

SenGupta, Swapnanil; Atal, Aakansha

Article — Published Version

Income inequality in the face of climate change: an empirical investigation on unequal nations, vulnerable regions and India

SN Business & Economics

Provided in Cooperation with:

Springer Nature

Suggested Citation: SenGupta, Swapnanil; Atal, Aakansha (2024) : Income inequality in the face of climate change: an empirical investigation on unequal nations, vulnerable regions and India, SN Business & Economics, ISSN 2662-9399, Springer International Publishing, Cham, Vol. 4, Iss. 8, <https://doi.org/10.1007/s43546-024-00685-8>

This Version is available at:

<https://hdl.handle.net/10419/316968>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



<http://creativecommons.org/licenses/by-nc-nd/4.0/>



Income inequality in the face of climate change: an empirical investigation on unequal nations, vulnerable regions and India

Swapnanil SenGupta^{1,2} · Aakansha Atal³

Received: 5 February 2024 / Accepted: 3 July 2024 / Published online: 17 July 2024
© The Author(s) 2024

Abstract

Climate change is the paramount challenge of our era. While considerable attention has been given to its impact on financial stability and economic productivity, there is limited focus on its effects on income inequality. We introduce a unique criterion for sample selection. We aim to provide an empirical analysis of how climate change impacts income inequality in 43 most climate-vulnerable countries, 39 most unequal countries in terms of income distribution, and India separately (1971–2021). We select the most vulnerable countries to investigate the magnitude of income inequality caused by climate change. Given that climate hazards enhance inequality in countries with prevailing socioeconomic inequalities, we choose unequal countries to investigate whether climate change is a significant determinant of their existing condition. We also analyse the relationship for India because India is one of the most climate-vulnerable and unequal countries. We use three climate change indices—vulnerability to climate change, annual surface temperature change, and frequency of climate-related disasters—to check the effects of particular aspects of climate change. We deploy a standard panel regression analysis followed by a series of robustness checks and an autoregressive distributed lag (ARDL) bounds test approach to analyse the link for India. We find that climate change has adverse impacts in both groups and in India, both in the long and short term. Our findings suggest that policymakers in developing countries may need to equally place importance on developmental and climate change abatement goals as well as expedite their environmental targets.

Keywords Climate change · Income inequality · Panel data · India · Fixed effects regressions · ARDL Bounds Test

✉ Swapnanil SenGupta
senguptaswapnanil1@gmail.com

¹ The University of Manchester, Manchester, UK

² University of Tübingen, Tübingen, Germany

³ Centre for International Trade and Development, Jawaharlal Nehru University, New Delhi, India

JEL Classification D31 · O10 · O15 · Q54

Introduction

“On climate change, we often don’t fully appreciate that it is a problem. We think it is a problem waiting to happen.”

- Kofi Annan.

(Former UN Secretary-General, Nobel Peace Prize Recipient).

Background

The onset of the Industrial Revolution marked a pivotal moment in human history, ushering in unprecedented global progress. This remarkable development, however, has come at a cost, most notably reflected in the paramount challenge of our era: climate change. Climate change, characterised by complicated and ever-evolving dynamics, represents a shift in environmental conditions towards extremes, affecting everything from temperature to a range of interconnected factors.

An extensive body of research highlights the urgency of addressing climate change. The National Oceanic and Atmospheric Administration (NOAA) reports that the earth’s temperature has risen by an average of 0.08 °C per decade since 1880.¹ Ongoing temperature analysis at NASA’s Goddard Institute for Space Studies (GISS) reveals that since 1880, the average global temperature has increased by at least 1.1 °C in total, with the majority of the global warming occurring since 1975 (at a rate of approximately 0.15–0.20 °C per decade).² Not limited to temperature, numerous other factors linked to climate change have registered worsening trends over the decades (Fig. 1). These have heightened the occurrence and magnitude of climate-related shocks on a global scale. As per the IPCC (2018), crossing the threshold of 1.5 °C above pre-industrial temperatures could trigger catastrophic outcomes, and the prospects become even graver with temperature rises surpassing 2 °C. The concerns become intensified as these extreme weather events and related consequences are likely to exacerbate. There are projections of a 66% likelihood of annual average near-surface global temperature remaining more than 1.5 °C above pre-industrial levels for at least one year between 2023 and 2027 (WMO 2023), and global mean temperature increasing by 4 °C over the next century (IPCC 2021).

