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THE EFFECTS OF ECONOMIC GROWTH, TRADE AND DEMOGRAPHIC TRANSFORMATION ON DISPOSABLE INCOME INEQUALITY: CS-ARDL ANALYSIS FOR ASIAN COUNTRIES

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ABSTRACT

This study empirically investigates the effects of economic growth, trade openness, and demographic transition on disposable income inequality in China, Japan, South Korea, Indonesia, India, and Türkiye using annual data covering the period 1990-2022. It uses the disposable income Gini coefficient as a measure of disposable income inequality, real income per capita to represent economic growth, and the trade openness ratio for trade integration. Old-age dependency ratio is used to represent demographic transition. Because there might be cross-sectional dependence and slope heterogeneity across countries, the Panel Cross-Sectionally Augmented Autoregressive Distributed Lag (CS-ARDL) approach is used to estimate both short-run and long-run relationships. The direction of causality among the variables is also examined using the Dumitrescu-Hurlin panel causality test. The empirical findings reveal that real income per capita, trade openness, and old-age dependency ratio increase significantly and both in the short run and long run decrease disposable income inequality. The estimated error-correction coefficient is negative and statistically significant, which means that short-run disequilibria gradually converge toward the long-run equilibrium path. Also, the causality results indicate predominantly bidirectional causal relationships between economic growth, trade openness, demographic transition, and income inequality. In other words, this study infers that economic growth which is inclusive and has deeper trade integration, combined with effective social transfer mechanisms related to demographic transformation, would result in a more equitable income distribution. These are significant findings for developing and emerging economies in their quest to reduce income inequality while maintaining sustainable economic development.

Keywords: CS-ARDL, demographic transition, disposable income inequality, economic growth, trade openness

SEÇİLMİŞ ASYA ÜLKELERİNDE EKONOMİK BÜYÜME, TİCARET VE DEMOGRAFİK DÖNÜŞÜMÜN HARCANABİLİR GELİR EŞİTSİZLİĞİ ÜZERİNDEKİ ETKİLERİ: CS-ARDL ANALİZİ

ÖZ

Bu çalışma, 1990-2022 dönemini kapsayan yıllık verileri kullanarak Çin, Japonya, Güney Kore, Endonezya, Hindistan ve Türkiye'de ekonomik büyüme, ticaret açıklığı ve demografik geçişin kullanılabilir gelir eşitsizliği üzerindeki etkilerini ampirik olarak araştırmaktadır. Kullanılabilir gelir eşitsizliğinin ölçüsü olarak kullanılabilir gelir Gini katsayısı, ekonomik büyümeyi temsil etmek için kişi başına reel gelir ve ticaret entegrasyonunu temsil etmek için ticaret açıklığı oranı kullanılmıştır. Demografik geçişi temsil etmek için yaşlılık bağımlılık oranı kullanılmıştır. Ülkeler arasında kesitsel bağımlılık ve eğitim heterojenliği olabileceği için, hem kısa hem de uzun vadeli ilişkileri tahmin etmek için Panel Kesitsel Olarak Genişletilmiş Otoregresif Dağıtılmış Gecikme (CS-ARDL) yaklaşımı kullanılmıştır. Değişkenler arasındaki nedensellik yönü de Dumitrescu-Hurlin panel nedensellik testi kullanılarak incelenmiştir. Ampirik bulgular, kişi başına reel gelir, ticaret açıklığı ve yaşlılık bağımlılık oranının önemli ölçüde arttığını ve hem kısa hem de uzun vadede kullanılabilir gelir eşitsizliğini azalttığını ortaya koymaktadır. Tahmin edilen hata düzeltme katsayısı negatif ve istatistiksel olarak anlamlıdır; bu da kısa vadeli dengesizliklerin kademeli olarak uzun vadeli denge yoluna doğru yakınsadığı anlamına gelir. Ayrıca, nedensellik sonuçları, ekonomik büyüme, ticaret açıklığı, demografik geçiş ve gelir eşitsizliği arasında ağırlıklı olarak çift yönlü nedensel ilişkiler olduğunu göstermektedir. Başka bir deyişle, bu çalışma, kapsayıcı ve daha derin ticaret entegrasyonuna sahip ekonomik büyümenin, demografik dönüşümle ilgili etkili sosyal transfer mekanizmalarıyla birleştiğinde, daha adil bir gelir dağılımına yol açacağını öne sürmektedir. Bunlar, sürdürülebilir ekonomik kalkınmayı korurken gelir eşitsizliğini azaltma arayışındaki gelişmekte olan ve yükselen ekonomiler için önemli bulgulardır.

