, allowing for an analysis of inequality within countries. This paper also tests the non-linearity of the relationship. Additionally, it aims to identify whether the association between diversification and income inequality is heterogeneous across country groups. Though we are unable to establish causation, examining the correlates, including the direction of the association between diversification and income inequality, is useful for policymakers in CDDCs wishing to diversify.

The rest of the paper is organized as follows. Section 2 discusses the relationship between diversification and inequality based on existing literature and presents the hypotheses to be tested. Section 3 presents the data, variable definitions, and econometric model. Empirical results and robustness checks are reported in Section 4. Section 5 concludes and outlines policy implications.

2. Literature Review

2.1 Diversification strategies

Diversification can take different forms and be analyzed at various levels. Indeed, there are two main diversification paths: vertical and horizontal. Given the different uses of commodities associated with each strategy, the pathway to diversification available to policymakers depends on various factors, including the commodity the country is endowed with.

Vertical diversification entails value addition to a primary commodity by engaging in downstream activities that expand the product offering from a specific commodity, including processing and beneficiation. An example is palm oil and rubber in Malaysia, where resource-based industries were encouraged in the mid-1980s to engage in higher-value addition and manufacturing (Central Bank of Malaysia, 2014). This resulted from a government-led diversification strategy to reduce the concentration in upstream commodities and strengthen the manufacturing sector, supported by fiscal incentives, trade promotion, skills development, and research and development (R&D) support (Lebdioui, 2022).

As a result, the palm oil industry created linkages to produce a wider range of palm-oil-based products, which presently include edible oils and fats, biofuels, and oleochemicals (Central Bank of Malaysia, 2014). Similarly, the rubber industry shifted from mainly exporting raw rubber to becoming a leader in producing and exporting rubber gloves and prophylactics (Central Bank of Malaysia, 2014). While latex goods comprise the largest share of Malaysian rubber exports, other exports include tires and industrial rubber goods (Malaysian Rubber Council, 2022).

Horizontal diversification refers to the emergence of sectors unrelated to the traditional commodities the country has relied on or that are situated outside a country's current productive structure. An example is Mauritius, which diversified its once sugar-focused economy to become a significant exporter of textiles, information technology components, and services, including tourism (Mosley, 2018). At the time of independence in 1968, sugarcane represented about 25 per cent of the GDP and 90 per cent of the value of exports in Mauritius (Central Statistical Office Mauritius, 1969; CABRI, 2019). After the collapse in sugar prices in the mid-1970s, and in anticipation of challenges to the preferential agreements previously in place, the Mauritian government decided to develop the textile industry through the establishment of export processing zones, which facilitated trade in low-tech textile,

[2] This aligns with the Sustainable Development Goals (SDG), particularly SDG 9 and 10. SDG target 9.2 calls for promoting inclusive and sustainable industrialization and, by 2030, significantly raise the industry's share of employment and gross domestic product. SDG 10 aims to reduce inequality within and among countries.

garment, and leather manufactures (UNCTAD, 2018b). This was supported by fiscal policy and various incentives on the inputs used by exporters, contributing to Mauritius' growth and development (Mosley, 2018). Later, the economy further diversified horizontally into tourism, financial services, business process outsourcing, and information technology (Zafar, 2011).

As seen above, diversification paths will be country-specific, as the possibility of linkages and prospects for, e.g., vertical diversification, vary across commodities. While there are more downstream linkages from oil production (e.g., petrochemicals), forward linkages from lithium are limited (e.g., electric batteries), and agricultural commodities can mainly be processed into foodstuffs or biofuels.

Challenges remain for CDDCs to effectively leverage natural resource rents to build diversified and more resilient economies. Choosing to follow a diversification strategy requires appropriate fiscal and macroeconomic policy. Transparency and good governance in the management of rents are also important to materialize strategic plans. Political and socioeconomic factors may influence the willingness and ability of governments to elaborate or follow a comprehensive diversification strategy supported by an appropriate policy mix (Lebdioui, 2022). While there are successful cases of export diversification, such as Malaysia and Mauritius, there are many CDDCs that have previously formulated diversification plans but have failed and continue to struggle to reduce their commodity dependence.

2.2 Export diversification, income, and income inequality

Research on export diversification has predominantly focused on the relationship between diversification and economic growth, with various studies ascertaining a positive association between per capita income and export diversification (Al-Marhubi, 2000; Hausmann et al., 2007; Cavalcanti et al., 2014; Mau, 2016). While it is difficult to establish causality between the two variables due to reverse causality, some studies, such as Mau (2016), have revealed that while there is some evidence for per capita income affecting the level of diversification, there is stronger support for diversification affecting GDP per capita. It is suggested that greater economic integration stimulates growth through diversification, as labour shifts towards capital-intensive activities (Mau, 2016). Aside from reducing the volatility of export earnings, export diversification can create new industries and expand existing sectors, which benefits economic activity through knowledge spillovers and incentives for capital formation and investments (Al-Marhubi, 2000).

While the positive relationship between export diversification and growth has been well documented, studies on the effect of growth and export diversification on income inequality remain inconclusive. The research on the inequality-growth nexus is abundant, but it is unclear whether inequality affects growth or if the relationship runs in the opposite direction.

High levels of inequality may limit access to education and healthcare and impede the ability of certain individuals to contribute to economic activities. This limitation can result in a less skilled and less healthy workforce, which could hinder economic growth (Cingano, 2014; Shen and Zhao, 2023). Similarly, disparities can distort incentives and limit access to credit for lower-income individuals and small businesses. Inequality can also lead to instability and social unrest, negatively impacting growth prospects. Conversely, economic growth may also affect inequality. The directionality of this relationship is more thoroughly examined in the literature, though studies have reported positive, negative, or inconclusive associations (Mdingi and Ho, 2021).

One perspective suggests a positive distributional effect, which aligns with the Kuznets curve (1955), whereby there is an inverted U-shaped relationship between a country's average income and income inequality. According to this hypothesis, as economies urbanize and industrialize, income inequality increases due to higher per capita income and productivity in urban settings (Kuznets, 1955). However, over the long term, inequality is expected to decline as more workers migrate and a smaller portion of the population remains in agriculture.

Critics challenge the Kuznets curve's validity, pointing to confounding shocks affecting the data, including the Great Depression, the World Wars, and the high taxes imposed on wealthy individuals at the time (Lyubimov, 2017). While Kuznets acknowledges that more data is required to prove this hypothesis, later studies such as Barro (2000) and Thornton (2010) find evidence of the Kuznets curve, showing positive distributional effects in the long run.

A few studies have similarly concluded that specialization and income per capita tend to follow a U-shaped relationship, where low-income countries diversify as their income rises and start re-concentrating once they reach a certain income level (Imbs and Wacziarg, 2003; Giri et al., 2019). This is arguably due to the interaction of productivity improvements and economies of scale, where an economy's productivity gains lead to a broader product array in the domestic economy until reaching a point where declining trading costs lead to increased concentration (Imbs and Wacziarg, 2003). Similarly, an economy's export basket becomes more diversified as income rises until a relatively high level, at which stage specialization occurs (Klinger and Lederman, 2006). The rationale behind this is that countries with low levels of development experience frequent product "discoveries"[3] and diversify (Klinger and Lederman, 2006). With increasing income, the frequency of these events declines, leading economies to re-focus on specialization. By contrast, concentration in trading activities negatively correlates with employment, labour force participation, and wages (Autor et al., 2013), suggesting that diversification is positively associated with growth.

By contrast, other researchers suggest a negative distributional effect between growth and income inequality due to occupational differences and a skilled-wage premium (Forbes, 2000). Accordingly, industrialization and rapid technological advancements lead to an increase in demand and training for skilled labour, resulting in higher wages in these sectors while low-skill labourers continue earning low incomes (Matano and Naticchioni, 2016). This creates a skills bias and a widening wage gap, which fuels inequality (Mdingi and Ho, 2021). Reconciling the negative and positive distributional effects of growth, some studies report heterogeneous results among low-income and high-income countries (Castelló-Climent, 2010). According to these, growth is negatively correlated with income inequality in low-income countries and positively correlated in relatively high-income countries.