The implications of climate change extend beyond the environment to cover economic aspects, including financial stability, fiscal health, long-term growth potential, and income distribution. The consequences of climate change have already caused global losses of approximately US\$ 3.64 trillion between 1970 and 2019, according to the estimates of WMO (2021). Furthermore, research by the Notre Dame Global Adaptation Initiative (ND-GAIN) reveals varying degrees of vulnerability to climate change impacts among countries (see Fig. 2), influenced by factors like economic

¹ See Lindsey and Dahlman (2023).

² See <https://earthobservatory.nasa.gov/world-of-change/global-temperatures>.

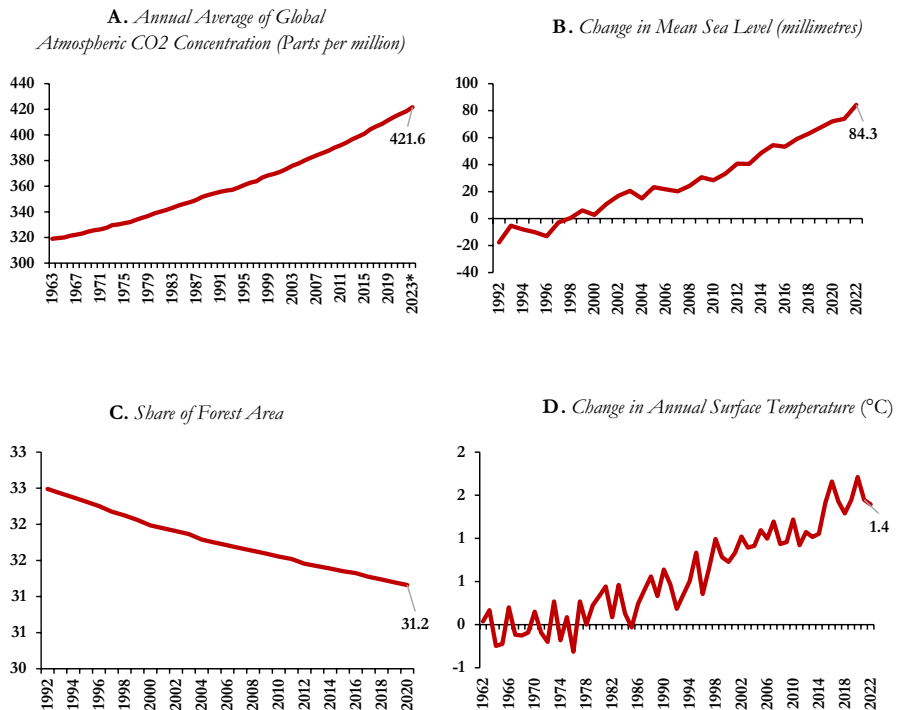


Fig. 1 Global Climate Change Indicator Trends. **A** Annual Average of Global Atmospheric CO₂ Concentration (Parts per million). **B** Change in Mean Sea Level (millimetres). **C** Share of Forest Area. **D** Change in Annual Surface Temperature (°C). Source: National Oceanic and Atmospheric Administration. Source: FAO, UN. *Annual Average for Global Atmospheric CO₂ Concentration for 2023 is taken until May 2023. For creating Fig. 1B, we take the final recording of each year

structure, institutional strength, and the capacity for climate mitigation and adaptation. Unchecked climate change could jeopardise poverty eradication efforts by pushing up to 130 million people into poverty in the coming years (Nishio 2021), disproportionately hit the most underdeveloped regions, and exacerbate income inequality within countries (World Bank 2020).

While considerable attention has been dedicated to examining the impact of climate change on financial stability and economic productivity, there has been comparatively less emphasis on exploring the income inequality impacts of climate change. This gains particular significance in light of the global increase in income inequality experienced over the last four decades across most countries. The widely recognised theoretical framework of the climate change-income inequality nexus states that inequality exacerbates the vulnerability of disadvantaged societal groups to the impacts of climate change in three significant ways: (i) rise in vulnerability to climate hazards; (ii) heightened sensitivity to the impact of climate hazards; (iii) diminished capacity to manage and recover from the damage. Due to the collective impact of the three channels mentioned, a vicious cycle ensues in which climate

