Journal of Developing Economies Vol. 9 No. 1 (2024): 158-184

JDE Journal of Developing Economies

JOURNAL OF DEVELOPING ECONOMIES
https://e-journal.unair.ac.id/JDE/index

POVERTY AND INEQUALITY DYNAMICS: MEASURING DAMPENING AND IGTI IN THREE CAFTA-DR COUNTRIES

Manuel Vanegas*[1]

Terry Roe[2]

[1,2] Department of Applied Economics, University of Minnesota, Saint Paul/Minneapolis, USA

ABSTRACT

This article examines the relationships between extreme poverty, economic growth, and inequality, assesses if changes in inequality dampen the impact of income on extreme poverty, and determines the magnitude of the inequality growth trade-off index in Costa Rica, the Dominican Republic, and Honduras. A country-specific ARDL bound regression was conducted. The findings indicate the presence of direct and indirect dampening impacts of changes in inequality on income growth and extreme poverty reduction. The magnitude of the inequality growth trade-off- index indicates whether to prioritize growth and/or inequality reducing policies. This means that the higher the inequality, as in Honduras, the higher the economic or average income growth rate required to compensate for the increase in inequality to achieve a given level of extreme poverty reduction. Accordingly, there is no one-size-fits-all policy approach to tackling extreme poverty.

Keywords: *Income Growth Elasticity of Poverty, Inequality Elasticity of Poverty, Income Inequality, Dampening, Kakwani's IGTI, Country-By-Country ARDL Bound Regression*

JEL: O11; O15; O40; D60; D63

ARTICLE INFO

Received: May 7th, 2023
Revised: January 2nd, 2024
Accepted: February 7th, 2024
Online: June 4th, 2024

*Correspondence:
Manuel Vanegas
E-mail:
vaneg001@umn.edu

To cite this document: Vanegas, M. & Roe, T. (2024). Poverty and Inequality Dynamics: Measuring Dampening and IGTI in Three CAFTA-DR Countries. *Journal of Developing Economies*, *9*(1), 158-184. https://doi.org/10.20473/jde.v9i1.45266

Introduction

Concerns about inequality, extreme poverty reduction, and economic growth have increased significantly in recent years. The international community, policymakers, and the public at large often point to rising inequality as a threat to economic and social stability. In this context, let us take stock of what is currently known about the evolution of poverty and inequality worldwide.

If we compare the way the world feels about poverty reduction in the beginning of 2020s with the way the world felt nearly seven decades ago, when many of us may have thought we had identified one formula for solid, steady economic growth and poverty reduction in the developing world. All of us joined in the effort. However, where did inequality stand? For whatever reason, it was forgotten. It was set aside. Moreover, what about the uncertainties: wars, political chaos, economic recessions, weather disruptions, and now COVID-19 and its aftermath? To be honest, perhaps, we all failed to give all these events the appropriate framework and forgot that a relatively high degree of national specificity exists.

What about today? Has extreme poverty decreased worldwide over the past seven decades? The results are mixed. The aggregates show progress, but the fact is that if we take China and India out of the equation, the number of extremely poor people worldwide has increased. The number of people living in extreme poverty has increased in several sub-Saharan African countries, in parts of Latin America and the Caribbean, and in Western Asia (Sumner et al., 2020; United Nations, 2020; UNCTAD, 2020; Valensisi, 2020; Vanegas, 2022, Vanegas & Roe, 2021).

A general emerging consensus is that economic growth alone is a relatively incomplete tool for extreme poverty reduction. In this context, extreme poverty reduction has become the primary development goal. It can be achieved through economic growth and/or via income distribution. Reducing and/or eradicating extreme poverty will increasingly depend on tackling inequality, which has become relatively more important. Therefore, a policy agenda that addresses both could lead to enhancing both economic growth and equality.

Developing countries in the Central America-Dominican Republic Free Trade Agreement (CAFTA-DR), comprising the United States, Costa Rica, El Salvador, Guatemala, Honduras, and Nicaragua, have experienced setbacks since 2015 despite significant progress between the mid-1990s and the early 2010s. The average rates of extreme poverty and inequality increased and worsened during the COVID-19 pandemic (ECLAC, 2021).

The relationship between economic growth and extreme poverty is not as straightforward as presented in cross-country estimates. Moreover, the growth elasticity of extreme poverty undoubtedly varies across countries, depending on both the extreme poverty measures and the procedures used in the estimation. This can be attributed to the fact that different developing countries have different levels of development and structural conditions of production. This is a clear indication that the combination of policies that promote economic growth and reduce inequality may vary considerably from one country to another.

This study has three objectives. First, it analytically examines how changes in inequality affect the relationship between income growth and extreme poverty reduction in three CAFTA-DR developing countries: Costa Rica (CR), Dominican Republic (DR), and Honduras (HO). CR, DR, and HO were examined because their economic development exhibit patterns and characteristics that can also be seen in other developing countries worldwide, such as Bolivia, Colombia, Ecuador, El Salvador, and Perú.

Second, it examines the magnitude of the total dampening impact of inequality on extreme poverty, which is defined as the negative impact of increasing inequality on the income growth of extreme poverty. It is categorized into direct and indirect dampening impacts. The direct dampening impact is equal to the estimate of the inequality elasticity of poverty. The indirect dampening impact is calculated as the difference between the estimate of income growth elasticity of poverty from the benchmark model and the estimate of income growth elasticity of poverty, when the model allows inequality to be different from zero.

Third, it examines the magnitude of the income growth inequality trade-off index (IGTI) between income growth and inequality, which establishes that it can be explained in terms of changes in inequality. The IGTI was first proposed by Kakwani (1993). The magnitude of IGTI shows the average income growth required to offset the adverse impact of an increase in inequality on extreme poverty, which is just enough to keep the poverty rate unchanged. The elasticity value estimates derived in this study were used to compute the economic growth rates that would be required to maintain the incidence of extreme poverty unchanged in CR, DR, and HO.

The country-by-country empirical analysis consists of two related sections. In the first section, the static benchmark (inequality-neutral income growth) and the unrestricted (allowing inequality to change) models were estimated using the two stage least squares (2SLS). In the second section, the dynamics of extreme poverty reduction were analyzed using the autoregressive distributed lag bounds (ARDL) testing to cointegration proposed by Pesaran et al. (2001).

This study attempts to answer the following research questions. First, is there a long-run relationship between income, extreme poverty, and inequality? Second, is there a dampening impact of changes in inequality on income and extreme poverty rates for the three CAFTA-DR developing countries and what is its magnitude? Third, if an IGTI exists, what is the magnitude for each country and how much income growth is needed to offset the adverse impacts of an increase in inequality to maintain extreme poverty unchanged? Therefore, from a poverty reduction policy perspective, it is important not only for the governments of the three developing countries considered in this study, but also for other developing countries with similar characteristics to understand from an empirical perspective the relationship between extreme poverty reduction, income, and inequality.

This study makes four main contributions to the existing literature. First, by focusing on benchmark and unrestricted models, it provides a comprehensive analysis of the long- and short-run dynamics of extreme poverty reduction in CR, DR, and HO. Second, based on the literature review, this study is the first to comprehensively measures: (i) the direct, indirect, and total dampening impacts of changes in inequality on income and extreme poverty reduction, and (ii) the magnitude of the IGTI, which determines how much income growth is needed in each CAFTA-DR country to offset the adverse impacts of an increase in inequality. Fourth, in accordance with both CR, DR, and HO policy analysis practices and the United Nations Statistics Division directive, this study uses only annualized official or national and comparable country-specific data with the advantages and disadvantages associated with increasing the underlying variation of the data.

Development Trends

Has extreme poverty decreased in CR, DR, and HO over the past four decades? The estimates in Table 1 suggest that extreme poverty has both decreased and increased, but they also suggest a remarkable heterogeneity. Table 1 shows that, at the country level, the extreme poverty figures in CR and DR are alarming. However, it has increased consistently since 2010 in CR. HO continues to have one of the highest rates of poverty and inequality in Latin America, with only marginal and, at times, ephemeral progress over the past four decades.

Table 1: Evolution of Average Headcount Ratio of Extreme Poverty and Gini Coefficient

Period/Year	Costa Rica	Dominican Republic	Honduras
Extreme Poverty (%)			
1980-1990	10.06	31.18	49.31
1990-2000	7.27	26.21	47.94
2000-2010	4.92	16.83	43.39

Period/Year	Costa Rica	Dominican Republic	Honduras
2010-2020	6.1	9.61	44.03
1980-2020	7.09	20.96	46.17
2000	6.13	7.94	42.16
2005	5.61	16.14	47.12
2010	3.94	10.79	39.16[2]
2015	7.18	6.35	42.88[2]
2020	8.52	3.51	49.23[2]
2021	7.31	3.06[1]	-
Gini Index			
1980-1990	41.6	49.15	52.24
1990-2000	35.46	49.04	50.47
2000-2010	43.3	49.99	56.6
2010-2020	51.6	45.36	50.32
1980-2020	42.99	48.38	52.41
2000	41.3	51.3	54.7
2005	40.8	50.8	59.68
2010	50.7	48.5	54.04
2015	51.6	45.8	50.58
2020	51.9	40.5	51.90[2]
2021	52.4	39.06	54.92[3]

Source: Authors' calculations using the national/official datasets of the statistics offices of CR, DR, and HO. [1]Preliminary and under revision, due to changes in methodology in 2016. [2]Preliminary and under revision due to changes in methodology in 2018. Honduras established a technical commission in 2018 to update the national/official poverty measurement methodology. Therefore, a note of caution is appropriate about its extreme poverty number in 2020. [3]Preliminary estimates.

In spite of the proactive containment measures taken by the CR authorities to tackle the COIVD-19 pandemic and its well-established social system, real economic growth slowed down significantly to almost -4.1% in 2020, compared to almost 2.3% in 2019. As a result, the negative impact on extreme poverty and income inequality, as measured by the Gini coefficient, was significant (BCCR, 2021; INEC, 2018, 2020).