Anahtar Kelimeler: CS-ARDL, demografik geçiş, ekonomik büyüme, kullanılabilir gelir eşitsizliği, ticaret açıklığı

1. Introduction

The economic growth and trade integration process in Asian economies after 1990 has brought the long-debated growth–income inequality paradox back into focus (Kuznets, 1955). In this context, problems in income distribution have become a significant issue affecting the sustainable growth capacity of regional economies. Despite high growth rates, Asian countries have not achieved comparable performance in income distribution, and income generated by growth is not distributed equally across all segments of society (Bourguignon, 2018; Kanbur & Zhuang, 2013). This situation demonstrates that economic growth does not always reduce inequality, and that greater growth does not increase social welfare equally.

Kuznets' 1955 article, *Economic Growth and Income Inequality*, is a pioneering study examining the relationship between economic growth and income inequality. Kuznets proposed an inverted-U relationship, arguing that inequality would increase in the early stages of a country's development but would gradually decline once economic progress reached a certain level. Kuznets' hypothesis states that inequality may rise in the early stages of growth due to structural transformation. However, it may decrease over time and follow an inverted-U pattern as economic progress, human capital accumulation, and redistribution mechanisms strengthen (Nguyen et al., 2025).

Piketty (2014) argues that long-term income inequality does not follow a uniform pattern across all countries. He also states that institutional structures, especially those related to capital accumulation, can make income inequality more persistent. In this regard, he emphasizes that the leading causes of income inequality are not only production growth and technological development, but also political and fiscal policies and key institutional factors.

In Asian countries, income inequality is closely linked not only to economic growth but also to structural factors such as trade openness and demographic shifts. There is no clear consensus in the literature about how trade openness impacts inequality. Some studies argue that opening up trade helps reduce inequality by providing low-income groups with easier access to jobs and production opportunities (Kanbur & Zhuang, 2013; Rodrik, 1998). However, others contend that global competition can widen income gaps by encouraging capital-intensive sectors (Autor vd., 2016; Feenstra & Hanson, 1999). In addition to trade-related factors, demographic dynamics have also become increasingly important in Asian economies. In particular, the effect of a rapidly aging population on income distribution underscores the role of demographic change through its impact on labor markets, dependency ratios, and redistribution mechanisms (Bloom et al., 2010; Lee & Mason, 2011).

Income inequality and demographic pressures vary considerably across the countries examined in this study. While emerging economies such as China, India, Indonesia, and Türkiye continue to face relatively high levels of inequality, developed economies such as Japan and South Korea are facing growing challenges related to population aging and fiscal sustainability. These structural differences make it important to analyze economic growth, trade openness, and demographic variables together within a comprehensive framework.

Therefore, the main goal of this study is to examine the short- and long-term effects of per capita income, trade openness, and the old-age dependency ratio on disposable income inequality in China, Japan, South Korea, Indonesia, India, and Türkiye from 1990 to 2022.

This study aims to fill the gap in the literature in two ways. First, it focuses on Asian countries with different levels of economic development and demographic structures, many of which have followed export-oriented growth strategies, and examines how these factors jointly influence income inequality. Second, while studies focusing on Organisation for Economic Co-operation and Development (OECD) and Latin American countries are common, research on redistribution dynamics in Asian economies remains relatively limited. The empirical analysis employs second-generation panel methods that account for cross-sectional dependence and heterogeneity across countries to obtain more reliable results.

The remainder of the article is structured as follows. Section 2 presents the literature review and theoretical background. Section 3 describes the data set, variable definitions, and econometric methodology and reports the empirical findings. Finally, Section 4 concludes with an overall evaluation, policy implications, and suggestions for future research.

2. Literature and theoretical background

2.1. Theoretical background

Income inequality is one of the fundamental macroeconomic factors affecting the sustainability of economic growth. The main determinants of inequality include economic growth, trade openness, and demographic transformation (Reuveny & Li, 2003). The relationship between these factors varies across countries depending on their level of development, institutional structures, and social policies; therefore, the literature presents different findings.

According to classical theories, growth reduces income inequality by increasing social welfare through capital accumulation and employment (Valente, 2016). However, Kuznets (1955) argued that this relationship is not one-sided and developed his famous hypothesis, known in the literature as the Kuznets Curve. Later, Piketty (2014) and Bourguignon (2018) argued that the period of globalization and financial liberalization, during which capital returns increased more than labor income, made inequality a persistent problem.

In the case of the relationship between income inequality and economic growth, the Kuznets Curve Hypothesis posits that there exists a non-linear (inverted U-shaped) relationship between per capita income and income distribution. The Kuznets Curve theorizes that during early stages of economic development and as a result of structural changes in the economy (sectoral differences in productivity), income inequality will generally rise due to increasing levels of urbanization. Inequality under the Kuznets framework is expected to fall as economies reach higher levels of income through educational advancement, the development of institutions, and redistributive policies. However, more recent research has raised questions about the Kuznets hypothesis. Specifically, Piketty (2014) makes the case that when rates of return on capital exceed rates of economic growth, this leads to more concentrated wealth and can potentially lead to greater economic inequality in wealthier parts of the world. Likewise, Bourguignon (2018) has stated that globalization, technology, and other institutional factors interact with growth and therefore inequality outcomes may vary based on individual country conditions.