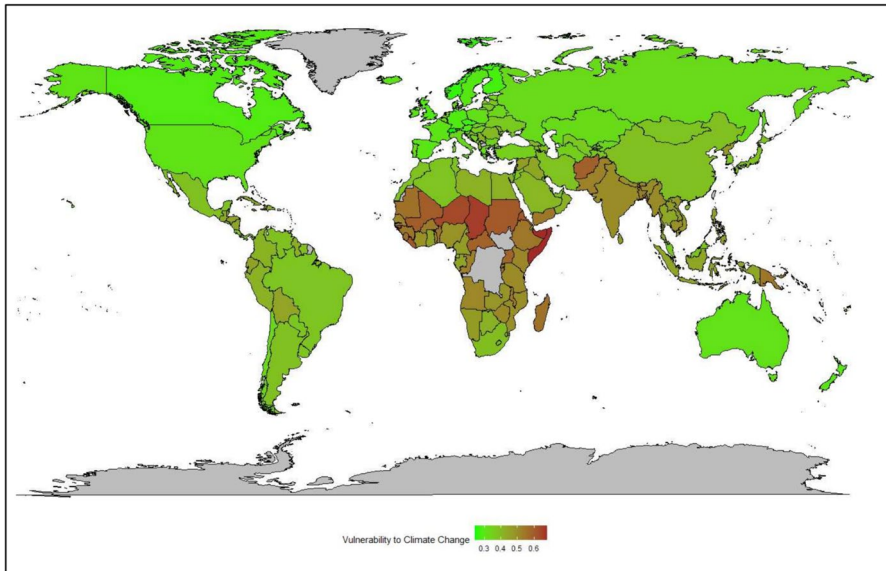


Fig. 2 ND-GAIN Vulnerability Index, 2021. Source: Notre Dame Global Adaptation Initiative; Authors' calculations

change hazards worsen existing inequalities.³ Diffenbaugh and Burke's (2019) empirical evidence attests to the concept suggesting that many wealthy countries have benefited disproportionately from the activities that have caused global warming and have been made even more opulent, while many poor nations have become poorer. Figure 3 provides an overview of the existing income inequality in the world.

Research goals and methodology

The objective of this paper is to provide a detailed empirical analysis of how climate change impacts income inequality in 43 countries most vulnerable to climate change,⁴ 39 most unequal countries in terms of income distribution,⁵ and India separately, spanning from 1971 to 2021 (check Online Appendix I for the list of countries). We select the most vulnerable countries to climate change because we want to investigate the magnitude of income inequality caused by climate change and, hence, form an idea about how worse the situation can be should climate change go unchecked. UNDESA (2016) mentions that initial socioeconomic inequalities determine the disproportionate adverse effects of climate hazards on people at a disadvantage, and the effects of climate hazards in turn result in greater inequality. Following this line of thought, we choose unequal countries to empirically

³ See Islam and Winkel (2017) for details.

⁴ List compiled using reports from Germanwatch's Global Climate Risk Index 2021, INFORM Climate Change Risk Index and IPCC 2022.

⁵ List compiled from World Inequality Lab's Top 10% Income data, and SWIID database.

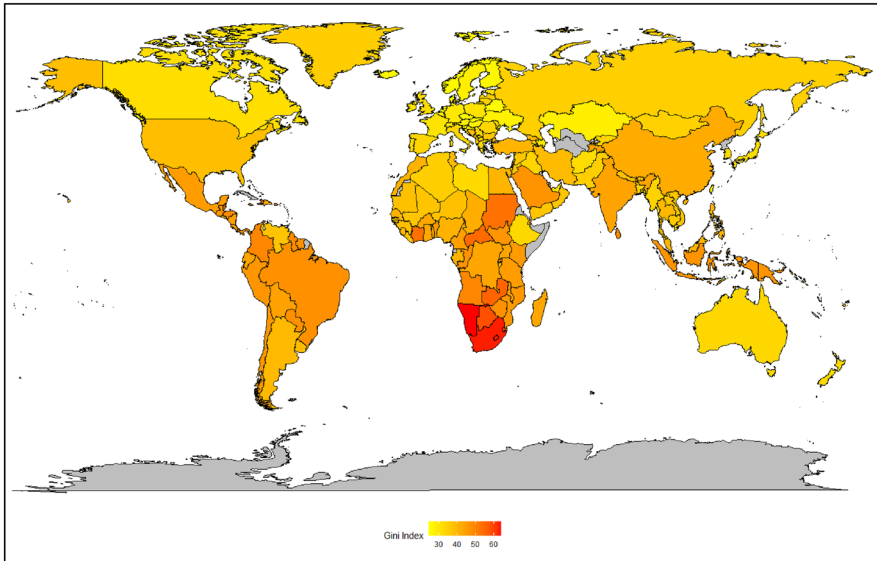


Fig. 3 Average Disposable Gini (2007–2020). Source: Standardized World Income Inequality Database (SWIID); Authors' calculations

investigate whether climate change is a significant determinant of their existing condition. We also take motivation from Cevik and Jalles (2023) who recommend replication of their results in different contexts such as geographical areas and time periods.