Has extreme poverty decreased in CR over the past four decades? The answer is yes, but only until the 2000-2010 period. As shown in Table 1, extreme poverty in CR has declined steadily, from an annual average of nearly 10.09% in the 1980-1990 period to nearly 4.92% in the 2000-2010 period, a decline of nearly 5.14% over three decades. The percentage of people living in extreme poverty increased to nearly 6.10% in the 2010-2020 period. This is a worrying increase of nearly 1.18% in just one decade (see Table 1). However, a higher increase of 1.34% was noted in just five years, covering the period between 2015 and 2020. As shown in Table 2, over the four decades, the average annual growth of extreme poverty reflects a declining trend of nearly -2.17% per year.

What do the number of extreme poverty tell us? CR experienced a sharp setback between 2010 and 2020. The number of extremely poor people increased from 178,635 in 2010 (3.94% of the national or official population) to 346,954 in 2015, and to 439,891 in 2020 (8.52% of the national or official population). The number of extremely poor people, however, declined to 377,418 in 2021 (INEC, 2008, 2009, 2012, 2013, 2021). The increase in extreme poverty would have been greater if measures to transfer emergency income to households had not been implemented.

Is there a reverse persistence in inequality? As shown in Table 1, the answer is yes. After a historical decline from the 1980s to 2005, the Gini index was consistently on the rise in CR, from nearly 40.80 in 2005 to a relatively high level of nearly 51.90 in 2020. This trend continued to nearly 52.40 in 2021, which is one of the highest rates of inequality in Latin America. This was mainly due to an increase in unemployment and decrease in labor income (INEC, 2020 2021; Vanegas & Roe, 2021; Vanegas, 2022).

The trend changes in inequality in CR have not been constant. As shown in Table 1, the value of the Gini coefficient decreased from its average value of nearly 41.60 during the 1980-1990 period to nearly 35.46 during the 1990-2000 period. Its value, however, rose relentlessly in the last two decades, reaching a value of nearly 43.30 during the 2000-2010 period and nearly 51.60 during the 2010-2020 period. This was a huge jump of nearly +7.84 Gini points in 2000-2010 and nearly +8.3 Gini points in 2010-2020. As shown in Table 2, over the four decades, the average annual growth of the Gini index reflects an increasing trend of nearly 0.05% per year.

Dominican Republic

Despite the recession of 2003-2004 and until 2019, the DR has enjoyed strong real economic growth, averaging nearly 6% per year since the 2000s. In 2020, the DR's targeted social programs helped cushion the impact of COVID-19. Real economic growth, compared to 2019 (5.1%), slowed down significantly in 2020, contracting to nearly 6.7% in 2020.

Has extreme poverty decreased in the DR over the past four decades? The answer is yes. It has decreased dramatically since the early 2010s. As shown in Table 1, extreme poverty in the DR declined consistently, from an annual average of nearly 31.18% in the 1980-1990 period to nearly 9.61% in the 2010-2020 period. This represents a decline of nearly 21.57% over four decades, or a long-term growth trend of nearly -2.70% per year between 1980 and 2020 (see Table 2).

Table 2: Evolution of Annual Compound Average Growth Rates[1] of Income, per Capita Income, Extreme Poverty[2], and Gini Coefficient

Country Statistics	1980-1990	1990-2000	2000-2010	2010-2020	1980-2020
Income					
Costa Rica[3]	3.09	5.14	4.81	3.58	4.39
Dominican Republic	3.19	5.54	5.44	4.97	4.54
Honduras	3.46	3.33	4.53	3.05	3.61
Average	3.25	4.67	4.93	3.87	4.18
Per Capita Income					
Costa Rica[3]	0.3	2.57	3.32	1.77	1.99
Dominican Republic	0.1	3.08	3.66	2.76	2.4
Honduras	-0.8	-0.33	6.16	1.33	1.59
Average	-0.13	1.77	4.38	1.95	1.99

Country Statistics	1980-1990	1990-2000	2000-2010	2010-2020	1980-2020
Extreme Poverty					
Costa Rica[3]	-1.58	-5.58	-5.51	4.01	-2.17
Dominican Republic	7.92	-7.38	3.9	-15.24	-2.7
Honduras	-2.44	0.49	-2.61	1.17	-0.85
Average	1.3	-4.16	-1.41	-3.35	-1.9
Gini Coefficient					
Costa Rica[3]	-1.43	0.61	0.95	0.08	0.05
Dominican Republic	0.26	0.54	-0.74	-1.75	-0.42
Honduras	-0.15	0.18	-0.35	-1.02	-0.34
Average	-0.44	0.44	-0.05	-0.9	-0.24

Source: Authors' calculations based on national/official datasets. Consultations with Honduras as related to extreme poverty and Gini coefficient values between 2018 and 2020 still ongoing. [1] The growth rate is calculated using the following exponential equation: $\ln Y = \alpha + \beta Time$ where β multiplied by 100 provides the growth rate value. [2] Defined as a specific share of the country's population whose income or a consumption of a basic food basket is below the official poverty line, that is, the percentage of population that cannot afford to buy a defined basic basket of food. [3] Values for 1970-1980 can be provided upon request.

What do the number of extreme poverty in the DR tell us? According to the Ministry of Economy, Planning and Development (MEPD) (2021), the number of extremely poor people decreased from nearly 1,022,983 people in 2010 (10.79% of the estimated official population) to nearly 366,484 people in 2020 (3.51% of the estimated official population) and 322,771 people in 2021 (3.06% of the estimated official population).

Income inequality, while not negligible, has been lower than Honduras since 2000 and Costa Rica since 2010. What has happened to inequality in the DR? The value of the Gini coefficient decreased from its average value of nearly 49.15 during the 1980-1990 period to nearly 45.36 during the 2010-2020 period. This represents a decline of nearly 3.79 Gini index points over the past four decades, or as shown in Table 2, an average growth rate of nearly -0.42% per year. Moreover, in contrast to the increasing trend observed in CR and HO, income inequality decreased to nearly 40.5 and 39.6 in 2020 and 2021, respectively (see Table 1).

Honduras

Despite positive real economic growth of almost 3.61% annually, and per capita GDP growth of almost 1.59% per year, extreme poverty in Honduras has hardly changed since 1980s. This result, however, can only partially explain the lack of progress in extreme poverty reduction (see Tables 1 and 2). The combined impacts of relatively high and persistent inequality, past shocks, and the current COVID-19 induced crisis have reinforced the cycle of extreme poverty in Honduras (Vanegas, 2022).

Subsequently, a pertinent question is appropriate. Has extreme poverty decreased, increased, or stagnated in Honduras over the past four decades? At best, the answer is that Honduras has made relatively little progress. Its extreme poverty trends present relatively little variation between 1980 and 2020 (Trejos & Gindling, 2004; Vanegas, 2014, 2022; Vanegas & Roe, 2021). As shown in Table 1, extreme poverty in Honduras declined from an average of nearly 49.31% in 1980-1990 to nearly 44.03% in 2010-2020. This is relatively marginal decline of nearly 5.28% over four decades, or an average annual growth rate of nearly -0.85% per year, versus CR (-2.17%) and the DR (-2.79%), as seen in Table 2.

What do the number of extreme poverty in Honduras tell us? According to the Honduras National Statistics Institute (INEC, 2008, 2020), the number of extremely poor people (not adjusted due to methodology changes) increased from nearly 3.26 million people in 2010 (39.1% of the population) to nearly 3.86 million people in 2019 (42.2% of the population) and nearly 4.47 million people in 2020 (48.2% of the population). The increase in extreme poverty in 2020, however, would have been even greater if social measures to transfer income to vulnerable households had not been implemented.

Inequality in Honduras as measured by the Gini coefficient reflects one of the highest levels of income inequality in the CAFTA-DR countries and across Latin America and the Caribbean region. As shown in Table 1, however, changes in inequality have not been steady. The value of the Gini coefficient declined from its average value of nearly 52.24 in 1980-1990 to nearly 50.32 in 2010-2020. This represents a relatively modest decline of nearly 1.92 Gini points over the last four decades, or an average growth rate of nearly -0.34% per year (Table 2). Using different databases and methodologies, among others, Gasparini et al. (2007) and Trejos & Gindling (2004); Gindling & Trejos (2013) found similar trend results.

Literature Review

There are several countries that have made tremendous progress in extreme poverty reduction, including Botswana, Cape Verde, Chile, China, Costa Rica, Dominican Republic, El Salvador, Indonesia, India, Kenya, Singapore, South Korea, and Taiwan. In addition, the following countries have left the United Nations' infamous list of Least Developed Countries: Botswana, Cape Verde, Equatorial New Guinea, Maldives, Mauritius, and Samoa. However, the most striking fact is still the persistent, ruthless, pervasive extreme poverty and growing inequality (ECLAC, 2020; United Nations, 2020; UNCTAD, 2020; Vanegas, 2012, 2022).

Moreover, on the basic needs approach, or on the relative poverty reduction line, preliminary estimates from national or official figures (partially including the COVID-19 pandemic) indicate that there are other horror stories. These include the horrors of Nigeria with nearly 90 million people in poverty; the Democratic Republic of the Congo with nearly 65 million people; Haiti with nearly 7.8 million out of nearly 11.5 million people, and Honduras with nearly 7 million and perhaps more when the full impact of the COVID-19 is taken into account (ECLAC, 2020; Sumner et al., 2020; United Nations, 2020; Valensisi, 2020).

Despite relatively good economic performance, the movement of protests and unrests that swept across Central America, the Middle East, North Africa, and South America regions since the beginning of the 2000s has continued in different forms. In addition to demands for greater economic, social, and political equality, the protests were largely sparked by a refusal to tolerate any longer the gross inequalities perpetuated by long-entrenched social, economic and political disparities (Boushhey et al., 2017; Keeley, 2015; Stiglitz, 2013; UN DESA, 2020; UNCTAD, 2020; Vanegas & Roe, 2021; Vanegas, 2022).