More recent research finds that the relationship between diversification and total GDP follows an S-curve shape, where economies with higher GDP export a greater variety of products initially, but growth in diversification eventually slows down and reaches an upper limit (Lei and Zhang, 2014; Freire, 2017). Further diversification after this stage occurs by unit value, which is not captured by more aggregated production (Freire, 2017). According to this view, the premise remains that growth is positively associated with export diversification.

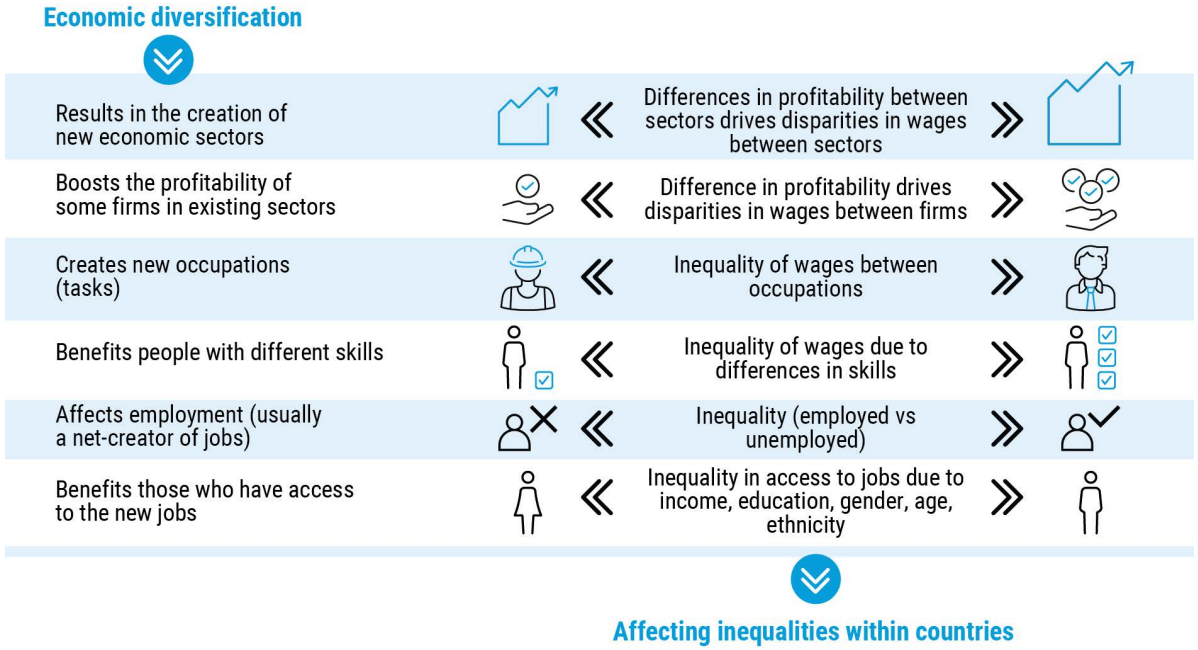
Similar to economic growth, export diversification can influence income inequality in a country through various channels, including disparities between sectors, firms, occupation levels, and skills (Figure 1). Economic diversification creates new sectors with varying productivity levels that can contribute to inequality between sectors; those more productive can claim higher average profits and pay higher average wages.

Diversification can also boost firms' profitability within existing sectors, affecting inequalities across firms (Mueller et al., 2017). Firms that embrace innovation and diversify production can achieve higher profits and offer higher average wages. Inequalities can also arise from wage differences, where emerging occupations or increased demand for specific skills command higher wages. These disparities result from differences in occupations within a firm and skills at the same occupation level (Barth et al., 2016; Juhn et al., 1993).

Diversification can also determine employment opportunities (Hartmann et al., 2017), impacting inequalities between the employed, who are receiving a labour income, and the unemployed. Moreover, diversification in some sectors can impact individuals' access to skills and occupations, influencing work opportunities and income levels. For instance, in CDDCs, the absence of industries such as light manufacturing, automotive, electronics, and digital products like online gaming restricts employment opportunities in these sectors. From the gender perspective, gender disparities in education, for example, can limit girls' access to skills and opportunities in certain social contexts and are likely to constrain skills development. Similarly, social perceptions may discourage women from working in some sectors, such as construction and mining, limiting their options for employment.

[3] Defined as the emergence of a new product the country did not previously produce.

Figure 1. Transmission channels from economic diversification to the potential impact on inequalities



Source: UNCTAD, 2023. *Commodities and Development Report 2023: Inclusive Diversification and Energy Transition*

While there has been extensive literature on the association between export diversification and income, there has been less attention to the empirical relationship between diversification and inequality. And, similar to the research on income and inequality, the results have been mixed. Few studies indicate a monotonic relationship, where diversification leads to a greater distinction between low and high-skilled workers, translating to higher wages for the more skilled workers and increasing income inequality (Blancheton and Chhorn, 2019; Lee et al., 2022). In line with this view, Blancheton and Chhorn (2019) use a Generalized Method of Moments estimation on a panel of 52 countries spanning from 1988 to 2014. Their findings suggest that sectoral export diversification, measured by a Theil Index, increases inequality in 34 high-income Asian countries and EU Member States (Blancheton and Chhorn, 2019). However, they did not obtain statistically significant results either in low-income or Anglo-Saxon countries (ibid, 2019). Using a panel quantile regression approach based on a sample of 90 countries from 2002 to 2014, Lee et al. (2022) report that export diversification exacerbates income inequality for countries with low and middle levels of inequality. Following a different line of thought, a third study (Lee et al., 2007) finds that export concentration is negatively associated with income inequality using a panel of 60 countries between 1970 and 1994.

On the other hand, export diversification may also expand employment opportunities and learning to a larger share of the population, which would result in narrowing inequalities. The mix of products an economy produces can constrain occupational choices, and learning opportunities (Hartmann et al., 2017). Consistent with this perspective, Hartmann et al. (2017) find that economic diversification, measured by an economic complexity index, is associated with lower levels of inequality in a multivariate regression analysis. This is examined with a pooled regression from 1996 to 2008 (with average values for 1996—2001 and 2002—2008 to accommodate the slow-moving nature and sparseness of Gini coefficients) and a panel regression for each decade between 1960 to 2008 (ibid, 2017). Beyond changes in the economic structure associated with export diversification, this may also be attributed to the co-evolving factors accompanying changes in an economy's export mix, which may include better institutions and education (Hartmann et al., 2017).

There is a third proposition in the literature of an inverted-U-shaped relationship (Le et al., 2020). This is based on a panel of 90 countries from 2002 to 2014, using export-extensive (changes in the number of goods exported) and export-intensive (changes in the quantity of existing products) margin indices. According to this view, at an early stage of diversification, there is a higher demand for high-skilled labour as firms seek productivity and efficiency to ensure the benefits of diversification outweigh the costs (Le et al., 2020). This may be particularly true for smaller

firms, which often lack the knowledge, experience, and economies of scale to expand their product offering. In the long run, however, as the benefits spread throughout the economy, more diverse production creates more jobs for high and low-skilled workers, and inequality falls (Le et al., 2020). Nonetheless, changes in the demand for high-skill labour will likely depend on an economy's diversification approach; for instance, increasing domestic backward linkages may favour lower-skilled labour.

Despite the potential concerns a positive correlation between export diversification and income inequality raises, it is important to account for income per capita levels to gain a comprehensive understanding of the relationship. It may be the case that diversification is positively correlated with income inequality *and* GDP per capita. This would imply that while diversification can uplift impoverished households with higher incomes, it may increase inequality due to a wider gap between the average and lower-earning segments of the population. This was the case for a microeconomic study in rural India (Himanshu et al., 2013), where diversification towards non-farm activities led to upward mobility for various households previously at the bottom of the income distribution. However, this process also resulted in higher village-level inequality due to increasing wages in non-farming sectors. This was the case as opportunities were not universally accessible, and some households continued to be excluded from the diversification process. Therefore, diversification can benefit society with rising incomes but might still be positively associated with income inequality.