The research utilises different climate change datasets to check the effects of particular aspects of climate change. We deploy a standard panel regression analysis followed by a series of robustness checks to confirm the soundness of the results and an autoregressive distributed lag (ARDL) bounds test approach to analyse the link for India.

Novelty and contribution

We contribute to the existing literature in the following ways: (i) We utilise the longest available data period. This extended time frame allows us to account for longer periods of climate change, providing a more comprehensive understanding of its impact on income inequality. Such an approach yields more insightful results and establishes a solid foundation for assessing the long-term consequences of climate change on income distribution. (ii) We introduce a unique criterion for the selection of countries. By focusing on 43 of the most climate-vulnerable countries and 39 of the most unequal countries in terms of income distribution, we investigate the magnitude of income inequality caused by climate change and its implications. This distinctive approach facilitates a nuanced analysis, offering insights that were previously lacking in the literature. (iii) Our study addresses a significant gap in

the existing research by examining the link between climate change and income inequality in India. To the best of our knowledge, there is a scarcity of studies that explore this relationship in the Indian context.⁶ By confirming climate change as a determinant of income inequality in India, our research not only paves the way for further investigation but also holds direct policy implications for a country with a rapidly evolving climate and economic landscape.

In terms of its relevance, our study bears importance on multiple fronts. From an academic perspective, it extends current knowledge on the relationship between climate change and income inequality. By examining the issue and providing detailed insights into specific groups of countries, our research adds depth and nuance to the existing discourse. From a policymaking standpoint, our findings shed light on the magnitude of climate change's impact on income distribution, providing policymakers with data-driven insights. This information can help in prioritising and tailoring interventions for countries facing varying levels of vulnerability and inequality. Notably, our findings offer valuable insights into the ongoing debate about the priorities of developing and emerging nations—whether to focus on tackling climate change or achieving development goals. Our research concentrates on these specific economies, revealing a substantial impact of climate change on income inequality in these regions. While the common stance of prioritising developmental goals over climate change abatement in the developing world (e.g., Tongia 2022) is understandable, our study introduces a critical consideration. Many developing and emerging economies, despite being proactive in climate change abatement, have set long-term goals. For example, India aims for net-zero carbon emissions by 2070 (Ministry of Environment Forest and Climate Change 2022). This prompts us to question whether there is a need to expedite the process. Waiting for such an extended period might not only slow down but also potentially reverse development progress, working against their primary goals instead of supporting them. Therefore, our research contributes to informed decision-making and effective policy responses in the global effort to balance both immediate needs and long-term sustainability in these developing and emerging economies.

The rest of the paper is structured as follows: Section "[Theoretical framework and literature review](#)" provides the theoretical framework and literature review; Section "[Research gap](#)" presents the research gap; Section "[Methodology](#)" presents the empirical analyses; Section "[Conclusion](#)" concludes the study; Section "[Policy implications](#)" sheds light on the policy recommendations; and Section "[Limitations and recommendations](#)" presents the limitations of this study and further recommendations.

⁶ The only existing study on a related subject matter is by Aggarwal (2021) who analyses the impacts of climate shocks on real monthly per capita consumption expenditure in India. He uses micro-level data and sheds light on consumption inequality. Hence, we believe that this study on India features unprecedented characteristics.

Theoretical framework and literature review

The discussion surrounding the impacts of climate change is consistently deliberated within the multi-dimensional framework of poverty and socio-economic inequality. However, the relationship between climate change and within-country income inequality has been given relatively less attention. In this section, we mainly focus on the relationship between our chosen indices (annual surface temperature, climate disasters or hazards, and vulnerability) of climate change and income inequality. The existing body of literature studying the climate change and income inequality relationship can be categorised into two primary themes: (i) investigating the influence of climate change on income disparity among distinct socioeconomic segments within a given nation; and (ii) analysing the impact of climate change on within-country income inequality across diverse countries, considering economic development, exposure to long-term climate changes, and related factors. In this review section, we emphasise both (i) and (ii), aiming to offer a comprehensive conceptual and empirical insight into the discussed themes.