What about the raw evidence of the Gini? Since late 1980s, the Gini coefficient of income inequality has increased in most developed countries and in some developing countries. This is not new. The Gini coefficient of inequality declined in several African, Asian, Latin American and Caribbean countries until around 2007. Unfortunately, the global economic crisis of 2008-2012, combined with the impact of COVID-19 pandemic (ECLAC, 2020), caused a reversal and inequality is on the rise again, but not everywhere (Cingano, 2014; UN DESA, 2013, 2020; UNCTAD, 2020).

Moreover, due to the current COVID-19 pandemic, most developing and developed countries, scholars, as well as the international community have been increasingly concerned about the distributional effects of the crisis and those of the recovery, and with good justification. In this context, the issue of income inequality has come to the front line of their development agendas with the aim of reconciling economic growth with a better income distribution (ECLAC, 2020; Piketty, 2015; UN DESA, 2020; Valensisi, 2020).

However, because of the relevance of the theoretical underpinnings and empirical evidence of the dampening and inequality-growth trade-off, the relationship has been examined relatively less extensively in the development literature. In this context, Kakwani (1993) in his seminal work measured the tradeoff between growth and inequality for Cote D'Ivoire and found an IGTI value of 4.59 for the extremely poor. The implication is that Cote D'Ivoire needs an income growth rate of 4.59% to compensate for an increase of 1% in the Gini index. He also found that the value of the IGTI was significantly lower for the moderately poor, implying that the lower the poverty line, the greater the relative sensitivity of poverty to changes in income inequality than to changes in the mean income. He went on to argue that the high values of the IGTI suggest that it is of crucial importance to know if there is a systematic tendency for inequality to increase with economic growth.

Additionally, Kakwani (2000) applied the IGTI methodology to four countries, namely Korea, Laos, Philippines, and Thailand. He found that in Thailand, reducing inequality has a greater payoff for poverty reduction than promoting economic growth as the value of IGTI in that country was about 4.04, indicating that inequality is a more important problem than growth. Meanwhile, in Korea and Laos, growth maximization was probably a better strategy for poverty reduction because the value of IGTI for these countries were around 1.23 and 0.94, respectively.

Son's (2007) study examined the relationships between economic growth, inequality, and extreme poverty and calculated the IGTI for 17 Asian countries for the 1981-2001 period. For both China and India, the poverty elasticity of inequality is much greater for the urban sector than for the rural sector. The results further indicated that the IGTI is greater for China than India, regardless of the sector. For both countries, the rural sector requires lower growth rates to offset an increase in inequality to reduce a given level of poverty, compared to the urban sector. This suggests that the rural sector may adopt growth-enhancing policies. Such policies appear to be applicable to the Indian economy as a whole.

For Malaysia, it was found that the average IGTI was equal to 5.84 (1984-1996), implying that a 1% increase in the Gini index requires a growth rate of 5.84% to offset the adverse effect of the increase in inequality. For Bangladesh, on the other hand, the average IGTI was equal to 0.56 (1996-1999), implying that a 1% fall in the Gini index results from following inequality reducing policies. This strategy is equivalent to achieving an additional 0.56% in growth rate. Hence, the magnitude of the IGTI can be indicative of the growth or development strategy that a country might consider. For a country where the trade-off index is small, for example, less than 1 such as in Bangladesh, its policy focus should be on increasing growth to achieve a relatively higher level of poverty reduction.

Islam et al. (2012) in their study found that inequality has a significant effect on poverty alleviation. Moreover, some countries have experienced a faster increase in poverty despite significant increases in their per capita income (Cornia & Court, 2001; UNCTAD, 2020; Vanegas, 2022). In the Latin American region, during the 1985-1998 period, the number of poor people increased by 14 million despite a moderate increase in per capita income (Fuentes & Ricardo, 2005, p.16). Hence, a relatively large body of evidence shows that inequality is detrimental to the achievement of poverty reduction.

Nasir & Mridha (2017) estimated the dampening effect of rising inequality on the growth effect on poverty rates using the U.S. country-level data from 2006 to 2010. They found that while income growth alleviates poverty, growing inequality, directly and indirectly, dampens the effect of income growth on poverty rates. Moreover, their estimated total dampening effect of inequality indicated that the rising inequality lifted 129,405 fewer people out of poverty annually between 2006 and 2010 (Nasir & Mridha, 2017, p. 167 and p. 176).

The above results indicate that a more equal distribution of economic growth is needed to overcome the challenge. It can be done through asset and income redistribution policies targeted at poor people, as has been done, among others, in Brazil, Colombia, El Salvador, and South Africa. Overall, it means that the provision of social programs targeting the poor could be a sound alternative policy to deal with the challenge (Attanasio & Binelli, 2000).

Research Methods

The autoregressive distributed lag (ARDL) modeling approach to cointegration was proposed by Pesaran & Shin (1999). Further development, however, is attributed to Pesaran et al. (2001). The ARDL is recognized as one of the most flexible cointegration methods, particularly when the research framework is shaped by system off-events and changes. The ARDL tests for the existence of a long-run relationship, as well as to make an estimation of long-run and short-run parameters. From the error correction model, a dynamic specification can be derived that integrates short-run dynamics with long-run equilibrium without losing long-run information. Given the fact that the ARDL method can tolerate different lags in different variables, this makes the method very appealing, adaptable, and flexible (Menegaki, 2019; Vanegas, 2018).

The methodology has certain advantages over the common practice of univariate (Engle & Granger, 1987) and multivariate (Johansen, 1988, 1991; Johansen & Juselius, 1990, 1992) cointegration analysis. The ability of ARDL to accommodate sufficient lags allows for the best capturing of the data generating process. It can be applied regardless of whether the time series is I(0), that is, stationary at levels, I(1), that is, stationary at first differences, or fractionally integrated. Nonetheless, within the ARDL framework, the series should not be I(2), because this integration order invalidates the F-statistics and any critical values established. Furthermore, the ARDL method provides unbiased estimates and valid t-statistics regardless of the endogeneity of some regressors and provides robust results with small sample sizes, such as the sample size of the present study (Halicioglu, 2007; Menegaki, 2019; Pesaran et al., 2001; Ozturk & Acaravci, 2013; Vanegas, 2018).

Moreover, the ARDL framework requires a single form equation, distinguishes between dependent and independent variables, allows for the correction of outliers with impulse dummies, estimates the short- and long-run effects simultaneously, and has the ability to test hypotheses on the estimated coefficients in the long-run. With respect to the short-run adjustment, it can be integrated with the long-run equilibrium through the error correction mechanism. This is done through a linear transformation without sacrificing information about the long-run horizon (Ali et al. 2017; Bayer & Hanck, 2013; Harris & Sollis, 2003; Jalil & Ma, 2008; Menegaki, 2019). The steps in the ARDL procedure are as follows: (a) unit root testing to determine the level of integration, (b) bound testing for cointegration, and (c) estimation of coefficients.

Modeling Framework

In this section, we estimate two alternative specifications of extreme poverty models for CR, DR, and HO, denoted as: benchmark model 1 which sets inequality equal to zero and unrestricted model 2 which allows inequality to change. These models are set as equation (1) and (2), respectively.

$$\ln POE_{it} = \beta_0 + \beta_{1i} \ln PIB_{it} + u_{it} \tag{1}$$

$$\ln POE_{it} = \beta_2 + \beta_{3i} \ln PIB_{it} + \beta_{4i} \ln Gini_{it} + \varepsilon_{it} \tag{2}$$

Where POE_{it}, represents a proxy for the extreme poverty headcount index in country (i) at time (t); PIB_{it} (for its acronym in Spanish) represents the real gross domestic product (2015 = 100 prices), which is used as a proxy for income in country (i) at time (t); and inequality is proxied by the $Gini_{it}$ (1912) coefficient in country (i) at time (t). It is assumed that, if income distribution is neutral, income growth, which is the benchmark model, leads to the benchmark or restricted income growth elasticity value of extreme poverty. On the other hand, increasing inequality with constant income growth usually increases extreme poverty in CR, DR, and HO.

Model 1 captures the benchmark (neutral of inequality) estimate of the income growth impact on extreme poverty rates ($\beta_1 \leq 0$) in each CAFTA-DR country. Model 2 estimates both the income growth impacts ($\beta_3 \leq 0$) and the direct dampening impacts measured by the inequality elasticity estimates of extreme poverty ($\beta_4 \geq 0$).

Data

In this study, the national or official datasets for the GDP were provided by the CAFTA-DR Central Banks and can be obtained from their respective websites: www.bccr.fi.cr (BCCR, Costa Rica); www.bancentral.gov.do (BCRD/Dominican Republic); and www.bch.hn (BCH, Honduras). The extreme poverty and the Gini coefficient datasets were provided by their respective Statistical Offices and can be obtained from their corresponding websites: www.inec.cr (INEC, Costa Rica); www.one.gob.do (ONE, Dominican Republic); and www.ine.gob.hn (INE, Honduras).

The time series datasets were based solely on the information that was available at the time of this manuscript was written. It is important to note that the data were officially made available, critically reviewed, and taken from official or national archives, publications, and reports. However, to achieve the best possible combination of consistency, comparability, reliability and completeness, all the data were cross-checked, where possible, through physical visits and guided telephone interviews with government officials to further validate quantitative and qualitative information.