Differences in the direction of the effect of export diversification and inequality can be attributed to the differing variable definitions, methodologies, and underlying assumptions among estimators. Varied definitions of export diversification, such as using the number of products exported versus economic complexity or Theil Index indices, are likely to play a factor. Methodological distinctions, along with variations in samples and considered time periods, may also play a role. For instance, Blancheton and Chhorn (2019) find that diversification is positively related to income inequality in a relatively small sample of 34 higher-income countries using a dynamic model.

In the case of income inequality, different methods of aggregation or approximations to handle missing data can also account for differences. Hartmann et al. (2017) address sparse data by aggregating Gini coefficients by periods, while, Blancheton and Chhorn (2019) interpolate missing values, creating a yearly panel and employing a dynamic model. Differences in model specification may also be important, particularly when linear models would provide only a partial understanding if the relationship is non-monotonic.

The relationship between export diversification and income inequality might be negative, positive, non-linear, or non-significant, as the discussion above has highlighted. Our contribution to the literature is premised on using the more comprehensive UNU-WIDER World Income Inequality Database, analyzing a larger sample of countries over a more recent and extensive period covering several business cycles. The large number of observations allows for examining heterogeneity across income groups and commodity-dependence status (CDDCs vs non-CDDCs) to unveil any possible differences. We also test the linearity of the relationship. This sheds further light on a subject that has thus far shown inconclusive results.

2.3 Determinants of inequality

In addition to the level of economic development and GDP, other variables may be associated with income inequality, such as levels of technology, human capital, globalization of trade and fiscal policy variables (Blancheton and Chhorn, 2019; Furceri and Ostry, 2019; Osakwe and Solleder, 2023).

Similar to the growth and diversification hypotheses, research posits that inequality may follow an inverted U-shape curve during periods of technological advancements (Galor and Tsiddon, 1997). Inequality may increase during technological catch-up due to its associated mobility and the concentration of highly skilled workers in technologically advanced sectors. As technologies become more accessible, the returns to skills decline, and inequality may decrease (Galor and Tsiddon, 1997). In addition, technological catch-up may lead to new jobs and learning opportunities for workers in emerging economies, which can benefit from the country's changing productive structure and contribute to a better income distribution (Hartmann et al., 2017). Closely interlinked is the accumulation of human capital, which increases worker mobility and technology absorption, eventually leading to greater knowledge diffusion and reducing the skill and income gap (Asteriou et al., 2014). However, this depends on the extent to which opportunities to build capital are equally distributed in the population, for example, through the location of training institutions in a country.

The effect of trade on inequality may depend on a country's level of development (Stolper and Samuelson, 1941; Furceri and Ostry, 2019; Dorn et al., 2021). Opening trade in advanced economies where high-skilled labour is abundant may increase the wage premium between high and low-skilled workers, exacerbating inequality. Conversely, greater trade openness in developing countries may benefit the income share of the poorer segments of the population. Recent studies, such as Dorn et al. (2021), suggest that trade openness can benefit the poorest segments of the population in some developing countries. However, trade openness was linked to increased inequality in China and transition economies in Central and Eastern Europe (Dorn et al., 2021). In China, this was possibly due to a rapid process of trade openness and a limited welfare system. In the case of transition economies, it is likely that institutional and structural change towards market economies may have contributed to this effect (Dorn et al., 2021). Meanwhile, trade openness negatively affects inequality in advanced economies with redistributive policies (ibid, 2021).

Government spending is an important tool for redistribution policies, which aims to improve the welfare of vulnerable groups. Existing studies (Blancheton and Chhorn, 2019; Sidek, 2021) report a negative association between government expenditure and income inequality. However, the effectiveness of such spending will depend on how the government targets recipients through social protection, training and education, and related measures (Blancheton and Chhorn, 2019).

3. Data, variables measurement, and methodology

3.1 Income inequality: measures

The Gini coefficient is a common indicator of inequality, which measures the deviation of an income distribution from perfect equality on a scale of 0 to 100, where 0 represents perfect equality, and 100 represents perfect inequality (UN DESA, 2015). Independent of country and population size, this measure allows for comparisons between the income distribution of countries (UN DESA, 2015).

However, the Gini coefficient has limitations. It is more responsive to changes in the middle of the distribution than in the opposite tails, where the most extreme income disparities would be reflected (Trapeznikova, 2019; UN DESA, 2015). The Gini coefficient can also vary depending on what is measured, for example, income inequality pre- or post-tax, or consumption inequality pre- or post-housing costs (Trapeznikova, 2019). Therefore, using the same measurement unit or source is crucial for cross-country comparisons.

Other inequality indicators include general entropy measures and ratios. These will be used in the paper as robustness checks. General entropy measures are based on ratios of incomes to the mean. A parameter alpha is used to compute these, assigning a weight to distances between incomes in different parts of the distribution (UN DESA, 2015). The most popular is the Theil's L index, also known as the mean log deviation, where alpha equals 0, meaning it is more sensitive to changes in the lower tail of the distribution. The Theil's L index is 0 in the case of perfect equality and increases as incomes become more unequally distributed.

The Palma and the inter-decile ratio are part of a group of percentile and share ratios that focus on specific differences in the distribution. These are simple to calculate and interpret (Trapeznikova, 2019). The Palma ratio measures the income gap between the richest 10 per cent and the poorest 40 per cent of the distribution. A higher Palma ratio indicates greater income inequality. Lastly, the inter-decile ratio measures the income gap between the top 10 per cent and the bottom 10 per cent of earners. A higher inter-decile ratio also indicates higher income inequality. These ratios are particularly sensitive to changes in the opposite ends of the distribution. We have incorporated a correlation matrix in Table A 1. in the Appendix featuring various measures of income inequality to facilitate a comparison of their interrelationships. This allows for an examination of the degree of correlation among the different measures.

3.2 Data

The data for this paper were primarily collected from the United Nations University World Institute for Development Economics Research (UNU-WIDER) and UNCTAD. Inequality data was drawn from the UNU-WIDER WIID Companion, which provides the most comprehensive adjusted income inequality statistics for 201 economies from 1960 to 2021 (UNU-WIDER, 2022). The study focused on data from 1998 to 2018 based on the availability of export diversification and covariates data from UNCTAD. To address the spareness of inequality statistics, we use 3-year average values, following a similar approach to Hartmann et al. (2017). The study's primary dependent variable for income inequality is the post-tax Gini coefficient. The Palma ratio, Theil's L index and the inter-decile ratio are used in the study as robustness checks.

For this study, we measure export diversification as the number of country products exported classified using the Harmonized System (HS) at a 6-digit level and further disaggregated by unit value. The greater the number of products exported at the 6-digit level, the greater the diversification. This variable also reflects differences in unit value, and considers products of different prices as different products, as the capabilities in these countries needed for production will be inherently different (Freire and Slany, 2023). This variable was constructed by UNCTAD following the method outlined in Freire (2017) based on UN COMTRADE data.

We include various country-level time-variant variables expected to impact income inequality. These include GDP per capita (in log),[4] population size (in log) to account for country size, trade openness (expressed as the sum of imports and exports over GDP, in log), human capital (expressed as a composite score)[5] and government spending (expressed a percentage of GDP). All national-level data were drawn from the UNCTAD database. We also include an income group categorical variable to analyze differences across income groups, following the World Bank classification of 2021:

Table 1. Country classification by income level

Group	Income level
Low-income	Lower or equal to $1,045
Lower-middle income	Between $1,046 and $4,095
Upper-middle income	Between $4,096 and $12,695
High income	Higher than $12,695

Source: World Bank, 2021

Note: This income classification was used due to the relevance of income differentiation across groups. The thresholds are based on 2021 prices in United States dollars.