Surface temperature

Higher temperatures can lead to more frequent and severe weather events, such as floods, droughts, wildfires, etc. These events often disproportionately affect poor communities, resulting in economic disruptions. Low-income populations often rely more on sectors like agriculture and fisheries, which are highly sensitive to climate variations. Precipitation variability can affect agricultural productivity, leading to crop failures and shortages. The loss of livelihoods in these specific sectors could increase poverty and within-country income inequality. Precipitation variability can also drive food prices, impacting the budgets of lower-income households. Agriculture relies mainly on rainfall, with minimal irrigation coverage, making it vulnerable to changes in rainfall patterns that impact both agricultural output and food security (Di Falco and Chavas 2009). Wealthier households may have more resources to adapt to changing food availability and rising prices, potentially leading to a widening gap in food security between different income groups. The increase in temperatures is expected to increase within-country income inequality through various events discussed below (Hallegatte et al. 2016):

1. Warmer climates in the drylands of the Middle East and Northern Africa would shift vegetation to the north, triggering desertification and soil salinization. These long-term climate shocks can result in potential livelihood impacts for poor people by increasing water stress, affecting livestock and crop production, and having negative impacts on smallholding farmers and herders.
2. In Europe and Central Asia, arid areas are expanding and droughts are becoming more frequent and intense, resulting in desertification, which leads to a reduction of areas available for rain-fed crop production and puts pressure on livestock, negatively impacting smaller agricultural producers.

3. The shift of boreal and temperate forests with heat waves, water stress, forest fires, and tree mortality in boreal forests in Russia could contribute to a decline in timber harvest, endangering the jobs of workers in the forestry sector.
4. Latin America and the Caribbean's dry season length, extreme drought, and forest fires can cause tropical forest degradation, resulting in reduced availability of forest resources for indigenous people, forest dwellers, and communities living on the forest fringe.
5. In South Asia, the melting of glaciers in the Himalayas and Hindu Kush leads to increased seasonal variability of water flows in rivers, which may negatively affect food production for smallholder farmers in the river basins.
6. The retreat of glaciers in Europe and Central Asia is causing a rise in seasonal water variability, leading to a significant water shortage in the long run. This could result in increased water stress, affect irrigated agriculture, and have negative impacts on workers on commercial farms.
7. In Latin America and the Caribbean, negative impacts on water supply due to similar climate shocks can reduce crop production, affecting smallholder farmers and indigenous communities in the Andes.
8. In South Asia, changes in monsoonal precipitation increase river floods, the number of dry days, the severity of droughts, and the reduction of groundwater resources could result in increased water stress affecting crop production with negative impacts for smallholder farmers.
9. In South Asia, alterations in monsoonal precipitation patterns lead to an increase in river floods, a higher number of dry days, severe droughts, and a reduction of groundwater resources. These changes cause an increase in water stress, affecting crop production and negatively impacting smallholder farmers.

A few major studies examine the empirical relationship of the effects of increasing surface temperatures on within-country income inequality. A comprehensive study conducted by Paglialunga et al. (2020), estimates pooled OLS and Fixed Effects estimation techniques on a panel dataset covering 150 nations over the period from 2003 to 2017. They reveal that the increase in temperatures has exacerbated income distribution, exerting a significant influence on the escalation of within-country income disparities. Specifically, rising temperatures and irregular precipitation patterns were found to have adverse and significant effects on within-country inequality, particularly in nations characterized by a larger proportion of their population residing in rural areas and a substantial labour force engaged in agriculture. In their analysis using a global dataset covering subnational poverty in 134 countries, Dang et al. (2023) conclude that a one-degree Celsius increase in temperature correlates with a 1.4 percent rise in the Gini inequality index in a panel of 134 countries. Notably, while climate change disproportionately affects poorer nations, particularly those in South Asia and Sub-Saharan Africa, the research suggests that household adaptation measures may have partially mitigated some of the long-term adverse effects. Chisadza et al. (2023) examine the effects of rising temperatures on income inequality in 50 U.S. states between 1940 and 2015 by computing impulse response functions (IRFs) from the local projections' method. They find an immediate temporary

positive response to income inequality from rising temperatures in the first year, but this response is not permanent. However, if the impacts of rising temperatures remained unabated during earlier periods, income inequality would begin to increase in subsequent periods.

Hypothesis 1: Increase in temperature worsens income inequality.