The data included sequential annualized observations: 53 for CR (1968-2020), 40 for DR (1982-2021), and 39 for HO (1982-2020). The process for constant value of the PIB variables included in the analysis is as follows. The first step involved rebasing each country's PIB current value in constant currency to the common base year, while the second step involved converting the estimates obtained into 2015 US dollars. The first step was necessitated by the fact that CR, DR, and HO use different base years for their calculations of constant price series in their national accounts

The datasets comply with the common international definitions established by the United Nations and the International Monetary Fund. In the process of generating the data for the National Accounts, the country endeavors to apply standard United Nations procedures, definitions, and classifications while using its country-specific knowledge to fit the data. The datasets were shared by the CAFTA-DR national institutions, whereupon the terms of use for disclosure were agreed upon and adhered to with the original data producers.

2SLS Correlation Results

The 2SLS section first examines the relationships between extreme poverty, income, and inequality for CR, DR, and HO. Second, it examines how much income growth is required to offset the adverse impact of an increase in inequality on extreme poverty, which both in terms of its magnitude as measured by the IGTI and in terms of being just enough to keep the extreme poverty rate unchanged. The results are presented in Table 3. Third, it examines the magnitude of the dampening impact of inequality on extreme poverty. The results are presented in Table 4.

As presented in Table 3, the estimated elasticities have the expected signs, which are negative for the average income and positive for the inequality variables. Moreover, all coefficients are significant at the 5% confidence level or better. In the unrestricted model 2, the values of the extreme poverty income elasticity vary from nearly -0.48 for HO to a maximum of nearly -1.61 for CR, with an average of nearly -1.22. The elasticities are interpreted as usual, for instance, a 1% increase in real income, assuming inequality remained constant throughout the whole period, leads to nearly 1.61%, 1.59%, and 0.48% decrease in the extreme poverty rates of CR, DR, and HO, respectively.

Empirically, substantiated by positive signs for the extreme poverty elasticity of inequality, Table 3 also presents the proportional increases in extreme poverty with respect to a 1% change in the Gini coefficient. As expected, a 1% increase in the Gini leads to an increase in extreme poverty (other factors held constant) as follows: nearly 1.68% (elastic-largest) for HO; nearly 0.88% (inelastic) for DR; and nearly 0.77% (inelastic) for CR.

Table 3: 2SLS Estimates of Income and Inequality Elasticity Values and IGTIs

Model	Costa Rica 1968-2021	Dominican Republic 1982-2021	Honduras 1982-2020
Benchmark[1]			
lnPIB	-1.7142***	-1.7597***	-0.8918**
	(0.3174)	(0.3012)	-0.3813
lnGini	-	-	-
	-	-	-
R2 adjusted	0.9013	0.9127	0.8923
Unrestricted[2]			
lnPIB	-1.6075***	-1.5859***	-0.4778**
	-0.3314	-0.2929	-0.1854
lnGini	0.7697***	0.8829***	1.6786***
	-0.1421	-0.2211	-0.2734
R2 adjusted	0.9611	0.9573	0.9592
IGTI	0.4788	0.5567	3.5129

Notes: Robust standard errors in parentheses. * 10%, ** 5%, and *** 1% significance levels.
[1] Gini set up equal to zero; [2] Gini set up different from zero.

2SLS IGTI Results

The IGTI relationship, defined as minus the ratio of the poverty elasticity of inequality to the extreme poverty elasticity of income, suggests that reducing poverty cannot simply rely on income growth. Its magnitude indicates how much income growth is required to offset the adverse effect of an increase in inequality on extreme poverty in CR, DR, and HO. Table 3, indicates that the magnitude of the IGTI is larger for HO, nearly 3.5129, than CR, nearly 0.4788, and DR, nearly 0.5567. For example, for HO, this means that an increase of 1% in the Gini index requires an income growth rate of nearly 3.51% for the incidence of extreme poverty not to change.

In other words, a 1% reduction in inequality is equivalent to an increase in income growth rate of nearly 3.51%. Moreover, it is interesting to compare, for example, the cases of CR, DR, and HO. According to their magnitudes, the IGTI results clearly suggest that a strategy of inequality reduction will have a greater payoff for extreme poverty reduction in HO than a similar strategy for the cases of CR and DR. This is because the payoff of the strategy of inequality reduction for CR and DR is much lower. Subsequently, income growth expansion is the most appropriate extreme poverty reduction policy for CR and DR.

2SLS Dampening Results

In addition to directly dampening the impact of income on extreme poverty reduction, rising inequality also indirectly weakens the impact of income on extreme poverty. The indirect dampening impact is calculated as the difference between the estimated income elasticity of extreme poverty in the benchmark model 1($\beta_1 \leq 0$) minus the estimated income elasticity of extreme poverty in the unrestricted model 2($\beta_3 \leq 0$). Comparisons between benchmark model 1 and unrestricted model 2 can be seen in Table 3. The impact of income growth on extreme poverty weakens: for CR from nearly -1.71 to nearly -1.61, for DR from nearly -1.76 to nearly -1.59, and for HO from nearly -0.89 to nearly -0.48. As presented in Table 4 column 3, these indirect impacts of dampening income elasticity of extreme poverty are nearly 0.1067 for CR, 0.1738 for DR, and 0.4140 for HO.

Table 4: 2SLS Estimates of Dampening Impacts

Country/Model	Direct Dampening Impacts[1]	Indirect Dampening Impacts[2]	Total Dampening Impacts[3]	Net Extreme Poverty Reduction Rates[4]
Costa Rica				
Benchmark	0	0	0	-1.7142
Unrestricted	0.7697	0.1067	0.8764	-0.8378
Dominican Republic				
Benchmark	0	0	0	-1.7597
Unrestricted	0.8829	0.1738	1.0567	-0.7030
Honduras				
Benchmark	0	0	0	-0.8918
Unrestricted	1.6786	0.414	2.0926	+1.2008

Notes: [1] Values of inequality elasticity of extreme poverty; [2] Values of economic growth elasticity of extreme poverty from benchmark model minus estimates from unrestricted model; [3] Direct impacts plus indirect impacts; [4] Estimates of economic growth elasticity of poverty from benchmark model minus total dampening impacts.

Moreover, as shown in Table 4 column 4, these calculations render the total dampening impacts of inequality elasticity of poverty (which is equal to the direct impacts in Table 4 column 2, plus the indirect impacts in Table 4 column 3), almost equal to nearly: 0.8764 for CR, 1.0567 for DR, and 2.0926 for HO. Hence, HO has experienced relatively higher levels of both poverty and inequality than CR and DR with a 1% increase in the Gini coefficient. The last column of Table 4, also presents the net extreme poverty reduction rates, which are calculated as equal to the estimated benchmark of income elasticity of extreme poverty (Table 3) minus the estimated total dampening impact for each CAFTA-DR country. For example, the net extreme poverty reduction rates are -0.8378% for CR, and -0.7030% for DR. On the other hand, the net reduction rates for Honduras are +1.2010%.

For example, for CR, the above results indicate the total dampening impact at 0.8764% or nearly 3,855 fewer people were expected to be lifted out of extreme poverty in 2020. For DR, the above results indicate the total dampening impact at 1.0567% or nearly 3,873 fewer people were expected to be lifted out of extreme poverty.

On the other hand, the story for HO is a dire one. At 2.0926%, which is the total dampening impact of increasing inequality, nearly 102,141 fewer people were expected to be lifted out of extreme poverty in 2020. This has happened in HO, even during periods of income growth. Overall, there is a possibility, however, that the above results, are perhaps largely driven by the COVID-19 effect on employment which has had a relatively large impact on the incidence of extreme poverty. For HO, this makes sense, because a very large percentage of the labor force in Honduras, nearly 44% on average, is considered to be in extreme poverty (Gindling & Terrell, 2010).

The ARDL Approach to Cointegration

A common characteristic of studies similar to this study is that the dynamic relationship between dependent and independent variables is reflected in the value of the coefficient of the lagged dependent variable (Baltagi, 2013). The ARDL bound testing approach to cointegration (Pesaran et al. 2001) is the methodology used in this study, which is a cointegration analysis developed within an autoregressive distributed lag framework.

The ARDL approach is the most efficient cointegration technique when dealing with small or finite sample data sizes as is the case with this study, and it can be applied even when the variables of the model are of mixed order of integration, that is to say, they are I(0) and I(1) (Pesaran & Pesaran, 1997, pp. 302-303). The country-by-country estimation strategy makes it possible to compare the cross-country distribution of the slope coefficients. As described above, however, one of the major shortcomings of the ARDL approach to cointegration is that it does not provide robust results in the presence of I(2) variables (Pesaran et al., 2001, p. 291).

Following Pesaran et al. (2001), Narayan (2004, 2005), and Sami (2011), the ARDL model to cointegration implies estimating the following unrestricted error correction model as expressed in equation (3).

$$\begin{aligned}\Delta \ln POE_{it} = \beta_0 + \sum \beta_{1it} \Delta \ln PIB_{it-j} + \sum \beta_{2it} \Delta \ln Gini_{it-j} + \sum \beta_{3it} \Delta \ln POE_{it-j} + \\ \delta_{1it} \ln PIB_{it-1} + \delta_{2it} \ln Gini_{it-1} + \delta_{3it} \ln POE_{it-1} + u_{it}\end{aligned} \quad (3)$$

Where Δ is the first difference operator. All variables are as previously defined. The estimated coefficients δ_1, δ_2, and δ_3 are the long-run coefficients; β_1, β_2, and β_3 are the short run coefficients, and μ represents the residual.

The next step is to test the joint hypothesis that the long-run multipliers of the lagged level variables are all equal to zero, against the alternative that at least one is non-zero. It is important to note that the F-statistic obtained by performing the Wald test has a non-standard distribution, whose asymptotic critical values are provided by Pesaran et al. (2001). Narayan (2004, 2005), however, argued that these critical values are inappropriate for small samples, which are common for annual macroeconomic variables. For this reason, Narayan (2004, 2005) provides a set of critical values for samples ranging from 30 to 80 observations for the usual significance levels. If the test statistic exceeds the respective upper critical value, it may be argued that there is evidence of a long-run equilibrium relationship. If the test statistic falls below the lower critical value, the null hypothesis of no cointegration cannot be rejected. Finally, if the test statistic fails between the two bounds, the test becomes inconclusive.