3.3 Descriptive statistics

Table 2 presents the descriptive statistics of the variables used in the analysis. The data spans from 1998 to 2018, covering 182[6] economies with an unbalanced panel of 1,109 observations.[7] Among these observations, 224 are from low-income economies, 354 from lower-middle-income economies, 272 from upper-middle-income economies, and 259 from high-income economies. About 56 per cent of the sampled countries are considered CDDCs. Around 27 per cent of sampled countries are agricultural CDDCs, 17 per cent are fuel CDDCs, and 13 per cent are mining CDDCs.

[4] The lagged term of GDP per capita is included to address endogeneity between income per capita and inequality in time *t*.

[5] This variable captures the population's education, skills and health conditions, and society's R&D involvement measured by the number of researchers and research expenditure. The fertility rate reflects the gender dimension; its increase reduces the human capital score.

[6] Refer to Table A 9. in the appendix for the full list of countries included in the analysis.

[7] This is based on the final regression as specified in the econometric model outlined in the methodology.

Table 2. Descriptive statistics

Variables	(1) N	(2) Mean	(3) Median	(4) Min	(5) Max	(6) Source
Gini coefficient	1,109	44.73	44.35	16.69	75.15	UNU-WIDER
Palma ratio	1,109	2.964	2.348	0.591	18.32	UNU-WIDER
Theil's L index	1,109	38.8	33.92	4.454	124.3	UNU-WIDER
Inter-decile ratio	1,109	12.61	8.603	2.049	129.7	UNU-WIDER
No. of products exported (log)	1,109	7.958	7.947	4.055	10.36	UNCTAD
GDP per capita (log)	1,109	8.325	8.258	4.668	11.56	UNCTAD
Income group (categorical variable)	1,109					World Bank
High-income		23.35				
Upper-middle-income		24.53				
Lower-middle-income		31.92				
Low-income		20.2				
Trade openness (log)	1,109	3.731	3.798	2.073	4.6	UNCTAD
Population (log)	1,109	8.801	9.061	2.236	14.17	UNCTAD
Human capital index	1,109	46.42	45.34	18.66	87.89	UNCTAD
Government spending (% of GDP, log)	1,109	-1.864	-1.848	-4.614	-0.008	UNCTAD
Commodity dependence group (categorical variable)	1,109					UNCTAD
Non-CDDC		43.82				
Agriculture CDDC		26.51				
Fuel CDDC		16.5				
Mining CDDC		13.17				
Number of countries	182	182	182	182	182	

Note: The variable commodity dependence group is a categorical variable based on the UNCTAD classification. An economy falls under a specific commodity dependence group if 60% of its exports come from commodities and 30% of those commodity exports are from a particular group (i.e. agricultural, mining or fuel products). The variable income group is a categorical variable corresponding to the World Bank's income classification described above. This variable takes a value between 1 and 4, indicating the income group to which the country has been assigned. The mean values show the percentage of countries in the sample belonging to a particular group.

3.4 Methodology

With a panel dataset structure of small time-series dimensions (T=seven of three-year intervals from 1998 to 2018) and large cross-sectional dimensions (N=182 countries), this paper uses a fixed effects linear model to examine the relationship between income inequality and export diversification. A fixed effects model explains the within-dynamics of individual countries, but not the differences between countries. Potential sources of bias in the regression of inequality and diversification include country-specific factors that may affect economic development and the distribution of income, such as institutional quality. A fixed effects methodology accounts for time-invariant factors and removes such bias, allowing for an analysis of inequality within countries.[8] While our model accounts for key country-specific time-varying controls in vector $\boldsymbol{Z}_{it}$, as detailed below, there may exist unobserved factors contributing to inter-country variations in income inequality. Nonetheless, we have considered the most recurrent factors found in the literature. The econometric model is given by:

$$Inequality_{it} = \alpha + \beta_1 Diversification_{it} + \beta_4 \boldsymbol{Z}_{it} + \mu_i + \delta_t + \varepsilon_{it}$$

In this model, *Inequality* is the dependent variable representing income inequality of country *i* in time *t*. The variable *Diversification* represents export diversification, measured by the number of products exported at a 6-digit HS level and further disaggregated by unit value. Coefficient β_1 signifies the average change in income inequality within a country *i* at a given time *t,* corresponding to a one percentage change increase in diversification. This coefficient

[8] Fixed effects was preferred over a dynamic model due to the slow-moving nature of income inequality, which makes inequality dynamics difficult to capture. Moreover, some time series data is imputed, making it less suitable for capturing realistic dynamics.

captures within-country dynamics, explaining how export diversification relates to shifts in income inequality within countries over time.

$\boldsymbol{Z}_{it}$ is a vector of country-specific time-varying controls that are expected to impact income inequality. This includes the logarithm of GDP per capita *lagged* by one period *(t-1)*. This lagged term addresses potential endogeneity issues arising from the bidirectional relationship between income per capita and inequality in time *t*. To mitigate the risk of omitted variables, we incorporate other controls in $\boldsymbol{Z}_{it}$ that may influence the dependent variable, including trade openness, population size, a human capital index and government spending. Additionally, we assess multicollinearity using a correlation matrix[9] and find that all correlation coefficients were below the threshold of 0.8, indicating no signs of severe multicollinearity among the independent variables.

The term μ_i captures the country-fixed effects to account for unobserved time-invariant heterogeneity across countries, while δ_t denotes a full set of time effects capturing unobserved time-specific factors that affect all countries simultaneously, including macroeconomic conditions and financial crises (e.g. financial crisis of 2008). This would help isolate the relationship between export diversification and inequality. Finally, ε_{it} is the error term.

Contrary to other studies using single years for their panel, this model excludes a lagged dependent variable. This choice is motivated by the use of three-year averages, which smooths the influence of individual years. Inequality is already characterized by slow movement and low variability within countries over time; therefore, adding a lagged inequality term does not significantly enhance explanatory power and compromises model parsimony.

To determine whether the relationship is non-linear, we include the square term of *Diversification* in a second regression:

$$Inequality_{it} = \alpha + \beta_1 Diversification_{it} + \beta_2 Diversification_{it}^2 + \beta_4 \boldsymbol{Z}_{it} + \mu_i + \delta_t + \varepsilon_{it}$$

Both regressions are run on the full sample. Establishing causality is challenging due to potential simultaneity bias, where the association between inequality and diversification in time *t* makes it difficult to disentangle the direction of the causal relationship. Nonetheless, this exercise provides insights into whether a positive or negative association exists between the two variables, a valuable contribution given the lack of consensus in the literature. Additionally, regressions are run on different subsamples across income groups, development and CDDC status to unveil potential differences in the relationship between export diversification and income inequality. Robustness checks using a randomized sample exercise and different measures of income inequality are performed to support the validity of the results.

4. Results

4.1 Main results

Table 3 presents the results of the linear fixed effects model for the overall sample, examining the relationship between export diversification (measured by the number of products exported at the HS 6-digit level and further disaggregated by unit value) and income inequality (Gini coefficient). Employing a step-wise approach, we systematically introduce the impact of the independent variables on the relationship, which reveals a nuanced dynamic. Initially, when considering only diversification and income inequality, the relationship appears negative. However, with the inclusion of income in the regression, the direction of the effect turns positive and persists across multiple specifications. This positive association may be attributed to the intricate interplay between diversification, economic growth and their collective impact on income inequality. As a country diversifies its exports and experiences economic growth, higher income levels may be concentrated among certain segments of the population, leading to an increase in income inequality.

Column 6 considers all time-invariant controls specified in the methodology, and column 7 incorporates the time dummies, presenting the full model. Although coefficients for diversification diminish in magnitude in the last column, their persistence and statistical significance in subsequent robustness checks, presented in the next sub-

[9] Refer to Table A 2. in the Appendix

section, affirm the positive association. This implies that export diversification is positively correlated with income inequality, consistent with the results obtained by Lee et al. (2007), Blancheton and Chhorn (2019), and Lee et al. (2022). This positive correlation may be attributed to a more differentiated occupational structure and wage differentials that arise from economic diversification.