The link between open trading systems and income inequities cannot be measured like other relationships because it is less straightforward. Classical trade theory suggests that trade openness will reduce income inequality in developing nations by raising prices (returns) for abundant factors of production (low-skilled workers), but it can also have the opposite effect if trade openness facilitates capital-intensive and technology-upgrading processes. This dynamic is confirmed with evidence from the United States and other developed nations (Autor et al., 2016; Feenstra & Hanson 1999). Trade exposure can also create sectoral changes, labor market splits, and disparities on a regional basis - especially in less developed countries with weak institutional frameworks; thus there are multiple variables influencing the overall relationship between open trading systems and income levels, such as institutional framework gaps and comparative positional advantages through trade mechanisms.

Population aging is an important factor in how income is distributed among people. According to Bloom et al. (2010) and Lee and Mason (2011) as populations age, it tends to create greater income disparities via decreased labor supply and higher levels of dependency. However, in nations with well-established social security systems for older adults, the amount of assistance through government programs received by older people may offset or reduce income inequality. Therefore, although demographic factors affect inequality, these effects will differ depending on a nation's demographic characteristics, institutional characteristics, and social policy environment.

2.2. Literature review

The concept of income inequality is important because it is a globally comparable measure across countries. In recent years, Solt (2020) has examined income inequality from a different perspective in the SWIID database. This database attempts to explain the impact of the state's redistribution policies by separating disposable and market incomes. The literature has examined the effects of globalization, economic growth, foreign trade, and demographics on income inequality. Table 1 lists some studies related to this work.

Table 1 | Literature review

Author(s)	Countries and Analysis Period	Method	Findings
Kavya and Shijin (2020)	19 developed moreover, 16 developing countries, 1990–2016.	Panel ARDL and Granger Causality Test.	They found that the effects of per capita GDP and trade openness on inequality vary by level of development, but that an increase in the old-age dependency ratio significantly increases income inequality across all countries.
Lee and Vu (2020)	113 countries, 1965–2014.	Ordinary Least Squares (OLS) and GMM	They found that per capita GDP and trade openness increase income inequality.
Michael and Stelios (2020).	NATO Countries, 1980–2013	Fixed Effects and System GMM	They found that an increase in per capita GDP reduces income inequality, whereas an increase in the old-age dependency ratio worsens it. Income distribution thereby increases inequality.
Topçu and Tuğcu (2020).	Developed Countries (G7, European Union, OECD)	GMM and DCCE analysis	The old-age dependency ratio and trade openness increase inequality, while per capita GDP reduces it.
Dorn et al. (2021)	139 countries from different income groups,	Two-stage Least Squares method	In both developed and developing countries, openness to trade significantly increases income inequality.
Bucak and Saygılı (2022)	1970–2014 15 OECD countries, 2004–2016	Panel cointegration analysis and Granger causality	The findings suggest that trade openness exacerbates income inequality, while per capita GDP contributes to reducing inequality once a certain income level is reached.
Han (2022)	BRICS-T countries, 1992-2019	Panel VAR and Granger causality test	Trade openness increases income inequality. There is a unidirectional causality relationship between the variables.
Tekbaş (2022)	ASEAN-5 Countries, ddd 1992-2014	Westerlund cointegration, CCE-MG coefficient estimator and causality analysis	Economic growth increases income inequality. A unidirectional causality was found between growth and income inequality.
Wolde et al. (2022)	Ethiopia (1980–2017)	ARDL boundary test	In the long term, economic growth (real GDP per capita) reduces income inequality.
Cengiz and Demir (2023)	MIST Countries, 1987–2019.	Panel regression analysis (Driscoll- Kraay)	According to the results of the study, while trade openness reduces income inequality in MIST countries, no significant relationship was found between per capita income and inequality.
Gao and Fan (2023)	Belt and Road Initiative (BRI) countries, 1999–2018	SGMM, OLS, and Fixed Effects analysis	The statistical relationship between income inequality and economic growth was found to be weak.
Lazar and Litan (2024)	Romania, 1990–2020	ARDL cointegration analysis	There is a non-unidirectional relationship between income inequality and GDP per capita.
Seabela et al. (2024)	South Africa (1975–2017)	VECM	Economic growth increases income inequality.
Tabash et al. (2024)	18 developing countries, 1991–2021	Two-stage least squares (2SLS)	Trade openness and foreign direct investment have been found to reduce income inequality in developing countries' economies.
Khan et al. (2025)	G7 Countries	CS-ARDL, Westerlund Cointegration Test, and Dumitrescu-Hurlin Causality Test.	Trade openness and the old-age dependency ratio increase income inequality.
Nguyen et al. (2025)	Vietnam (63 regions), 2004–2021	Fixed Effects and GMM analysis	As real GDP per capita increases, income inequality initially rises and then declines.
Soyhan and Mollavelioğlu -2025	Türkiye, 1990–2024	ARDL analysis	It has been concluded that trade openness increases income inequality.