Having identified the existence of a cointegration relationship, the following step involved the selection of the optimal ARDL specification on the basis of a set of criteria (Akaike, 1974; Schwartz, 1978). After the estimation of the ARDL specification and the calculation of the associated long-run multipliers, the final step was the estimation of the short-run dynamic coefficients using the following error correction model (4).

$$\Delta \ln POE_{it} = \psi_0 + \sum \psi_{1it-j} \ln PIB_{it-j} + \sum \psi_{2it-j} \ln Gini_{it-j} + \sum \psi_{3it-j} \ln POE_{it-j} + \varphi EC_{it-1} + \varepsilon_{it} \quad (4)$$

The EC_{it-1} is the error correction term resulting from the verified long-run equilibrium relationship and ϕ is a parameter indicating the speed of adjustment to the equilibrium level after a shock. Three dummy variables were used to capture the impact of unexpected events: (D1) captures the terror attacks in the United States in 2001 and the aftermath; (D2) measures the impact of the global economic and financial crisis in 2008-2011; and (D3) measures the COVID-19 pandemic in 2020. The dummy variables take the value of 1 in the year of the occurrence of the special event and 0 otherwise.

Unit Root and Bound Testing

Table 5 provides a summary of descriptive statistics for each variable and country, including maximum, mean, median, minimum, standard deviation, coefficient of variation, kurtosis, and skewness. In order to rule out the possibility of dealing with I(2) variables, this part begins with the Augmented Dickey–Fuller (ADF) (1981) test, with and without a trend. Table 6 below shows the results according to which the set of variables used in our study is a mixture of I(0) and I(1). In addition to the ADF test, we implemented the Generalized Least Squares detrending Dickey-Fuller test (GLS-DF), introduced by Elliot, et al. (1996), which improves the power of the standard ADF test.

Table 5: Summary Statistics

Variable	Costa Rica 1968-2020	Dominican Republic[1] 1982-2021	Honduras 1982-2020
POE[1]			
Maximum	2.5091	3.1911	4.0513
Mean	2.0186	2.9688	3.8329
Median	1.9893	2.9387	3.8293
Minimum	1.1881	2.7716	3.5971
SD[1]	0.3294	0.1173	0.1017
CV[2]	0.1632	0.0397	0.02.64
Kurtosis	-0.3363	0.3349	-0.1813
Skewness	-0.5618	-0.8662	0.5742

Variable	Costa Rica 1968-2020	Dominican Republic[1] 1982-2021	Honduras 1982-2020
Gini Index[2]			
Maximum	3.9557	3.9534	4.0893
Mean	3.7828	3.8806	3.9889
Median	3.7799	3.8892	3.9956
Minimum	3.6273	3.7015	3.8339
Standard Deviation	0.0994	0.0527	0.0594
Coefficient of Variation	0.0268	0.0133	0.0149
Kurtosis	-0.6921	2.9768	-0.2078
Skewness	0.4494	-1.3452	-0.4052

Source: [1] Authors' calculations using national/official extreme poverty datasets. POE covers food essentials only but is not enough to purchase other basic goods and services. On the other hand, the general poverty line is defined as income that covers food essentials plus a basket of basic goods and services such as clothing, footwear, housing, education, healthcare, and transportation, [2] For Dominican Republic, the values of the Gini coefficient as well as its POE, covering 2016-2021, were obtained from the updated labor market survey (ENCFT). The period 1982-2015 were obtained from the former labor market survey (ENFT).

Table 6: Unit Root

Variable	Costa Rica 1968-2021	Dominican Republic 1982-2021	Honduras 1982-2020
Level			
lnPOE	-2.3729 (2)	-0.6581 (0)	-0.9738 (1)
lnGini	-3.9641 (1)	-3.3293 (1)	-2.6337 (2)
lnPIB	-1.8113 (1)	-1.6861 (1)	-1.5861 (1)
First Differences			
ΔlnPOE	-5.1849 (1)	-6.2727 (0)	-6.0866 (1)
ΔlnGini	-8.8313 (2)	-8.8546 (0)	-7.3271 (0)
ΔlnPIB	-4.3679 (1)	-5.9012 (1)	-3.4249 (1)

Notes: (1) Estimates with intercept and trend. (2) The numbers in brackets are lag lengths used to remove serial correlation. (3) The corresponding critical values used for the statistics are from Dickey and Fuller (1981). (4) Since all series are I(0) and/or I(1) and none are higher than I(1), we can proceed with the cointegration analysis. (5) The optimal lags are based on the minimum of the Akaike Information Criterion, and the Schwartz Information Criterion.

To rule out the case of false identification of the exact order of integration of the variables, the LM-type test was used with one and two breaks, assuming initially only a level change in the series, followed by a simultaneous change in the level and the trend of the series (Lee & Strazicich (2003, 2013). The results confirm the findings from the ADF-type unit root tests. For reasons of space, the results of both the GLS-DF and the structural breaks tests are not included but can be provided by the authors upon request.

The ARDL approach to cointegration requires the testing of the following null hypothesis: Ho: $\delta_1 = \delta_2 = \delta_3 = 0$, against the alternative that at least one of these coefficients is different from zero. Given that the value of the *F*-statistic is sensitive to the number of lags imposed each time on the differenced variables (Bahmani-Oskooee & Goswami, 2003), the Wald test was applied by imposing one and two lag lengths. The results shown in Table 7 confirm both that the null hypothesis of zero cointegrating relationship is without doubt rejected and the existence of a long-run equilibrium relationship in the case of one and two lags, at the 5% significance level.

Table 7: Results of the ARDL Bound Testing

Function	F-statistics calculated	
(CR) POE = f1 (PIB, Gini)	Cointegration 5.4327	
(DR) POE = f2 (PIB, Gini)	Cointegration 5.4339	
(HO) POE = f4 (PIB, Gini)	Cointegration 6.1183	
Critical Values	Lower Levels	Upper Levels
Pesaran et al. (2001)[1]		
1% level	3.746	5.061
5% level	2.862	4.013
10% level	2.458	3.524
Narayan (2005)[2]		
1% level	4.592	6.371
5% level	3.287	4.632
10% level	2.703	3.902

Notes: [1] Table CI. Iii: Case III. [2] As an illustration, the critical values developed by Narayan (2005) have been included: Appendix A4, A5, and A6 Case III.

ARDL Long-Run Elasticities and the IGTI Results

The ARDL estimated long-run elasticities have the expected signs which are negative for the income and positive for the Gini coefficient. Moreover, all long-run elasticities are significant at the 1% confidence level. Table 8 shows interesting results. The long-run responsiveness of a 1% increase in mean income to changes in poverty varies, ranging from almost -0.69 for HO to almost -1.79 for CR, with an average of almost -1.23. For the average income elasticity in CR and DR, the extreme poverty reduction in response to a 1% increase in income was quite parallel. In comparison, they differ significantly from HO where extreme poverty reduction was marginal or relatively much slower. The elasticities were interpreted as usual, for instance, a 1% increase in mean income, *ceteris paribus*, leads to nearly -1.79%, and -1.78%, and -0.69% decrease in the extreme poverty rates of CR, DR, and HO, respectively.

In the long-run, the impact of inequality is unequivocally positive and statistically significant at the 1% confidence level. Its values range from 0.83 for CR to almost 1.87 for HO, with an average of nearly 1.17. Therefore, a 1% increase in the Gini index, other things being equal, leads to a 0.83%, 0.86%, and 1.87%, increase in the extreme poverty rates of CR, DR, and HO, respectively. This result clearly establishes that income inequality significantly dampens the income effect on poverty in Honduras and, to a lesser extent, in CR and DR.

Table 8: ARDL Long and Short-Run Income and Inequality Elasticities and the IGTI: Dependent Variable, lnPOE

Variable	Costa Rica 1968-2021	Dominican Republic 1982-2021	Honduras 1982-2020
Long-Run			
lnPIB	-1.7880***	-1.7763***	-0.6942**
	(0.4133)	(0.3843)	(0.2229)

Variable	Costa Rica 1968-2021	Dominican Republic 1982-2021	Honduras 1982-2020
lnGini	0.8305***	0.8643***	1.8739***
	(0.1463)	(0.1624)	(0.3218)
IGTI	0.4645	0.4866	2.6994
R2 adjusted	0.9454	0.9626	0.9464
Short-Run			
ΔlnPIB	-0.8244**	-0.7732**	-0.3107*
	(0.3356)	(0.3078)	(0.1624)
ΔlnGini	0.4987***	0.5276***	1.1224***
	(0.1148)	(0/1641)	(0.2411)
ECt-1	-0.3107**	-0.3036***	-0.2488***
	(0.0794)	(0.1008)	(0.0634)
IGTI	0.6049	0.6824	3.6125
R2 adjusted	0.9238	0.9307	0.9318
D1	-0.0316^{NS}	-0.0439*	-0.0127^{NS}
	(0.0224)	(0.0259)	(0.0135)
D2	0.1653*	0.2107**	0.2513**
	(0.0824)	(0.0944)	(0.1031)
D3	0.7318***	0.2436***	0.7493***
	(0.158)	(0.0674)	(0.1822)

Notes: (i) Akaike (1974) information criterion and Schwartz (1978) criterion were used to select the number of lags required in the cointegration test and both gave the same level of lag order; (ii) all the model specifications pass the diagnostic tests: Ramsey (1969) test for specification; Jarque-Bera (1980) test for normality; Breusch-Godfrey (1978) test for serial correlation; White (1980) test for heteroscedasticity; ARCH-LM (Engle, 1982) test for autoregressive conditional heteroscedasticity; and Brown et al. (1975) CUSUM and CUSUM squared for parameter stability. Significant at ***(1%), **(5%), and *(10%) confidence level.