Concerning the effect of income, there is a significant negative association between lagged GDP per capita and inequality for the whole sample. This implies that as income increases, inequality declines. Past income data helps address potential endogeneity issues between income and inequality since the variable represents income three years before current inequality, making it pre-determined. Moreover, the seemingly positive relationship between diversification and GDP suggests that while diversification may increase incomes, it does not necessarily reduce inequality. This finding is similar to Himanshu et al. (2013) and may be attributed to uneven access to diversification opportunities. While diversification could result in upward mobility for some individuals previously at the lower end of the income distribution, thereby boosting per capita income, inequality could increase as another portion of the population remains in their existing labour conditions.

Table 3. Fixed effects coefficients, number of products exported (linear, full sample)

	Dependent variable: Gini						
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
No. of products exported HS 6-digit (in log)	**-1.923*** **	**-0.838***	0.500	**1.040***	**1.389****	**1.416*****	**1.338****
	(0.438)	(0.430)	(0.504)	(0.565)	(0.535)	(0.526)	(0.590)
Trade openness (in log)		-1.656***	-1.436***	-1.108***	-1.281***	-1.265***	-1.575**
		(0.416)	(0.407)	(0.412)	(0.452)	(0.454)	(0.667)
L.GDP per capital (in log)			-2.550***	-2.230**	-2.548**	-2.748**	-2.110*
			(0.869)	(0.863)	(1.089)	(1.089)	(1.260)
Population (in log)				-3.009***	-4.243***	-4.050***	-2.835*
				(1.116)	(1.511)	(1.443)	(1.561)
Human capital index					0.0949*	0.105*	0.149***
					(0.0551)	(0.0539)	(0.0554)
Government spending (% of GDP, in log)						-1.143	-1.106
						(0.728)	(0.749)
Constant	59.75***	57.37***	67.24***	85.32***	92.43***	89.48***	73.67***
	(3.444)	(3.292)	(6.256)	(9.434)	(13.59)	(13.25)	(17.90)
Observations	1,501	1,501	1,294	1,294	1,109	1,109	1,109
R-squared	0.061	0.094	0.134	0.153	0.159	0.168	0.182
Number of countries	187	187	186	186	182	182	182
Time dummies	No	No	No	No	No	No	Yes

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

Trade openness is consistently negatively correlated with income inequality across all specifications (column 2 to 7). This suggests that trade offers opportunities to different segments of the population, reducing their income gap. Contrary to Hartmann et al. (2017), human capital appears to be positively correlated with income inequality. As a composite variable,[10] this unexpected result could be due to uneven education or healthcare access among economic groups, which would lead to higher disparities in the labour market. This could also be the result of a wage premium allowing greater access to education and skill building opportunities. Microeconomic studies are needed to further explore the transmission channels between human capital and inequality.

When accounting all other factors, population size shows a statistically significant negative coefficient. This implies that, on average, countries with larger populations exhibit smaller income disparities. One possible explanation for

[10] Opposed to Hartmann et al. (2017), who specifically use a measure for education.

this result is that large economies often have bigger markets and are able to mobilize more resources to address income disparities. Also, diversification in these countries may create opportunities to a larger portion of the population. Contrary to our priors, there is no statistically significant relationship between government spending and income inequality. This holds true across all specifications in Table 3.[11] As noted earlier, for government spending to influence inequality, resources must be directed towards sectors and services that address the root causes of inequality, including equal allocation of education, training, and health infrastructure across the country. The current measurement of government spending may also not accurately reflect how resources are allocated, considering the issue of resource leakages in some countries. Altogether, the results show no evidence of a non-linear association and instead suggest that the relationship between export diversification and income inequality is linear.[12]

Table 4 shows the outcomes for the linear fixed effects model for different subsamples. Notably, the positive and statistically significant association persists for both developing and developed countries. However, heterogeneity is observed across income groups and commodity dependence status. As it relates to income group, the positive relationship between diversification and inequality only holds in low-income countries, reflected by the significant coefficient compared to high income countries, where the diversification coefficient is non-statistically significant. There were no statistically significant results for the lower-middle income and upper-middle income subsamples, which have been excluded from the table. Similar results are observed when distinguishing CDDCs (column 5) and non-CDDCs (column 6), with the association being statistically significant only in the former. These results appear to be robust when considering other income inequality measures, as presented in the next sub-section.

This heterogeneity may be attributed to differences in productive capabilities compared to higher-income and more diversified counterparts (UNCTAD, 2021). Productive capabilities are needed for job mobility towards new production that demand different skills and technology (UNCTAD, 2021). Lower-income countries and commodity-dependent developing countries with limited human capital and productive capabilities may face restricted economic mobility, resulting in disparities between higher and lower-skilled workers. Consequently, during diversification, fewer people in lower-income countries and CDDCs would be able to transition to other economic sectors, resulting in a wage premium associated with specific skillsets and increasing inequality.

In low-income countries, institutional frameworks may also impede income distribution from catching up with economic expansion.[13] The roles of political and economic institutions are likely to influence redistribution policies. Income gaps often coincide with disparities in economic and political power, allowing influential elites to engage in rent-seeking behaviour (Chong and Gradstein, 2007; Josifidis et al., 2017). This means that policies depend on how institutions aggregate preferences based on their interests (Robinson, 2010). These factors would influence the design of diversification policies and the extent to which income inequality and inclusiveness are considered. Good governance, supported by robust policies and institutions, would be thus needed to reduce the potential positive correlation between export diversification and income inequality.

Governments should consider additional interventions to ensure inclusive outcomes when designing diversification strategies, ideally providing opportunities to all groups from an early stage. The positive association between human capital and inequality (in the overall sample) highlights the importance of coordinating diversification strategies with policies for public goods to promote equal access to education, healthcare and skill-building needed for inclusive development. This is essential in countries where resource rents tend to benefit a small elite (De Soysa and Neumayer, 2007).

Despite these findings, it is important to recognize that diversification brings various advantages, as outlined in the introduction. This includes stimulating growth and building resilience against commodity price fluctuations that hamper long-term budgeting and development planning.

These results also suggest that trade openness decreases inequality in developing countries. This aligns with the Stolper-Samuelson (1941) theorem, where increased trade in countries with abundant low-skilled labour leads to lower inequality (Furceri and Ostry, 2019).

[11] In order to ensure a parsimonious model, we exclude government spending from Table 4.

[12] Refer to Table A 3. for this set of results.

[13] However, this remains a challenging empirical question due to difficulties associated with the measurement of institutional quality.

Table 4. Fixed effects coefficients (subsamples)

	Dependent variable: Gini					
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Low income	High income	Developing	Developed	CDDCs	Non-CDDCs
No. of products exported HS 6-digit (in log)	**3.374****	0.300	**1.507****	**3.123***	**2.585*****	0.0545
	(1.289)	(0.845)	(0.678)	(1.633)	(0.835)	(0.526)
Trade openness (in log)	-0.925	-0.545	-1.721**	-0.0717	-1.995**	-0.358
	(1.555)	(0.770)	(0.753)	(1.041)	(0.968)	(0.800)
L.GDP per capital (in log)	-1.659	-1.510	-1.569	-3.267	-2.567	-0.995
	(2.478)	(1.686)	(1.413)	(2.743)	(1.664)	(1.117)
Population (in log)	-8.241	-1.400	-0.769	1.373	-0.764	-5.987***
	(7.999)	(0.895)	(1.660)	(2.943)	(1.746)	(2.164)
Human capital index	-0.0853	-0.0357	0.134*	0.0284	0.119	0.0613
	(0.187)	(0.0554)	(0.0714)	(0.0552)	(0.0900)	(0.0686)
Constant	123.8	63.60***	57.71***	21.54	58.56***	101.3***
	(78.45)	(17.69)	(19.21)	(38.40)	(20.10)	(23.07)
Observations	224	259	855	254	623	486
R-squared	0.137	0.058	0.225	0.093	0.233	0.127
Number of countries	46	48	136	46	114	99
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes

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

In addition, this exercise was repeated to unveil differences in commodity dependence by commodity type (agricultural, fuel, and mining products).[14] Within this context, only the sub-sample containing fuel-CDDCs was statistically significant. The R-squared values indicate a high degree of explanatory power in the fuel-CDDCs sub-sample, suggesting that the model effectively captures variations in income inequality within this specific context. Nonetheless, given the variation observed in subsequent robustness checks, further research may be needed to confirm this finding.