The literature on the relationship between economic growth and income inequality has not reached a clear conclusion, and findings vary by country's level of development. Some studies conclude that economic growth increases income inequality, especially in developing countries. For example, Tekbaş (2022), in his analysis of the ASEAN-5 countries, found that economic growth increases income inequality and that there is a unidirectional causal relationship between the two. Similarly, Seabela et al. (2024) concluded that economic growth increases long-term income inequality in South Africa.

On the other hand, studies show that per capita income growth reduces income inequality once it exceeds a certain point. Michael and Stelios (2020) and Wolde et al. (2022) state that income growth improves distribution, while Bucak and Saygılı (2022) and Nguyen et al. (2025) indicate that the relationship between development and inequality is not linear but rather follows an inverse U-shape. These findings show that the effect of economic growth on income inequality is not direct and is shaped by specific determinants, primarily institutional structure, human capital level, and redistribution policies.

The literature on the relationship between trade openness and income inequality yields more complex results than for other variables. Many studies argue that trade openness leads to higher income inequality. Lee and Vu (2020), Dorn et al. (2021), Han (2022), and Soyhan and Mollaveliöğlu (2025) show that trade openness increases income inequality, especially in developing countries.

On the other hand, some studies find that trade openness reduces income inequality. Cengiz and Demir (2023) reveal that trade openness reduces income inequality in MIST countries, while Tabash et al. (2024) show that trade openness and foreign direct investment together improve income distribution in developing countries. These conflicting findings indicate that the effect of trade openness depends on factors such as a country's export structure, level of industrialization, and labor market.

The relationship between the aging rate and income inequality yields relatively more consistent results. A large portion of studies show that rising old-age dependency ratios are associated with higher income inequality. Kavya and Shijin (2020), Michael and Stelios (2020), Topçu and Tuğcu (2020), and Khan et al. (2025) show that an increase in the old-age dependency ratio significantly increases income inequality, even across different country groups.

In general, the literature shows that the effects of economic growth, trade openness, and population aging on income inequality vary across countries. The findings show that these relationships are not linear or unidirectional, but are shaped by institutional structures, levels of development, and demographic dynamics. In this context, the findings from analyses that account for heterogeneity and cross-sectional dependence are more consistent.

The existing literature shows that findings on the effects of economic growth, trade openness, and the demographic transition on income inequality vary significantly across country groups, periods, inequality measures, and econometric methods. However, studies that simultaneously address Asian economies and countries such as Türkiye, which are both developing and undergoing structural transformation and demographic change, are relatively limited. Furthermore, there appears to be relatively less focus on testing per capita income, trade openness, and old-age dependency ratio using second-generation panel data techniques.

This study aims to contribute to the literature by jointly examining the short- and long-term effects of these three determinants on disposable income inequality in a sample of China, Japan, South Korea, Indonesia, India, and Türkiye for the period 1990–2022. It seeks to produce more consistent and generalizable findings using an approach that does not exclude country-specific dynamics and standard shocks.

In conclusion, literature reviews show that the effects of independent variables on the dependent variable, income inequality, depend on countries' levels of development, trade structures, and demographic characteristics; therefore, panel data analyses that account for country-specific dynamics yield more consistent results.

3. Data, method, and findings

3.1. Data and model

This study employs annual data covering the period 1990–2022 for six Asian countries: China, Japan, South Korea, India, Indonesia, and Türkiye. The sample selection is not based solely on data continuity; rather, it relies on clearly defined criteria including economic size, regional and global economic relevance, representation of different levels of development, and structural as well as demographic diversity. The selected countries rank among the leading Asian economies in terms of GDP and trade volume and play influential roles in regional and global trade integration. Moreover, the sample incorporates advanced, emerging, and developing economies, thereby enabling a comparative analysis of the relationships among economic growth, trade openness, demographic dynamics, and income inequality under differing structural conditions. Although continuous data are also available for countries such as Malaysia, the Philippines, and Vietnam, the scope of the study is deliberately confined to the more economically prominent and systemically influential Asian economies in order to preserve analytical coherence and methodological consistency.