Table 8 further indicates that in the long-run, the IGTI is greater for Honduras at almost 2.70, than for Costa Rica at almost 0.47, and Dominican Republic at almost 0.49. For example, for HO, this means that a 1% increase in the Gini index requires an income growth rate of nearly 2.70% in order not to change the incidence of extreme poverty, and that improved social policies and/or programs have a greater payoff for poverty reduction. Another way of interpreting this is that a 1% reduction in the Gini index is equivalent to having an additional 2.70% in its income growth rate. For CR and DR, however, the relatively good performance in income growth would have been enhanced if there had been a reduction in income inequality.

Another interesting finding is that the higher the inequality, the higher the income growth rate that required to compensate for the increase in inequality to achieve a given level of extreme poverty reduction. Due to the importance of inequality, this suggests that there is a greater need for HO to adopt and/or to enhance targeted social policies and/or programs in favor of the most vulnerable groups of its society with the specific objective of reducing inequality. On the other hand, improving economic growth policies may be more adequate for CR and DR. This is because for both countries, the payoff for the strategy of inequality reduction is much lower.

ARDL Short-Run Elasticities and the IGTI Results

The error-correction model specification provides a way of combining both the short-run adjustments and the long-run equilibrium process simultaneously. As shown in Table 8, the elasticity values of income range from nearly -0.31 for HO to nearly -0.82 for CR. On the other hand, the short-run Gini elasticity values are both positive and range from nearly 0.50 for CR to nearly 1.13 for HO, with an average of nearly 0.72. The estimated short-run elasticities are lower than their long-run counterparts.

In each country specification, as can be observed in Table 8, the coefficients of the error correction term (EC_{t-1}), are all negative and statistically significant at 5% level, indicating that short run disequilibrium is corrected in the long-run equilibrium. The ARDL short-term results further confirm the hypothesis that extreme poverty reduction does not adjust immediately to changes in income and inequality, but rather adjusts to the optimum extreme poverty reduction level over time.

Moreover, the short-run IGTI estimates range from nearly 0.60 for CR to nearly 3.59 for HO. If we take the case of HO on average, this country would need to increase its average income, in the short-run, by nearly 3.59% just to maintain its extreme poverty rate, which is much higher than its long-run counterpart. As in the long-run, the results in the short-run support the argument about the direct and indirect independent importance of inequality as a potential factor that negatively affects extreme poverty reduction as well as weakens the impact of income growth.

ARDL Long and Short-Run Inequality Dampening Impacts

The derived long- and short-run inequality dampening impacts for the underlying ARDL model can be seen in Table 9. In both the short and in the long-run, increasing inequality directly dampen the extreme poverty reduction rate. In addition, it indirectly weakens the income impacts on extreme poverty, relatively much less in CR and DR, and relatively much more in HO. The total long-run dampening impacts are +0.929 for CR, +0.9885 for DR, and +1.884 for HO, with an average of nearly +1.3367. On the other hand, the total short-run dampening impacts are nearly +0.5270 for CR, +0.5740 for DR, and +1.1304 for HO, with an average of nearly +0.7438.

Table 9: ARDL Long and Short-Run Estimates of Dampening Impacts

Country/Model	Direct Dampening Impacts[1]	Indirect Dampening Impacts[2]	Total Dampening Impacts[3]	Net Extreme Poverty Reduction Rates[4]
LONG-RUN				
Costa Rica				
Benchmark	0	0	0	-1.8866
Unrestricted	0.8305	0.0985	0.929	-0.9576
Dominican Republic				
Benchmark	0	0	0	-1.9003
Unrestricted	0.8643	0.1242	0.9885	-0.9118
Honduras				
Benchmark	0	0	0	-0.7043
Unrestricted	1.8739	0.0101	1.884	+ 1.1797

Country/Model	Direct Dampening Impacts[1]	Indirect Dampening Impacts[2]	Total Dampening Impacts[3]	Net Extreme Poverty Reduction Rates[4]
SHORT-RUN				
Costa Rica				
Benchmark	0	0	0	-0.8507
Unrestricted	0.4987	0.0283	0.527	-0.3237
Dominican Republic				
Benchmark	0	0	0	-0.8196
Unrestricted	0.5276	0.0464	0.574	-0.2456
Honduras				
Benchmark	0	0	0	-0.3123
Unrestricted	1.1224	0.0071	1.1295	+0.8172

Notes: [1] Estimates of inequality elasticity of extreme poverty; [2] Estimates of income growth elasticity of extreme poverty from benchmark model minus estimates from unrestricted model; [3] Direct impacts plus indirect impacts; [4] Estimates of economic growth elasticity of poverty benchmark model minus total dampening impacts.

The last column of Table 9 also presents the net extreme poverty reduction rates. For example, the net extreme poverty reduction rates are -0.3237% (short-run) and -0.9576 (long-run) for CR, and -0.2456% (short-run) and -0.9118 (long-run) for DR. On the other hand, the net reduction rates for HO are +0.8172% (short-run) and +1.1797 (long-run). These results, consistent with the ones obtained using 2SLS, confirm that HO has experienced relatively higher levels of both extreme poverty and inequality than CR and DR.

In counting the total effect of inequality dampening on extreme poverty performance, we can determine the following results in extreme poverty. For CR with a total dampening impact of 0.527% and 0.929% in the short-run and long-run, respectively, it is estimated that between 2,318 and 4,087 fewer people were expected to be lifted out of extreme poverty in 2020 (0.527% and 0.929%, time 439,891 POE people). For DR, with a total dampening impact of +0.574% and +0.9885% in the short-run and long-run, respectively, it is estimated that in between 2,104 and 3,623 fewer people were expected to be lifted out of extreme poverty in 2020 (0.574% and 0.9885%, time 366,484 POE people). On the other hand, HO presents a bleak picture. With a national or officially estimated number of extreme poor people of nearly 4,881,078, and with a total dampening impact of 1.1295% and 1.884% in the short-run and long-run, respectively, it is estimated that in between 63,649 (short-run) and 91,960 (long-run) fewer people were expected to be lifted out of extreme poverty in 2020.

Speed of Adjustment

Having identified the long-run relationship, we then estimated an error correction model that indicates the speed of adjustment back to the long-run equilibrium after a short-run disturbance. The specification of the error correction model allows the long-run behavior of the endogenous variables to converge to their cointegrating relationships, while accommodating short-run dynamics. As shown in Table 8, the coefficient of the lagged residual in the error correction model shows the speed of adjustment towards the equilibrium following a shock to the system.

The coefficients of the error correction model, -0.3107 for CR, -0.3036 for DR, and -0.2488 for HO, are significant and indicate that nearly 31.1%, 30.4%, and 24.9% of the deviation of extreme poverty from its long-run level is corrected in one year, respectively. The results indicate that it will take nearly 3.22 years, nearly 3.29 years, and nearly 4.02 years for CR, DR, and HO to restore the long-run equilibrium, respectively. Moreover, it also suggests that extreme poverty in HO has both a relatively modest speed of recovery toward its equilibrium state and a more unstable behavior as compared to CR and DR.

Dummies

As expected a priori, terrorist incidents, economic crisis and health concerns negatively affected the level of extreme poverty in CR, DR, and HO. Most of the dummies were statistically significant at the 5% level or better. The dummy variable D1, accounting for the terrorist attacks in the United States, has a negative sign but shows no significant impact on extreme poverty reduction for CR and HO, and was significant only at the 10% confidence level for DR. The dummy variable D2, accounting for the global economic and financial crisis, has a positive sign and shows significant impact on increased extreme poverty for DR and HO, and was significant only at the 10% confidence level for CR.

The COVID-19 pandemic (D3) had larger and significant repercussions of increasing extreme poverty in the three countries. Both their level of significance and magnitude vary from one country to another. As shown in Table 8, the aftermath of the COVID-19 crisis was that extreme poverty increased by nearly 73.18% in CR, by nearly 24.36% in DR, and by nearly 74.93% in HO. Two important points emerge from these results. In support of the first one, it can be argued that the mitigation measures of COVID-19 worked relatively much better in DR. The second is a question related to how long these developing countries take to recover the declining trend in extreme poverty to the pre-COVID19 levels. It is fair to say here that the speed period depends on whether CR, DR, and HO have an effective crisis, recovery, and economic development management strategy to restore the declining trend in extreme poverty to its full potential.

Robustness

To test the above results, several robustness checks were performed. First, we examined whether and to what extent including the initial level of inequality changes the empirical results. The results showed a marginal improvement in the overall performance, relatively negligible coefficient values, and statistically non-significant, at least in the present empirical setup. These results suggest that the level of initial inequality would not impact on the rate of extreme poverty reduction in the developing countries of CR, DR, and HO. These results can be interpreted as an indication that initial inequality cannot make the difference between relatively slow and rapid extreme poverty reduction. These results are consistent with Vanegas (2014), which used time series, but contrary to Adams (2004), Fosu (2010), and Iradian (2005), among others, which used average cross-country evidence.

Second, we estimated different specifications which entered the income variable both as real per capita gross domestic product in levels and as growth rates. The findings are similar in terms of signs, magnitudes of the coefficients, and significance. Third, one might think that what matters is how extreme poverty is defined. In particular, we considered the number of poor people instead of the headcount extreme poverty ratio and re-estimated the regressions. The results showed that there are no significant differences in the qualitative model performance and the coefficients are also quite similar in magnitude and statistical significance.

Finally, for HO only, we provide further evidence with the adoption of an alternative poverty measure, namely, the number of households in extreme poverty. The results are virtually unchanged. Indeed, the long-run income coefficients associated with extremely poor households are -0.6731 versus -0.6942 (headcount ratio model) and in the short run -0.3229 versus -0.3107 (headcount ratio model). The same can be said for inequality in the long-run: 1.8602 versus 1.8730 (headcount ratio model), and in the short-run: 1.1037 versus 1.1224 (headcount ratio model). See also Table 8.