Climate disaster

Extreme weather events or climate hazards such as heatwaves, floods, droughts, hurricanes, storms, etc. contribute to economic losses and damages, e.g., losses in income, assets, and livelihoods. Individuals with lower incomes frequently inhabit regions that are particularly susceptible to climate disasters, including flood-prone zones and coastal areas. If a country or region encounters a rise in the frequency of extreme weather events, it has the potential to exacerbate within-country income inequality due to the disproportionate impact of economic losses and damages suffered by disadvantaged low-income individuals. Without sufficient support mechanisms like strong unemployment insurance and disaster assistance programs, extreme climate disasters can lead to job losses or reduced working hours, affecting low-income individuals disproportionately due to their limited financial resilience. Pleninger (2022), through a simple model of total income (also see Fig. 4), explains the different impacts of climate disasters on various income groups as follows:

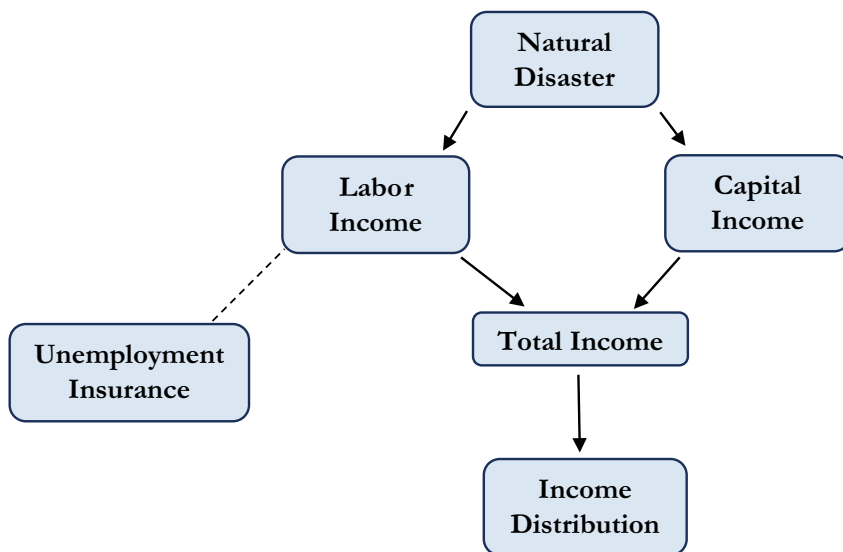


Fig. 4 Mechanism model

$$\begin{aligned}
 Y_{i,t}^{Total} &= Y_{i,t}^{Capital} + Y_{i,t}^{Labour} \\
 &= Y_{i,t}^{Capital} + Y_{i,t}^{Earnings} + Y_{i,t}^{Transfer}
 \end{aligned}$$

In this model, labour income for an individual i at time t , denoted as $Y_{i,t}^{Labour}$, is the sum of earnings ($Y_{i,t}^{Earnings}$), and transfer income ($Y_{i,t}^{Transfer}$). Earnings include wages, salaries, and income from self-employment (e.g., farm income, business income) for individual i , in year t . Capital income, $Y_{i,t}^{Capital}$, denotes any income derived from capital, such as interest payments, rents, and dividends. $Y_{i,t}^{Transfer}$ includes among others unemployment benefits, retirement, social security, and educational assistance. For lower income groups, capital income is low and decreasing, while labour income shares are rising. Within labour income, earnings decline with lower total income, but transfer income increases.

According to this model, individuals with high incomes tend to allocate resources toward financial assets, thereby earning capital income. However, the adoption of advanced technologies, which replace traditional capital, introduces a dynamic shift. While short-term capital income losses may occur initially, the long-term trajectory suggests a potential rise in capital income due to creative destruction. It is important to note that a high-income individual's total income is predominantly composed of labour earnings, mitigating the overall impact of capital losses. Furthermore, insurance coverage for this income group may cushion these losses. Nonetheless, the resilience of high-income individuals in adapting to such economic shifts suggests that the overall impact of climate hazards on their total income is minor.

Climate disasters disproportionately impact low and medium-income groups, with varying degrees of severity. Low-income individuals, typically reliant on wage labour with minimal income stability, are particularly vulnerable to fluctuations in labour income resulting from shifts in employment patterns post-disaster. While some may benefit from post-disaster employment booms and social safety net programs such as unemployment insurance, those without access to such resources face economic hardship. Middle-income earners, often employed in paid labour roles, may have more stable income streams but are still susceptible to the effects of natural disasters. This group commonly includes small to medium-sized business owners who rely on capital income, making them vulnerable to disruptions in business operations and income losses. While social security compensations may offer some relief, the overall impact on the middle-income group is likely to be substantial. In a study by Ghosh (2018), it is found that natural disasters disproportionately impact low-income groups. The research highlights declining local livelihoods in the Sundarbans, Asia's largest mangrove forest, due to fish loss and increasing salinity. Evers and Pathirana (2018) find that flooding and salinization in Vietnam's Mekong Delta, along with rapid social development, have deteriorated agricultural and fisheries livelihoods, widening the income gap.