The Gini coefficient was used as the dependent variable to represent income inequality. The independent variables used were real GDP per capita to represent growth, trade openness to represent trade integration, and the old-age dependency ratio to describe demographic characteristics. Table 2 provides the variables, abbreviations, and data sources for the model,

Table 2 | Definition and sources of variables

Variable	Definition	Period	Source
LNGINI	Income inequality indicator (0–100)	1990–2022	SWIID
LNGDP	Real GDP per capita (2015 constant prices, US dollars)	1990–2022	World Bank, WDI
LNT0	Trade openness ratio (Exports + Imports)/GDP	1990–2022	World Bank, WDI
LNAGE	Old-age dependency ratio (65+/15–64)	1990–2022	World Bank, WDI

The logarithms of the variables were taken, and cross-sectional dependence and homogeneity tests were applied before analysis. The results of these analyses were used to determine the stationarity levels of the series using a CPIS unit root test from second-generation root analyses. The study concluded that the variables were stationary at different levels of I(0) and I(1), but no variables were found at the I(2) level.

3.2. Econometric method and findings

Based on cross-sectional dependence and heterogeneity analyses, the Cross-Sectionally Augmented Autoregressive Distributed Lag (CS-ARDL) method was initially preferred because it explicitly accounts for cross-sectional dependence and allows for regressors with different orders of integration. Panel ARDL models that ignore cross-sectional dependence may produce biased and unreliable estimates, particularly for economies that are closely integrated and simultaneously exposed to common global shocks, such as those in Asia. In such contexts, conventional Panel ARDL estimators may fail to capture the impact of unobserved common factors and, therefore, may not yield realistic results. Therefore, the CS-ARDL method is used when cross-sectional dependence and heterogeneity are present and provides more reliable estimates (Chudik & Pesaran, 2015; Pesaran, 2006).

Following Chudik and Pesaran (2015), the Split-panel (Half-panel) Jackknife bias-correction procedure is implemented. In this framework, the time dimension is divided into two sub-periods, the resulting estimates are appropriately combined, and bias-corrected coefficients are obtained. The study reports both the original CS-ARDL results and the Jackknife bias-corrected estimates, thereby showing that the main findings are robust to small-sample bias.

The countries examined in this study are at the center of production and demographic transformation processes and constitute an essential sample set. Since these countries have different levels of development

and exhibit similar responses to global economic shocks, such as fluctuations in international trade, commodity prices, or financial markets, indicating that they share common sensitivities to such shocks, the Pesaran (2006) CS-ARDL method, which considers heterogeneity and cross-sectional dependence simultaneously, was preferred.

First, the Pesaran (2004) CD test was applied to detect cross-sectional dependence among countries, and cross-sectional dependence was identified among the variables. Following the detection of cross-sectional dependence, the unit root levels of the variables were determined using the Pesaran (2007) CIPS test, a second-generation unit root test. The findings concluded that the variables have different stationarity levels, specifically I(0) and I(1), but not I(2). These results allow for the application of the CS-ARDL model.

Finally, the Dumitrescu–Hurlin (2012) panel causality test was applied to determine the causal relationships between the variables. This test identified the causal relationships between growth, trade, and demographic factors and income inequality. The general model equation of the study is shown in equation (1)

$$LNGINI_{it} = \alpha_i + \beta_1 LNGDP_{it} + \beta_2 LNT0_{it} + \beta_3 LNAGE_{it} + \varepsilon_{it} \quad (1)$$

$\beta_1 < 0$ is expected: An increase in real GDP per capita reduces income inequality,

$\beta_2 < 0$ is expected: Trade openness reduces inequality,

$\beta_3 < 0$ is expected: The old-age dependency ratio reduces inequality.

The coefficient 3 is expected to be negative because an increase in the old-age dependency ratio may reduce income inequality. This is theoretically justified as higher old-age dependency often implies greater social transfers and pensions that provide direct support to lower-income households. Additionally, demographic shifts associated with a higher proportion of the elderly can influence labor income distribution and savings patterns, leading to a more balanced allocation of resources. These channels are consistent with the theoretical framework discussed above.

Within this model, the coefficients obtained are expected to reduce income inequality in both the short- and long-term.

Table 3 | Cross-section dependency test results

Test name	LNGINI	LNT0	LNGDP	LNAGE
Breusch–Pagan LM	252,32***	354,95***	329,51***	116,77***
Pesaran scaled LM	91,85***	13,545***	37,491***	37,239***

Note: ***, **, * indicate significance levels of 1%, 5%, and 10%, respectively.

Based on the Breusch–Pagan LM and Pesaran scaled LM test statistics shown in Table 3, there is evidence of cross-sectional dependence at the 1% significance level. This indicates that the countries in the panel did not respond independently to standard shocks. Consequently, it is suitable to use second-generation methods that address cross-sectional dependence and heterogeneity in unit root and cointegration analyses

Table 4 | Homogeneity results

Test	Statistic	p-value
Pesaran–Yamagata (2008)	Delta = 20, 243	0,000***
	Adj. Delta = 21,976	0,000***
Swamy Test	$\chi^2 = 4078.35$	0,000***

Note: ***, **, * indicate significance levels of 1%, 5%, and 10%, respectively.