Policy Implications

Several policy messages emerged from the empirical analysis for the developing countries of CR, DR, and HO. The study has shown that, in the case of a developing country such as HO, similar to many other developing countries, relying only on the impact of economic growth alone has not been enough to reduce poverty significantly during the last four decades. This is because the relatively high level of inequality that accompanied such economic growth, which had detrimental impacts on extreme poverty reduction.

In this regard, the results clearly indicate that HO's authorities should not ignore the critical role of income distribution in shaping opportunities for poverty reduction. In the context of generalization, due to the importance of inequality, this suggests that HO and many other developing countries similar to Honduras, are in greater need to adopt and/or to improve social policies and programs, targeted at the most vulnerable groups of its society with the specific objective of reducing inequality. On the other hand, the path for CR and DR contains elements in favor of expanding economic growth.

Overall, it is clear that there are at least two factors that determine a developing country's performance in extreme poverty reduction. The first is the magnitude of income growth rate, which directly impacts the overall income of a developing country's society. The second is the inequality index which relates to both the distribution of benefits of income growth, through its dampening impacts and the policy guidelines to follow, through the magnitude of its inequality growth trade-off index. All this means that income growth alone is not sufficient to achieve a relatively rapid reduction in extreme poverty unless we can demonstrate that income growth remains distributionally neutral over time.

The magnitude of changes in poverty reduction depends on the specifications of each CAFTA-DR country, which leads to the implementation of a different strategy for poverty reduction to different countries. This is because every country has different level of productive and development organizational structure of the economy, income growth, and inequality rates. The magnitude of the IGTI increases as the Gini index increases. This is an indication of the relatively higher value of enhancing social policies/programs in countries with higher IGTIs than in countries with lower IGTIs. Similarly, policies/program that enhance income growth would be more effective in countries where the IGTIs are relatively small, namely about or less that one.

If this study should convey a policy message, it is that policymakers, scholars, and the international community at large should be advised that the challenges of inequality are more important, not only to CAFTA-DR developing countries, but to other developing countries as well, than many of us previously thought and not something to be pushed aside.

Conclusions

To summarize, reducing inequality in the short- and long-run is important for Costa Rica, the Dominican Republic, and Honduras, when holding domestic income growth constant.

The results from the pressure to reduce inequality suggest that the number of extremely poor people in Costa Rica, the Dominican Republic, and Honduras could have been reduced more. However, if Honduras's Gini index has been reduced by 1% per year, its total extreme poverty rate could have been reduced more over the last four decades, equivalent to thousands fewer people counted in extreme poverty. Reducing Honduras's Gini index by 1% per year, and in many developing countries similar to Honduras, will have a greater impact on its extreme poverty than increasing its annual income growth by 1%.

This means that extreme poverty reduction in developing countries can be greatly enhanced by distributional policies. The above evidence confirms that distribution is central to alleviating poverty. The evidence on dampening impacts has shown that income growth and better distribution are complementary, rather than competing objectives in poverty reduction. More equal distribution of income can promote income growth, whereas high inequality can slow it down. Therefore, reducing inequality can be doubly beneficial for the extreme poor.

Distribution policies should be pursued (a) in developing countries where they eliminate redundant/dysfunctional inequalities, and (b) in developing countries where the effect of inequality on extreme poverty is greater than the effect of income growth. The relative importance of income growth and income distribution varies across countries. The income growth effect dominates in Costa Rica and Dominican Republic and in many developing countries with similar characteristics. However, in a significant number of cases, such as Honduras, small changes in distribution can have a very large effect on extreme poverty reduction.

Relatively speaking, both the lack of knowledge of the determinants of inequality and the neglect of distribution issues in recent decades may indicate that there is untapped potential for reducing extreme poverty through distribution changes. Knowledge of the effects of non-income dimensions of inequality is very limited and the evidence somewhat anecdotal. Even the determinants of income inequality are also poorly understood. There is a need for further developing country-based research on the nature, extent, and determinants of various dimensions of inequality, and their effects on different dimensions of extreme poverty. With respect to data, however, we must not forget that in developing countries, only the national or official poverty numbers are the ones used for analysis and for targeting and monitoring policy or social program.

Declaration

This research article is original, is not under consideration for publication elsewhere nor is currently being published elsewhere.

Conflict of Interests

The authors declare that there is no significant competing financial, professional, or personal interests that might have affected the performance.

Availability of Data and Materials

For each country, the poverty and inequality data can be provided by the corresponding author from 1995 to 2021. The data prior to 1995, due to the disclosure agreement, have to be requested, directly, from the statistical offices from each country. Their respective web sites have been inserted in the paper under data and sources. The macroeconomic data are available from each central bank websites.

Authors' Contribution

Manuel Vanegas and Terry Roe (RIP-He passed away during this study process) conceptualized the study, elaborated the methodology, wrote, reviewed and edited the manuscript.

Funding Source

There is none.

Acknowledgments

In Memoriam Dear Terry, though you are no longer with us, you will never be forgotten. Your memory will be forever held in my heart as well as in the pages of this article.

References

Adams, R. H. (2004). Economic growth, inequality and poverty: estimating the growth elasticity of poverty. *World development, 32*(12), 1989-2014. https://doi.org/10.1016/j.worlddev.2004.08.006

Akaike, H. (1974). A new look at the statistical model identification. *IEEE transactions on automatic control*, *19*(6), 716-723. https://doi.org/10.1109/TAC.1974.1100705

Ali, W., Abdullah, A., & Azam, M. (2017). Re-visiting the environmental Kuznets curve hypothesis for Malaysia: Fresh evidence from ARDL bounds testing approach. *Renewable and sustainable energy reviews, 77*, 990-1000. https://doi.org/10.1016/j.rser.2016.11.236

Attanasio, O., & Binelli, C. (2004). Inequality, growth and redistributive policies. *Proceeding of the AFD-EUDN Conference 2003*, 179–213.

BCCR. (2021). *Memoria annual 2020.* San Jose: Banco Central de Costa Rica

BCCR. (2012). *Costa Rica: Economic Indicators, 1951-2010*. Central Bank of Costa Rica.

Bahmani-Oskooee, M. M., & Goswami, G. G. (2003). A disaggregated approach to test the J-curve phenomenon: Japan versus her major trading partners. *Journal of Economics and Finance*, *27*, 102-113. https://doi.org/10.1007/BF02751593

Baltagi, B.H. (2013), *Econometric Analysis of Panel Data (5th ed.)*. New York: John Wiley.

Bayer, C., & Hanck, C. (2013). Combining non-cointegration tests. *Journal of Time series analysis, 34*(1), 83-95. https://doi.org/10.1111/j.1467-9892.2012.00814.x

Boushhey, H., Bradford, D. L., & Steinbaum, M. (2017). *After Piketty: The Agenda for Economics and Inequality*. Cambridge: Harvard University Press.

Brown, R. L., Durbin, J., & Evans, J. M. (1975). Techniques for testing the constancy of regression relationships over time. *Journal of the Royal Statistical Society Series B: Statistical Methodology, 37*(2), 149-163.

Breusch, T. S. (1978). Testing for autocorrelation in dynamic linear models. *Australian economic papers, 17*(31), 334-355, https://doi.org/10.1111/j.1467-8454.1978.tb00635.x

Cingano, F. (2014). *Trends in income inequality and its impact on economic growth*. OECD SEM Working paper No. 163, OECD Publishing, Paris.

Cornia, G. A., & Court, J. (2001). *Inequality, growth and poverty in the era of liberalization and globalization—A Policy Brief*. Helsinki: UNU World Institute for Development Economics Research.

Dickey, D. A., & Fuller, W. A. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica, 49*(4), 1057-1072. https://doi.org/10.2307/1912517

ECLAC. (2021). *Social Panorama of Latin America, 2021*. Economic Commission for Latin Santiago: America and the Caribbean.

Elliot, G., Rothenberg, T. J., & Stock, J. H. (1996). Efficient tests for an autoregressive unit root. *Econometrica, 64*, 813-836. https://doi.org/10.2307/2171846

Engle, R. F., & Granger, C. W. J. (1987). Cointegration and error correction: Representation, estimation, and testing. *Econometrica, 55*, 251-276. https://doi.org/10.2307/1913236

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica, 50*, 987-1007. https://doi.org/10.2307/1912773

Fosu, A. K. (2010). Inequality, Income, and Poverty: Comparative Global Evidence. *Social Science Quarterly, 91*(5), 1432–1446. http://www.jstor.org/stable/42956468

Fuentes & Ricardo. (2005). *Poverty, Pro-Poor Growth and Simulated Inequality Reduction*. Human Development Occasional Papers 2005-11, Human Development Report Office (HDRO), United Nations Development Programme (UNDP).

Gasparini, L., Gutiérrez, F., & Tornarolli, L. (2007). Growth and income poverty in Latin America and the Caribbean: evidence from household surveys. *Review of Income and Wealth, 53*(2), 209-245. https://doi.org/10.1111/j.1475-4991.2007.00231.x

Gindling, T. H., & Terrell, K. (2010). Minimum wages, globalization, and poverty in Honduras. *World Development, 38*(6), 908-918. https://doi.org/10.1016/j.worlddev.2010.02.013

Gindling, T. H., & Trejos, J. D. (2013). The distribution of income in Central America. I*n Handbook of Central American Governance (pp. 75-94)*. Routledge.

Gini, C. (1912). *Variabilitá e mutabilitá: contributo allo studio delle distribuzioni e delle relazioni statistiche [Variability and mutability: contribution to the study of distributions and statistical relationships]*. Bologna: Tipografia di Paolo Cuppini.