Few major studies in the field examine this empirical relationship between climate disasters and income inequality, and the evidence presents a mixed picture. Bui et al. (2014), using the Vietnam Household Living Standards Survey (VHLSS), find that natural disasters cause significant drops in per capita income and expenditure

for affected households in Vietnam. The Gini, Theil L, and Theil T indices increase by 0.23%, 0.27%, and 0.30%, respectively, indicating higher poverty levels in both directly affected and overall samples following disasters. A cross-country panel data analysis for the period 1965–2004 is conducted by Yamamura (2015) to study the effects of natural disasters on income inequality, which suggests short-run increases in inequality levels but no effects in the long run. Abdullah et al. (2016), studied the economic impact of Cyclone Aila (2009) on the Sundarbans region of Bangladesh. They found that higher-income households in the Koyra subdistrict were more vulnerable, with damage costs averaging 42% of their annual income, compared to 16% and 15% for middle- and low-income groups, respectively. Keerthiratne and Tol (2018), using a panel fixed effects estimator to find that natural disasters and their immediate aftermath significantly reduce income inequality, as measured by the Theil index. These results are consistent across various inequality metrics, subsamples, and alternative estimators like Ordinary Least Squares and System GMM. However, natural disasters do not impact household expenditure inequality. Miljkovic and Miljkovic (2014) used a fixed-effects econometric model to study states affected by hurricanes over nearly a century. Their findings show that every 100 billion USD in hurricane damages results in a 5.4% increase in income inequality, as measured by the Gini coefficient, indicating that hurricanes tend to exacerbate state-level inequality.

Hypothesis 2: Frequent occurrence of climate disasters increases income disparity.

Climate vulnerability

Several global vulnerability assessments based on indicators have been developed over the past years, focusing on their internal and external validity (Birkmann et al. 2022). Since the IPCC Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation (SREX) report (IPCC 2012) and the evolving understanding of climate risks in the fifth assessment report (IPCC 2014), there is a growing agreement that it is more appropriate to view the vulnerability of societies or ecosystems as a starting point. When a country or region is deemed vulnerable to climate change, it signifies that climate-related events like droughts, floods, and heat waves have negative impacts that could potentially be irreversible. This condition is referred to as ecosystem vulnerability. Systemic societal vulnerability pertains to the attributes of society or its subsystems (such as demographic groups or infrastructure) and is mostly unaffected by the particular climatic threat. The term "systemic" denotes the intrinsic obstacles individuals face in coping with and adjusting to climate change and natural disasters (Birkmann et al. 2022). This is primarily because vulnerable areas have a substantial population that lacks resilience in coping with and adapting to climate disasters. The vulnerability arises from various development hurdles, including poverty, insufficient access to fundamental infrastructure services, poor governance and political influence, a high incidence of displaced individuals, state fragility, below-average life expectancy, and biodiversity degradation. These persistent structural social issues often endure over

many decades, hindering both the state and individuals from effectively responding to climate change and related aftereffects. A country or region exhibiting greater vulnerability to climate change, coupled with an increase in the occurrence of extreme weather events, can worsen domestic income inequality. This is attributed to the disproportionate impact of economic losses and damages experienced by disadvantaged individuals with lower incomes at the time of a climate crisis.

Studies exploring the effects of climate change vulnerability on income inequality remain largely underexplored. One study investigating this relationship is conducted by Cevik and Jalles (2023). Utilising an extensive dataset encompassing 158 countries spanning the period from 1955 to 2019 and employing fixed-effects and panel VAR model, find a positive association between an escalation in climate change vulnerability and the rise in income inequality. Notably, when segregating their sample, they observe that climate change vulnerability does not exert a statistically significant impact on income distribution within advanced economies. However, the coefficient measuring climate change vulnerability is sevenfold greater and statistically significant in the context of developing countries. This disparity can be primarily attributed to the weaker capacity of developing nations in terms of climate change adaptation and mitigation efforts.

Hypothesis 3: Greater vulnerability to climate change aggravates income inequality.