In both tests in Table 4, the assumption that the coefficients are the same across units is rejected. According to this finding, the slope coefficients across panels are heterogeneous. Therefore, it is preferable to use methods that account for unit-specific differences in panel data analysis and estimation

Table 5 | CIPS panel unit root test results

Variable	LEVEL	Stability Decision
LNGINI	-2.233	Non-stationary
LNT0	-1.516	Non-stationary
LNGDP	-4.637***	Stationary (I0)
LNAGE	-1.006	Non-stationary
1. DIFFERENCE		
Δ LNGINI	-5.681***	Stationary (I1)
Δ LNT0	-4.740***	Stationary (I1)
Δ LNGDP	-6.190***	Stationary (I0)
Δ LNAGE	-3.747***	Stationary (I1)

Note: CIPS statistic test critical values, 1%: -2,55, 5%: -2,33., %10: -2,21

Note: ***, **, * indicate 1%, 5%, and 10% significance levels, respectively

The CIPS results in Table 5 show that the variables generally contain a unit root at the level and are therefore non-stationary. The optimal lag lengths for the dependent and independent variables were determined using the Akaike Information Criterion (AIC). Considering the sample size, a maximum lag limit of 3 was set, and the selected lag was determined as the value that minimized the criteria. This ensured a balanced choice between model fit and simplicity. In contrast, only the LNGDP variable is stationary at the 5% significance level. However, when first differences are taken, all variables become statistically stationary, indicating that the series have different degrees of integration; that is, the panel has a mixed structure of I(0) and I(1). This makes the CS-ARDL approach, which does not require variables to be integrated to the same degree and can model short- and long-term relationships simultaneously, methodologically appropriate.

Table 6 | CS-ARDL (3, 1, 3) short- and long-term results

Variables	CS-ARDL Coef.	Z-value	Prob.	CS-ARDL Jackknife Coef.	Z-value	Prob.
Short Term						
L.LNGINI	-3.227	-5.37	0.000***	-0.435	-1.84	0.066*
Δ LNGDP	-1.135	-2.00	0.044**	-0.352	-2.28	0.023**
Δ LNAGE	-4.277	-3.21	0.001***	-0.530	-1.20	0.230
Δ LNT0	-0.146	-2.33	0.020**	-0.110	-1.98	0.047**
ECT(-1)	-0.307	-2.67	0.008***	-1.435	-6.07	0.000***
Long Term						
LNAGE	-0.322	-3.28	0.001***	-0.299	-1.05	0.295
LNGDP	-0.184	-2.11	0.035**	-0.298	-2.09	0.037**
LNT0	-0.018	-2.31	0.021**	-0.077	-2.22	0.026**

Note: ***, **, * indicate significance levels of 1%, 5%, and 10%, respectively.

The CS-ARDL model is specified as CS-ARDL (3,1,3), where 3 lags of the dependent variable capture short-run dynamics, 1 lag of the independent variable is included based on information criteria (AIC), and 3 lags of the cross-sectional averages are used following the $T^{1/3}$ rule. This specification ensures that both individual country dynamics and cross-sectional dependence are adequately modeled.

Table 6 reports both the CS-ARDL estimation results examining the determinants of income inequality and the split-panel Jackknife bias-corrected estimation results applied to address small sample ($T < 40$) bias. When examining the short-term results, the coefficient of the lagged income inequality variable (L.LNGINI) is -3.227 in the CS-ARDL model and is statistically significant at the 1% level. After the Jackknife correction, the absolute value of the coefficient decreases significantly to -0.435, and the significance level weakens to 10%. This indicates that the CS-ARDL estimator contains upward bias due to the dynamic structure in panels with small time dimensions, and that the Jackknife correction significantly reduces this bias.

When other short-term coefficients are examined, the change in per capita income (Δ LNGDP) has a negative effect on income inequality at the CS-ARDL model at the level of -1.135 and at the 5% significance level. Although the coefficient declined to -0.352 after the Jackknife correction, it remained statistically significant at the 5% level. For the change in the age structure of the population (Δ LNAGE), the CS-ARDL estimator shows a strong and statistically significant negative relationship at the 1% level with a coefficient of -4.277 in the short term; however, after Jackknife, the coefficient size falls to -0.530 and the significance disappears. The change in the openness variable (Δ LNT0) reduces income inequality in the short term in both estimations; while the coefficient of -0.146 is significant at the 5% level in CS-ARDL, the coefficient is obtained as -0.110 in the Jackknife estimation and remains significant at the 5% level.