4.2 Robustness checks

Robustness checks are important to assess the stability and reliability of the study's findings. In this sub-section, we present robustness checks performed on the initial regression results, aimed to validate the statistical associations observed in the overall sample and specific sub-samples.

We conduct a random sampling exercise, drawing from a dataset containing half of the original observations. Specifically, we sort the data by year and country identifiers and randomly select 50 per cent of the observations within each year. The rationale behind this approach is to create a reduced sample that maintains temporal and cross-sectional diversity while introducing variation through random selection. This helps to assess whether our results hold under a different subsample.

Table 5 replicates the main regression results corresponding to the full model in Table 3, focusing on columns 6 and 7. The findings from the random sample reaffirm a statistically significant positive association between income inequality (measured by the Gini coefficient) and export diversification. This consistency in results across the full sample and the random sample supports the robustness of the observed relationship.

[14] Refer to Table A 4. for this set of results.

Table 5. Robustness check, randomized sample

	Dependent variable: Gini coefficient	
Variables	(1)	(2)
No. of products exported HS 6-digit (in log)	**2.112***	**2.123***
	(1.213)	(1.189)
Trade openness (in log)	-3.032***	-2.794**
	(0.872)	(1.180)
L.GDP per capital (in log)	-3.076**	-1.361
	(1.498)	(1.564)
Population (in log)	-2.289	1.372
	(2.260)	(3.212)
Human capital index	0.0688	0.109
	(0.0694)	(0.0689)
Government spending (% of GDP, in log)	0.407	-0.111
	(1.309)	(1.207)
Constant	82.09***	32.22
	(18.76)	(35.11)
Observations	280	280
R-squared	0.272	0.343
Number of countries	128	128
Time dummies	No	Yes

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

To further validate the results, we explore the relationship between income inequality and export diversification using alternate measures of inequality. We consider the Palma ratio, the Theil's L index and the inter-decile ratio as dependent variables within the full sample. Table 6 summarises the regression results (corresponding to column 7 of Table 3) using these alternate measures. The positive association between income inequality and export diversification remains statistically significant for the Palma ratio and the Theil's L index. These measurements, being more sensitive to changes in income distribution tails, provide additional support for the robustness of the initial results.

However, when using the inter-decile ratio as the dependent variable, the diversification coefficient becomes non-significant. It is worth noting that, among all considered income inequality measures, the inter-decile ratio exhibits the lowest correlation with the Gini coefficient (with a correlation of 0.65) and other alternate measures.[15] The inter-decile ratio measures inequality as the ratio of the top 10 per cent and the bottom 10 per cent earners in the population, focusing on the extremes. This contrasts with the Gini coefficient, which is more responsive to changes in the middle of the distribution, the Palma ratio which considers the top 10 per cent relative to the bottom 40 per cent, and the Theil's L index which is more sensitive to changes at the lower end of the distribution.

Thus, the non-significant relationship observed when using the inter-decile ratio could suggest that the effect of income inequality on export diversification, may be more concentrated in the middle-income percentiles, rather than at the extremes in the overall sample.

[15] Refer to the correlation matrix under Table A 1.

Table 6. Robustness check, alternate inequality measures (full sample)

Variables	(1) Palma ratio	(2) Theil's L index	(3) Inter-decile ratio
No. of products exported HS 6-digit (in log)	**0.496****	**3.807****	2.661
	(0.244)	(1.732)	(1.955)
Trade openness (in log)	-0.381**	-3.849**	-3.170
	(0.187)	(1.775)	(2.113)
L.GDP per capital (in log)	-0.214	-3.577	-2.950
	(0.229)	(2.281)	(2.291)
Population (in log)	-0.829*	-7.068*	-4.510
	(0.469)	(4.115)	(4.011)
Human capital index	0.0145	0.277**	0.198
	(0.0150)	(0.128)	(0.138)
Government spending (% of GDP, in log)	-0.157	-2.402	0.660
	(0.203)	(1.799)	(2.738)
Constant	8.678*	98.23**	59.73
	(4.895)	(42.81)	(55.04)
Observations	1,109	1,109	1,109
R-squared	0.096	0.124	0.033
Number of countries	182	182	182
Time dummies	Yes	Yes	Yes

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

Additionally, we conduct a further robustness check to validate the heterogeneity observed in the income and commodity dependence subsamples (Tables A 5., A 6., and A 7. in the Appendix). Similar to the results presented in Table 4, the positive association between diversification and inequality remains statistically significant for the low-income and CDDC subsamples, while their counterparts are non-statistically significant. Comparable results are observed for most developing and developed subsamples as in Table 4, with the distinction that the diversification coefficient becomes non-statistically significant in the developing sample under the inter-decile ratio.

Differences across types of commodity dependence, using alternate measures of inequality, yield mixed results. Dissimilar from the results previously obtained in Table A 4., where only the sub-sample containing fuel-CDDCs was statistically significant, the regressions performed for the robustness check[16] reveal a statistically significant result only among agricultural CDDCs when using the Palma ratio, the Theil's L index and the inter-decile ratio. We are thus unable to support this result. This observation may be attributed to the relatively high and evolving skill requirements resulting from the transition away from labour-intensive activities in agriculture towards more capital-intensive activities in the case of horizontal diversification. The latter may initially demand more specialized labour, the availability of which could be constrained in these economies. Nonetheless, the variation in results from this last set of regressions warrants further research to unveil potential differences among these groups.

5. Conclusions

Export diversification is important for CDDCs and developing economies to strengthen economic performance and resilience by broadening income sources for foreign exchange creation, promoting higher value-added sectors, and fostering job creation. Nonetheless, the relationship between export diversification and income distribution remains unclear. Previous research has focused on diversification and growth (Hausmann et al., 2007; Klinger and

[16] Presented in Table A 8 under the Appendix.

Lederman, 2006; Cavalcanti et al., 2014) or the relationship between growth and income inequality (Barro, 2000; Kuznets, 1955; Forbes, 2000; Thornton, 2010). The few empirical studies that empirically examine the nexus between export diversification and income inequality report mixed results. This paper contributes to this literature by using a larger sample of countries over a longer period relative to previous studies.

The analysis indicates a statistically significant positive correlation between export diversification and income inequality, which remains robust when using a randomized sample and using other measures of income inequality. There seems to be heterogeneity across income and commodity dependence status, where the association holds in low-income and CDDCs subsamples. This indicates that the benefits of export diversification might initially be constrained to specific groups, particularly in these economies. Thus, governments may need to provide support to ensure that the benefits of diversification extend to low-income households.

While this could be challenging for financially constrained countries, there may be strategic ways to consider social safety nets and inclusiveness when designing diversification policies. For example, focusing on sectors aligned with the existing skills of a significant portion of the population can reduce funding needs for training. If an economy is primarily based on agriculture, diversifying into related sectors would engage a large number of households based on their existing skills. Export revenues from these activities can then fund vocational training and the necessary upskilling to diversify into more specialized sectors or social protection schemes to safeguard vulnerable groups.

Social dialogue and inclusive decision-making can also better inform the policymaking process. Engaging stakeholders can aid target-setting and anticipate policies that promote inclusiveness based on current conditions. To this end, governments should identify vulnerable workers and firms to provide support or technical capacity building to allow their participation in the labour market, wherever possible. Retraining and upskilling schemes should align with the changing economic landscape and national diversification plans. Moreover, these initiatives can be tailored to create opportunities for under-represented groups, including women, youth, and minority communities.

Coordination between industrial and education policies is vital to ensure that low-income groups benefit from employment opportunities requiring varying levels of skills resulting from diversification towards sophisticated value-added sectors. Such collaboration would avoid skills mismatches and ensure that the benefits from export diversification extend beyond those previously in higher-skilled positions. Gender considerations are equally important to ensure balanced participation and promote equitable outcomes.