Godfrey, L. G. (1978). Testing for Higher Order Serial Correlation in Regression Equations when the Regressors Include Lagged Dependent Variables. *Econometrica, 46(*6), 1303–1310. https://doi.org/10.2307/1913830

Government of the Republic of Honduras. (2000). *Interim poverty reduction strategy paper*. Tegucigalpa: Government of Honduras.

Halicioglu, F. (2007). Residential electricity demand dynamics in Turkey. *Energy economics, 29*(2), 199-210. https://doi.org/10.1016/j.eneco.2006.11.007

Harris, R., & Sollis, R. (2003). *Applied time series modelling and forecasting*. West Sussex: Wiley.

IMF. (2021a). *Costa Rica: 2021 Article IV Consultation and request for an extended arrangement under the extended IMF Fund Facility*. Washington, D.C.: International Monetary Fund.

IMF. (2021b). Guatemala*: 2021 Article IV Consultation*. Washington, D.C.: International Monetary Fund.

INEC (2008). *Encuesta Nacional de Hogares: resultados generals [National Household Survey: general results].* San José: Instituto Nacional de Estadísticas y Censos.

INEC. (2009). *Encuesta Nacional de Hogares: resultados generals [National Household Survey: general results].* San José: Instituto Nacional de Estadísticas y Censos.

INEC (2012). *Encuesta Nacional de Hogares: resultados generals [National Household Survey: general results].* San José: Instituto Nacional de Estadísticas y Censos.

INEC. (2013). *Estimaciones y proyecciones de población por sexo y edad, 1950-2050 [Population estimates and projections by sex and age, 1950-2050].* San Jose: Instituto de Estadistica y censo de Costa Rica, San Jose.

INEC. (2018). *Encuesta Permanente de Hogares de Propósitos Múltiples, LXI 2018 [Permanent Multipurpose Household Survey, LXI 2018]*. Tegucigalpa: Instituto Nacional de Estadística.

INEC. (2020). *Nivel de pobreza por LP según características de los hogares y las personas, Julio 2019 y Julio 2020 [Level of poverty by LP according to household and individual characteristics, July 2019 and July 2020]*. San Jose: Instituto de Estadistica y censo de Costa Rica.

Iradian, G. (2005). *Inequality, poverty, and growth: Cross-Country evidence.* IMF Working Paper WP/05/28, International Monetary Fund, Washington, DC.

Islam, S., Islam, M., & Abubakar, H. (2012). Economic growth, employment and poverty reduction nexus: evidence from Bangladesh. *Journal of International Economics*, *3*(1), 4-18.

Jalil, A., & Ma, Y. (2008). Financial development and economic growth: Time series evidence from Pakistan and China. *Journal of economic cooperation, 29(*2), 29-68.

Jarque, C. M., & Bera, A. K. (1980). Efficient tests for normality, homoscedasticity and serial independence of regression residuals. *Economics letters, 6*(3), 255-259.

Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of economic dynamics and control, 12*(2-3), 231-254. https://doi.org/10.1016/0165-1889(88)90041-3

Johansen, S., & Juselius, K. (1990). Maximum likelihood estimation and inference on cointegration with applications to the demand for money. *Oxford Bulletin of Economics and Statistics, 52*(2), 169-210. https://econpapers.repec.org/RePEc:bla:obuest:v:52:y:1990:i:2:p:169-210

Johansen, S. (1991). Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. *Econometrica, 59*(6), 1551-1580. https://doi.org/10.2307/2938278

Johansen, S., & Juselius, K. (1992). Testing structural hypotheses in a multivariate cointegration analysis of the PPP and the UIP for UK. *Journal of Econometrics, 53*(1-3), 211-244. https://doi.org/10.1016/0304-4076(92)90086-7

Kakwani, N. (1993). Poverty and economic growth with application to Cote D'Ivoire. *Review of Income and Wealth, 39*(2), 121-139. https://doi.org/10.1111/j.1475-4991.1993.tb00443.x

Kakwani, N. (2000). On measuring growth and inequality components of poverty with application to Thailand. *Journal of quantitative economics, 16*(1), 67-79.

Keeley, B. (2015). *Income inequality: The gap between rich and poor*. aris: OECD Insights, OECD Publishing.

Lee, J., & Strazicich, M. C. (2003). Minimum Lagrange Multiplier Unit Root Test with Two Structural Breaks. *The Review of Economics and Statistics, 85*(4), 1082–1089. http://www.jstor.org/stable/3211829

Lee, J., & Strazicich, M. C. (2013). Minimum LM unit root test with one structural break. *Economics Bulletin, AccessEcon*, *33*(4), 2483-2492.

Menegaki, A. N. (2019). The ARDL method in the energy growth nexus field: Best implementation strategy. *Economies*, *7*(4), 105. https://doi.org/10.3390/economies7040105

Narayan, P.K. (2004). *Reformulating critical values for the Bounds F-statistics approach to cointegration: An application to the tourism demand model for Fiji*. Department of Economics Discussion Papers No. 02/04, Monash University, Victoria, Australia.

Narayan, P. K. (2005). The saving and investment nexus for China: Evidence for cointegration tests. *Applied Economics, 37*(17), 1979-1990. http://dx.doi.org/10.1080/00036840500278103

Nasir, A. B. M., & Mridha, H. A. (2017). Does income inequality dampen growth effect on poverty? Evidence from the U.S. county data. *The Journal of Developing Areas, 51*(4), 167-177. https://www.jstor.org/stable/26416969v

Ozturk, I., & Acaravci, A. (2013). The long-run and causal analysis of energy, growth, openness and financial development on carbon emission in Turkey. *Energy Economics*, 36, 262-267. https://doi.org/10.1016/j.eneco.2012.08.025

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds Testing Approaches to the Analysis of Level Relationships. *Journal of Applied Econometrics, 16*(3), 289–326. http://www.jstor.org/stable/2678547

Pesaran, M. H., & Shin, Y. (1999). An Autoregressive Distributed-Lag Modelling Approach to Cointegration Analysis. In S. Strom (Ed.), *Econometrics and Economic Theory in the 20th Century.* Cambridge: Cambridge University Press.

Pesaran, M.H., & Pesaran, B. (1997). *Working with Microfit 4.0: Interactive econometric analysis*. Oxford: Oxford University Press.

Piketty, T. (2015). *The Economics of Inequality*. Cambridge: The Belknap Press of Harvard University Press.

Ramsey, J. B. (1969). Tests for Specification Errors in Classical Linear Least-Squares Regression Analysis. *Journal of the Royal Statistical Society. Series B (Methodological), 31*(2), 350–371. http://www.jstor.org/stable/2984219

Sami, J. (2011). Multivariate Cointegration and Causality between Exports, Electricity Consumption and Real Income per Capita: Recent Evidence from Japan. *International Journal of Energy Economics and Policy,* 1(3), 59–68. https://www.econjournals.com/index.php/ijeep/article/view/49

Son, H.H. (2007). Interrelationship between growth, inequality, and poverty: The Asian experience. ERD Working Paper Series No. 96, Asian Development Bank, Asian.

Stiglitz, J. E. (2013). *The price of inequality: How today's divided society endangers our future*. New York: W.W. Norton and Company.

Sumner A., Hoy, C., and Ortiz-Juarez, E. (2020). *Estimates of the impact of COVID-19 on global poverty*. WIDER Working Paper No. 2020/43, United Nations University, World Institute for Development Economic Research, Helsinki.

Schwarz, G. (1978). Estimating the Dimension of a Model. *The Annals of Statistics, 6*(2), 461–464. http://www.jstor.org/stable/2958889

Trejos, J. D. & Gindling, T. H. (2004). Inequality in Central America in the 1990s. *CEPAL Review, 84*, 175-196. https://www.cepal.org/en/publications/11054-inequality-central-america-1990s

United Nations. (2020). *World economic situation and prospects, 2020*. New York: United Nations.

UNCTAD. (2020). *The least developed countries report, 2020: Productive capacities for the new decade*. New York: United Nations Publications.

UN DESA. (2013). *Inequality matters.* New York: United Nations Publications.

UN DESA. (2020). *World social report 2020: Inequality in a rapidly changing world*. New York: United Nations Publications.

Valensisi, G. (2020). COVID-19 and global poverty: Are LDCs being left behind? *The European journal of development research, 32*(5), 1535-1557. https://doi.org/10.1057/s41287-020-00314-8

White, H. (1980). A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity. *Econometrica, 48*(4), 817–838. https://doi.org/10.2307/1912934

Vanegas, M. (2022). Tourism, development economics, poverty alleviation and inequality. In R. Croes & Y. Yang (Eds.), *A Modern Guide to Tourism Economics* (pp. 237–258). Cheltenham: Edward Elgar Publishing.

Vanegas, M., & Roe, T. (2021). *Economic growth, inequality and poverty: Tourism dynamics in 3 CAFTA-DR countries*. Paper presented at the 6th World Research Summit for Tourism and Hospitality, University of Central Florida, 14-15, December.

Vanegas, S. (2018). Tourism, macroeconomics, growth, and the St. Louis equation. *Tourism Review International, 22*(1), 3-21. https://doi.org/10.3727/154427218X15202734130413

Vanegas, M., Gartner, W., & Senauer, B. (2015). Tourism and poverty reduction: An economic sector analysis for Costa Rica and Nicaragua. *Tourism Economics, 21*(1), 159-182. http://dx.doi.org/10.5367/te.2014.0442

Vanegas, M. (2014). The triangle of poverty, economic growth, and inequality in Central America: does tourism matter? *Worldwide Hospitality and Tourism Themes*, *6*(3), 277-292. https://doi.org/10.1108/WHATT-03-2014-0014

Vanegas, M. (2012). Poverty reduction through tourism economics. In M. M. Uysal, R. M. Perdue, & J. Sirgy (Eds.), *Handbook of Tourism and Quality-of-Life Research: Enhancing the Lives of Tourists and Residents of Host Communities* (pp. 65–83). New York: Springer.