The error correction term ECT(-1) indicates a moderate convergence rate toward the long-run equilibrium relationship in the CS-ARDL estimation, with a coefficient of -0.307 and significance at the 1% level. After the Jackknife bias correction, the absolute value of the error correction coefficient increases significantly and is estimated at -1.435, maintaining its significance at the 1% level. This increase in the ECT coefficient suggests that the dynamic adjustment speed in the CS-ARDL estimator may be biased downward under small T conditions, while the Jackknife correction implies that the return to long-term equilibrium is faster.

When examining long-term results, it is observed that the LNAGE variable, which represents the age structure of the population, has a strong and statistically significant negative effect on income inequality with a coefficient of -0.322 in the CS-ARDL estimation at the 1% level. In the jackknife-corrected estimation, the LNAGE coefficient is calculated as -0.299, but it loses its statistical significance; this suggests that the long-term effect of age structure may be sensitive to small sample bias. In contrast, per capita income level (LNGDP) reduces income inequality in the long term in both estimates; while the coefficient of -0.184 is significant at the 5% level in CS-ARDL, the absolute value of the coefficient increases to -0.298 in the Jackknife estimate and remains significant at the 5% level. Similarly, the openness ratio (LNT0) has a negative and statistically significant effect on income inequality in the long term; while the coefficient of -0.018 is significant at the 5% level in the CS-ARDL estimation, after the Jackknife correction, the coefficient increases to -0.077 and remains significant at the 5% level.

In general, the Jackknife bias correction reduces the absolute values of short-term coefficients while partially increasing the magnitude of some long-term coefficients (particularly LNGDP and LNT0); nevertheless, the direction of the main findings is largely preserved. These results indicate that CS-ARDL estimates in panels with small time dimensions may contain small-T bias, while the split-panel Jackknife correction provides more consistent estimates, particularly for dynamic parameters and the error correction term.

Although the literature argues that an increase in the elderly population is a factor that increases income inequality within the Life Cycle Hypothesis, the different findings in this study are due to the data set's methodological structure and social policy mechanisms. The analysis uses a dataset developed by Solt (2020) that focuses not only

on market income but also on disposable income after government transfers, primarily taxes and pensions. The elderly population is expected to disrupt income distribution.

While strong social security systems and intra-family solidarity in countries such as Japan, South Korea, and Türkiye help stabilize older people's incomes, the standard income inequality measures used in this study, such as the Gini coefficient, do not provide age-specific information. To support our statements regarding the relative income stability of older populations, we relied on country-level demographic and social security data from (OECD, 2023) and (World Bank, 2022) which report income distributions by age group and show that pensions and family transfers mitigate income inequality among the elderly. This situation, as emphasized by Lindert (2004) and Milanovic (2000), shows that social spending and public transfers, together with their redistributive effects, help control inequality created by rapid demographic changes.

The long-term reduction in income inequality associated with the openness to trade (LNT0) variable is consistent with theoretical approaches on the effects of international trade on factor incomes. The fact that China, India, Indonesia, and Turkey, in particular, among the countries analyzed, have a relatively labor-intensive production structure within the global division of labor suggests that increased trade integration could raise the returns on the relatively abundant labor factor and that this situation could have an income distribution-improving effect.

In this context, increased integration with the global economy has raised demand for unskilled and semi-skilled labor, thereby contributing to higher wages and partially mitigating income inequality between capital owners and wage earners. Consistent with Rodrik (1998), trade liberalization in developing countries can enhance labor's share of income, further distributing welfare gains across broader segments of the population.

Table 7 since cross-sectional dependence was detected in the analysis, bootstrap critical values obtained through 400 replications were employed in the estimation process. This approach enhances the robustness of the results and allows for a more reliable statistical interpretation of the causality relationships. Furthermore, the optimal lag length was determined as 2, based on the Akaike Information Criterion (AIC). This procedure ensures appropriate model specification and maintains the parametric consistency of the econometric estimations

Table 7 | Dumitrescu-Hurlin panel Granger causality bootstrap test results

Causality direction (X → Y)	W-bar	Z-bar	Probability	Causality
LNGINI → LNGDP	6.070	8.782	0.017**	YES
LNGDP → LNGINI	2.435	2.486	0.000***	YES
LNGINI → LNTRADE	3.494	4.320	0.077*	YES
LNTRADE → LNGINI	2.728	2.993	0.125	NO
LNGINI → LNAGE	4.069	4.564	0.000***	YES
LNAGE → LNGINI	3.120	3.599	0.000***	YES
LNAGE → LNTRADE	4.230	5.475	0.000***	YES
LNTRADE → LNAGE	4.933	5.881	0.105	NO
LNAGE → LNGDP	1.766	1.327	0.200	NO
LNGDP → LNAGE	8.210	6.285	0.045**	YES
LNGDP → LNTRADE	3.803	4.855	0.030**	YES
LNTRADE → LNGDP	3.757	4.776	0.000***	YES

Note: ***, **, * indicate significance levels of 1%, 5%, and 10%, respectively.