If diversification occurs without creating new opportunities for marginalized groups, income inequality may deepen or remain unchanged. Developing skilled human capital to support new sectors and activities may also require shaping education and skills towards strategic areas. This may imply setting national education priorities based on existing and future needs to support a diversification strategy.

Contrary to our priors, the results suggest a positive correlation between human capital and income inequality in the overall sample. This further underlines the need for appropriate targeting to ensure government support reaches the intended recipients. Governments should additionally revise public education and health schemes to ensure equal access. This should also consider improving infrastructure and expanding services, particularly in rural and remote areas.

Governments may also support firms exploring diversification opportunities through technical and financial assistance. Small and medium-sized enterprises may particularly benefit from such support, considering their limited resources to adapt compared to larger firms. Improving credit access and fostering a favourable business environment for local businesses is thus encouraged to ensure domestic firms can leverage the opportunities brought by diversification. To this end, governments should also encourage links between multinational enterprises and smaller local firms to facilitate knowledge spillovers and enhance the host country's human capital.

CDDCs seeking vertical diversification would notably benefit, particularly those where forward linkages in the commodity chain require extensive human and physical capital, as is the case for producing batteries from various strategic mining commodities or more sophisticated petrochemicals in fuel-exporting countries. This could incentivize countries to invest in training excluded social groups to meet increasing demand from foreign investors.

Despite these contributions, the study has limitations. First, it establishes correlation rather than causation, which, while it may guide policymakers when designing diversification strategies, calls for further research to identify causal

links and consider unobservable factors that may influence income distribution. Second, data quality issues on income inequality and covariates may confound the results of subsamples. Appropriate and consistent data collection is imperative, particularly in low-income and least-developed countries, where data availability remains challenging. This study opted for a fixed-effects approach based on the slow-moving nature of income inequality variables, which makes inequality dynamics difficult to capture. Further work is recommended using dynamic panel settings, subject to quality data, over a longer period to better understand inequality dynamics for the full sample and different subgroups. Microeconomic analyses are also encouraged to better understand the mechanisms through which diversification affects inequality.

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Appendix

A.1 Correlation Matrices

Table A 1. Correlation Matrix income inequality measures

	Gini coefficient	Palma ratio	Theil's L index	Inter-decile ratio
Gini coefficient	1			
Palma ratio	0.909	1		
Theil's L index	0.9704	0.9657	1	
Inter-decile ratio	0.6546	0.7341	0.7765	1

Table A 2. Correlation Matrix independent variable and controls

	Export diversification	GDP per capita (log)	Trade openness (log)	Population (log)	Human capital	Government spending (log)
Export diversification	1					
GDP per capita (log)	0.5668	1				
Trade openness (log)	0.0905	0.2418	1			
Population (log)	0.6246	-0.1206	-0.2594	1		
Human capital	0.6696	0.7423	0.2362	0.0494	1	
Government spending (log)	-0.0507	0.2769	0.244	-0.3519	0.3241	1

A.2 Non-linear results

Table A 3. Fixed effects coefficients, number of products exported (non-linear, full sample)

Variables	(1) Gini	(2) Palma ratio	(3) Theil's L index	(4) Inter-decile ratio
No. of products exported HS 6-digit (in log)	-1.238	-0.982	-5.253	-5.289
	(2.469)	(0.763)	(6.767)	(9.852)
Square no. of products exported HS 6-digit (in log)	0.196	0.112*	0.688	0.604
	(0.197)	(0.0665)	(0.543)	(0.778)
Trade openness (in log)	-1.635**	-0.416**	-4.061**	-3.356*
	(0.663)	(0.182)	(1.734)	(2.014)
L.GDP per capital (in log)	-2.275*	-0.309	-4.156*	-3.458
	(1.282)	(0.227)	(2.280)	(2.148)
Population (in log)	-2.948*	-0.894*	-7.464*	-4.858
	(1.558)	(0.455)	(4.040)	(3.969)
Human capital index	0.147***	0.0130	0.268**	0.190
	(0.0557)	(0.0152)	(0.129)	(0.141)
Government spending (% of GDP, in log)	-1.066	-0.134	-2.260	0.784
	(0.763)	(0.205)	(1.823)	(2.817)
Constant	83.07***	14.47**	133.0**	92.21
	(22.75)	(5.850)	(52.86)	(66.06)
Observations	1,109	1,109	1,109	1,109
R-squared	0.184	0.103	0.128	0.035
Number of countries	182	182	182	182
Time dummies	Yes	Yes	Yes	Yes

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

A.3 Robustness checks

Table A 4. Fixed effects coefficients (subsamples, by commodity dependence groups)

	Dependent variable: Gini		
	(1)	(2)	(3)
Variables	Agricultural CDDCs	Fuel CDDCs	Mining CDDCs
No. of products exported HS 6-digit (in log)	1.766	**2.792****	1.779
	(1.167)	(1.346)	(1.763)
Trade openness (in log)	-1.925*	-5.589**	-1.960
	(1.060)	(2.137)	(2.509)
L.GDP per capital (in log)	0.335	-5.197*	-1.275
	(1.396)	(2.665)	(3.185)
Population (in log)	0.591	-0.718	4.176
	(3.569)	(1.085)	(8.523)
Human capital index	0.135	0.0506	0.110
	(0.135)	(0.194)	(0.476)
Constant	32.75	89.19***	13.71
	(29.31)	(27.16)	(87.22)
Observations	294	183	146
R-squared	0.224	0.503	0.128
Number of countries	70	43	38
Time dummies	Yes	Yes	Yes

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

Table A 5. Fixed effects coefficients, Palma ratio (subsamples)

	Dependent variable: Palma ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Low income	High income	Developing	Developed	CDDCs	Non-CDDCs
No. of products exported HS 6-digit (in log)	**1.930****	0.0720	**0.617****	**0.238***	**0.996****	0.0422
	(0.881)	(0.0892)	(0.300)	(0.133)	(0.417)	(0.116)
Trade openness (in log)	-0.623	-0.0665	-0.399*	-0.00724	-0.288	-0.281
	(0.513)	(0.0798)	(0.214)	(0.0855)	(0.321)	(0.224)
L.GDP per capital (in log)	-0.720	-0.127	-0.114	-0.277	-0.419	-0.147
	(0.761)	(0.156)	(0.264)	(0.206)	(0.284)	(0.171)
Population (in log)	-4.313	-0.181*	-0.463	0.176	-0.500	-1.139***
	(2.745)	(0.102)	(0.490)	(0.218)	(0.517)	(0.427)
Human capital index	-0.0840	-0.00362	0.00663	0.00222	-0.0135	0.0122
	(0.0792)	(0.00435)	(0.0208)	(0.00365)	(0.0305)	(0.0117)
Constant	42.09	4.297**	4.700	0.0824	4.479	14.72***
	(29.87)	(1.837)	(5.672)	(2.807)	(6.248)	(4.817)
Observations	224	259	855	254	623	486
R-squared	0.173	0.076	0.114	0.099	0.124	0.111
Number of countries	46	48	136	46	114	99
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes

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

Table A 6. Fixed effects coefficients, Theil's L index (subsamples)

	Dependent variable: Theil's L index					
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Low income	High income	Developing	Developed	CDDCs	Non-CDDCs
No. of products exported HS 6-digit (in log)	**12.34****	0.561	**4.433****	**4.985***	**7.504*****	0.412
	(4.914)	(1.359)	(2.069)	(2.659)	(2.646)	(1.200)
Trade openness (in log)	-3.425	-1.094	-4.257**	-0.169	-4.232	-2.190
	(4.441)	(1.353)	(2.050)	(1.719)	(3.009)	(2.414)
L.GDP per capital (in log)	-5.949	-2.825	-2.424	-5.296	-4.636*	-1.147
	(6.941)	(2.702)	(2.591)	(4.376)	(2.684)	(1.821)
Population (in log)	-32.96	-2.387	-2.630	0.273	-2.271	-13.51***
	(22.77)	(1.574)	(4.477)	(3.717)	(4.730)	(4.973)
Human capital index	-0.480	-0.0570	0.233	0.0446	0.0869	0.164
	(0.575)	(0.0819)	(0.169)	(0.0739)	(0.234)	(0.136)
Constant	350.5	75.74**	56.41	20.34	51.68	165.9***
	(241.1)	(30.62)	(49.70)	(52.00)	(53.23)	(55.57)
Observations	224	259	855	254	623	486
R-squared	0.153	0.081	0.148	0.099	0.156	0.116
Number of countries	46	48	136	46	114	99
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes

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

Table A 7. Fixed effects coefficients, Inter-decile ratio (subsamples)

	Dependent variable: Inter-decile ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Low income	High income	Developing	Developed	CDDCs	Non-CDDCs
No. of products exported HS 6-digit (in log)	**10.61****	0.182	3.324	**1.938***	**5.494***	0.995
	(4.678)	(0.710)	(2.311)	(1.038)	(2.989)	(1.355)
Trade openness (in log)	-3.414	-0.849	-3.773	-0.0977	-4.503	-1.503
	(3.858)	(0.714)	(2.497)	(0.748)	(3.139)	(1.462)
L.GDP per capital (in log)	-8.945	-1.680	-3.581	-1.602	-4.180	-1.146
	(6.511)	(1.233)	(2.504)	(1.702)	(3.422)	(1.476)
Population (in log)	-41.97*	-0.806	-2.725	-1.555	-2.283	-6.780**
	(23.31)	(0.886)	(4.585)	(1.697)	(4.997)	(2.925)
Human capital index	-0.495	-0.0174	0.234	0.0243	0.107	0.137
	(0.502)	(0.0349)	(0.178)	(0.0378)	(0.254)	(0.0952)
Constant	435.6*	34.42**	45.56	16.61	39.94	73.51**
	(255.8)	(15.82)	(65.20)	(22.26)	(73.42)	(32.30)
Observations	224	259	855	254	623	486
R-squared	0.177	0.104	0.041	0.133	0.048	0.062
Number of countries	46	48	136	46	114	99
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes

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

Table A 8. Fixed effects coefficients (subsamples, by commodity dependence groups)

	Palma ratio			Theil's L Index			Inter-decile ratio		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables	Agricultural CDDCs	Fuel CDDCs	Mining CDDCs	Agricultural CDDCs	Fuel CDDCs	Mining CDDCs	Agricultural CDDCs	Fuel CDDCs	Mining CDDCs
No. of products exported HS 6-digit (in log)	**1.079***	0.291	0.587	**6.758***	4.167	6.564	**5.075***	-5.635	15.86
	(0.543)	(0.242)	(0.530)	(3.752)	(2.872)	(5.084)	(2.987)	(7.702)	(10.52)
Trade openness (in log)	-0.286	-1.207**	-0.586	-3.710	-13.25**	-6.864	-1.302	-12.64	-15.71
	(0.293)	(0.581)	(0.755)	(2.527)	(5.600)	(7.595)	(1.787)	(7.774)	(11.85)
L.GDP per capital (in log)	0.154	-0.265	0.120	0.620	-5.878**	-2.164	-1.907	-4.004	-1.391
	(0.484)	(0.190)	(1.001)	(3.802)	(2.400)	(8.979)	(2.723)	(3.442)	(12.75)
Population (in log)	-0.584	-0.128	2.256	-0.716	-0.750	17.26	-2.798	3.620	34.84
	(0.957)	(0.214)	(2.399)	(9.687)	(2.123)	(22.17)	(8.348)	(5.534)	(31.34)
Human capital index	-0.00645	0.00667	0.0955	0.251	-0.0962	0.627	0.357	-1.327	2.639
	(0.0353)	(0.0352)	(0.154)	(0.371)	(0.396)	(1.372)	(0.299)	(1.156)	(2.270)
Constant	0.565	7.683**	-23.58	-1.394	110.7***	-140.7	3.269	166.4	-452.1
	(9.423)	(3.299)	(29.38)	(78.41)	(37.44)	(257.4)	(55.38)	(114.9)	(427.9)
Observations	294	183	146	294	183	146	294	183	146
R-squared	0.165	0.307	0.082	0.179	0.383	0.099	0.121	0.206	0.166
Number of countries	70	43	38	70	43	38	70	43	38
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

A.4 Sample

Table A 9. Countries in the analysis (full sample)

Afghanistan	Georgia	**Oman**
Albania	Germany	Pakistan
Algeria	**Ghana**	Palau
Andorra	**Greece**	Panama
Angola	Grenada	**Papua New Guinea**
Argentina	Guatemala	**Paraguay**
Armenia	**Guinea**	**Peru**
Australia	**Guinea-Bissau**	Philippines
Austria	**Guyana**	Poland
Azerbaijan	Haiti	Portugal
Bahamas	Honduras	**Qatar**
		Republic of Korea
		Republic of Moldova
Bahrain	Hungary	Romania
Bangladesh	**Iceland**	Russian Federation
Barbados	India	**Rwanda**
Belarus	Indonesia	Saint Lucia
		Saint Vincent and the
Belize	**Iran (Islamic Republic of)**	**Grenadines**
Benin	**Iraq**	**Samoa**
Bhutan	Ireland	**Sao Tome and Principe**
Bolivia (Plurinational State of)	Israel	**Saudi Arabia**
Bosnia and Herzegovina	Italy	**Senegal**
Botswana	**Jamaica**	Serbia
Brazil	Japan	**Seychelles**
Brunei Darussalam	Jordan	**Sierra Leone**
Bulgaria	**Kazakhstan**	Slovakia
Burkina Faso	**Kenya**	Slovenia
Burundi	**Kiribati**	**Solomon Islands**
Cabo Verde		**Somalia**
Cambodia	**Kuwait**	South Africa
Cameroon	**Kyrgyzstan**	**South Sudan**
	Lao People's Democratic	
Canada	**Republic**	Spain
Central African Republic	Latvia	Sri Lanka
Chad	Lebanon	**Sudan**
Chile	Lesotho	**Suriname**
China	**Liberia**	Sweden
Colombia	**Libya**	Switzerland, Liechtenstein*
Comoros	Lithuania	**Syrian Arab Republic**
Congo	Luxembourg	**Tajikistan**
	Madagascar	

Costa Rica
Côte d'Ivoire
Croatia
Cuba
Cyprus
Czechia
Democratic Republic of the Congo
Denmark
Djibouti
Dominica
Dominican Republic
Ecuador
Egypt
El Salvador
Equatorial Guinea
Eritrea
Estonia
Eswatini
Ethiopia
Fiji
Finland
France
Gabon
Gambia
Malawi
Maldives
Mali
Malta
Marshall Islands
Mauritania
Mauritius
Mexico
Mongolia
Montenegro
Morocco
Mozambique
Myanmar
Namibia
Nepal
Netherlands (Kingdom of the)
New Zealand
Nicaragua
Niger
Nigeria
North Macedonia
Norway
Thailand
Timor-Leste
Togo
Tonga
Trinidad and Tobago
Tunisia
Turkmenistan
Türkiye
Tuvalu
Uganda
Ukraine
United Arab Emirates
United Republic of Tanzania
United Kingdom of Great Britain and Northern Ireland
United States of America
Uruguay
Uzbekistan
Vanuatu
Venezuela (Bolivarian Republic of)
Viet Nam
Yemen
Zambia
Zimbabwe

Note: **CDDCs** are marked in bold, while non-CDDCs are in standard font. Grouping countries into CDDCs and non-CDDCs is based on UNCTAD's definition of commodity export dependence, when more than 60 per cent of its total merchandise exports are composed of commodities, in line with the *State of Commodity Dependence 2021*.

*This grouping is based on the UNCTAD target economies classification, available at https://unctadstat.unctad.org/EN/Classifications/DimCountries_TargetEconomies_Classification.pdf. In this *study,* they are counted as a single country.