Table 7 presents the results of the Granger causality analysis, indicating significant interdependencies among the variables. A bidirectional causality between LNGINI and LNGDP suggests a feedback mechanism, implying that income inequality not only affects economic growth but is also shaped by it. Such a finding supports the notion that redistributive policies and economic expansion processes

are jointly determined. Similarly, the bidirectional causality between LNGINI and LNAME highlights a mutual interaction between demographic structure and income inequality, in which population aging and income distribution reinforce one another.

Furthermore, the analysis reveals unidirectional causality from LNGINI to LNTRADE and from LNAME to LNTRADE, indicating that inequality and demographic characteristics significantly influence trade openness, while the reverse effects are statistically insignificant. The evidence of bidirectional causality between LNGDP and LNTRADE confirms a strong linkage between trade liberalization and economic performance, aligning with endogenous growth theories that emphasize trade as a driver of economic growth. Additionally, the unidirectional relationship from LNGDP to LNAME shows that economic growth can influence demographic variables, possibly through improvements in life expectancy or changes in population composition.

Overall, these econometric findings demonstrate that income inequality, economic growth, trade openness, and demographic dynamics form an interconnected and mutually reinforcing system. The results underscore the importance of designing integrated economic policies that address inequality and growth simultaneously, while considering demographic trends and trade dynamics as essential structural components of sustainable economic development.

4. Conclusion and discussion

This study examines the determinants of disposable income inequality (LNGINI) in China, Japan, South Korea, Indonesia, India, and Türkiye from 1990–2022, focusing on per capita real income (LNGDP), trade openness (LNT0), and the old-age dependency ratio (LNAME). First, cross-sectional dependence and heterogeneity were identified; second, panel data analyses of the second generation, which account for standard shocks and country-specific characteristics, were preferred.

CS-ARDL estimates indicate that all independent variables have negative, statistically significant effects on the dependent variable, LNGINI, in both the short- and long-term. The negative and considerable error-correction term indicates that short-term deviations are reversed in the long term.

Furthermore, examining the Dumitrescu–Hurlin causality results indicates that there are generally bidirectional and feedback relationships between inequality and LNGDP, LNT0, and LNAME, meaning that inequality is not only a result but also a determinant of growth, trade, and demographics.

The findings show that an increase in real per capita income reduces disposable income inequality in both the short and long term. This finding is consistent with studies showing that higher income reduces inequality (Michael & Stelios, 2020; Wolde et al., 2022). Additionally, the literature suggests that growth increases inequality and that there is a non-linear (inverse-U) relationship between them (Bucak & Saygılı, 2022; Nguyen et al., 2025).

The negative coefficients in the relationship between trade openness and inequality indicate that trade openness helps reduce inequality over the long term. This result is consistent with studies showing that trade openness reduces inequality in some country groups (Cengiz and Demir, 2023; Tabash et al., 2024). However, some studies suggest that trade openness increases inequality (Dorn et al., 2021; Han, 2022; Lee & Vu, 2020; Soyhan & Mollavelioglu, 2025). These differences in findings suggest that the impact of trade depends on specific determinants, such as export structure, labor market, institutions, human capital, and countries' social policies.

The study's findings differ from those of some studies in the literature (Khan et al., 2025; Topçu & Tuğcu, 2020), and three key determinants drive the reduction in income inequality through aging and trade openness. First, using disposable income data, which encompasses government redistribution policies and social transfers rather than market income inequality, minimized the adverse effects of demographic transformations on inequality. Second, the preference for the CS-ARDL method, which accounts for cross-sectional dependence among Asian economies, yields more reliable results than first-generation tests that ignore this dependence. Finally, the fact that the 1990–2022 analysis period covers a phase of structural transformation in Asia, marked by the rise of the middle class and the decline in poverty, has shaped

the relationship between the variables in a context different from that described in the literature.

Based on the study's findings, two key recommendations are presented to policymakers. First, social security and pension funds should be strengthened to sustain the inequality-reducing effects of an aging population. Second, the role of trade openness should be preserved through structural reforms, and the gains from foreign trade should be taxed to fund education, health, and social assistance for disadvantaged groups.

For future researchers, a comparative analysis of the market Gini and the disposable income Gini will provide a clearer picture. Furthermore, classifying Asian countries as developed or developing economies will contribute to the literature by allowing us to test whether the impact of demographic transformation on inequality varies across these groups and whether this relationship is linear.

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