Research gap

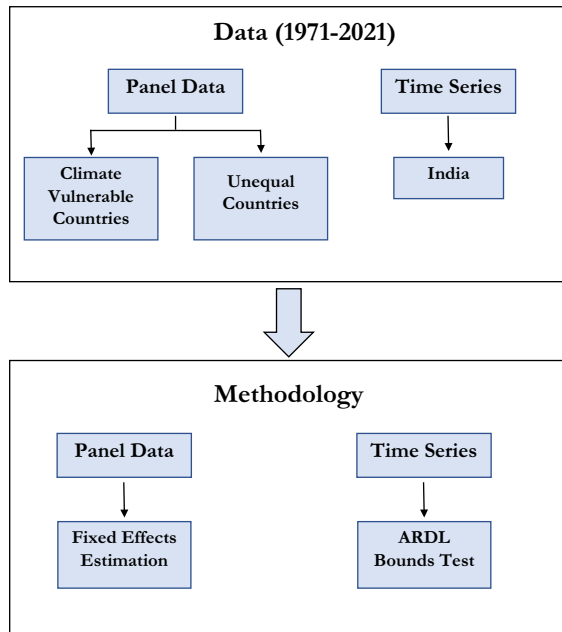
The literature examining the impacts of climate change on income inequality is very thin. A few studies have analysed the relationship collectively, incorporating all the available countries (e.g., Cevik and Jalles 2023; Paglialunga et al. 2020). Our research goes a step further. We facilitate a comparative analysis by delving into specific sub-samples of countries, offering a more detailed and nuanced understanding of climate change's impact on income inequality. The sub-sampling further helps to contextualise the findings in the specific groups as opposed to the generalised findings. Such insights were previously lacking.

Another significant research gap is the lack of research studying this relationship in the Indian context. Not only is India one of the countries most vulnerable to climate change and one of the most unequal countries in terms of income, but it also has a crucial position in the global economy. Hence, studying the climate change-income inequality relationship is necessary.

Methodology

Model specification and variable descriptions

We analyse the empirical relationship between climate change and income inequality while controlling for conventional income inequality determinants (e.g., Cevik and Jalles 2023; Deyshappriya 2017; Jaumotte et al. 2008; Kuznets 1955; Munir and

Fig. 5 Methodological Strategy

Sultan 2017; Odedokun and Round 2001; Skare and Stjepanović 2014; Tanzi 1998), in two different panel settings (39 most unequal countries and 43 countries most vulnerable to climate change) and for India separately. Check Fig. 5, which explains our methodological strategy. We prepare the panel data model following Cevik and Jalles (2023).

Panel model specification

The estimated reduced-form baseline regression model is as follows:

$$Gini_{i,t} = \phi Climate_{i,t} + \gamma X_{i,t} + \eta_i + \Omega_t + v_{i,t} \quad (1)$$

where $Gini_{i,t}$ represents income inequality as quantified by alternative Gini coefficients (gross and net Gini); $Climate_{i,t}$ denotes the different climate change indices we incorporate in this study namely, climate change vulnerability, annual surface temperature change, and total climate-related disaster frequencies; $X_{i,t}$ is a vector of control variables including the log of GDP per capita, square of the log of GDP per capita, age dependency ratio, GDP growth rate, consumer price inflation, trade, unemployment rate, population growth, percent of the urban population, the share of the population using the internet (as a proxy for technological innovation), and principal component analysis (PCA) of highly correlated variables—control of corruption, regulatory quality and rule of law—as a measure of institutional quality. η_i and Ω_t denote the time-invariant country-specific effects and the time effects controlling for common shocks that may impact income distribution across all countries in a

given year. Lastly, $v_{i,t}$ is the white-noise error term. This income-adjusted climate change vulnerability index is calculated by subtracting a country's measured vulnerability index from its expected value based on the regression of vulnerability and the log of GDP per capita. Consequently, the correlation between the adjusted index and the other variables diminishes significantly.

According to Kuznets (1955), income inequality follows an inverted U-shaped pattern, increasing until a certain income level and declining thereafter. Randolph and Lott (1993) further confirm this trend and propose that income inequality is influenced by linear and quadratic income terms, which we incorporate into our specifications, denoted by GDP per capita.

Age dependency can increase income inequality, contributing to the economic burden it places on the working-age population. It can strain resources, reduce investment in human capital, hinder economic productivity, and place a heavier financial burden on the working-age population. This can result in disparities in income and wealth, as those supporting dependents may face economic challenges. Existing empirical literature supports this notion (Dong et al. 2018).

The GDP growth rate is used as a measure of overall economic development. Economic development, via employment generations, inclusive policies, and skill development, reduces income inequality. However, if the development is concentrated in the affluent sections, income disparities might widen.

Inflation, as a measure of monetary policy, is included in this study because it affects (though not homogeneously) different income sources. Ever since the era of David Hume, a prevailing belief has persisted, asserting that wages consistently fall behind the inflation rate. During periods of inflation, price escalations tend to outpace the corresponding increments in monetary wages. Consequently, inflation triggers a reallocation of income away from wage earners and toward profits. It is maintained that this phenomenon exacerbates income inequality, disproportionately affecting the economically disadvantaged (Fischer and Modigliani 1978; Laidler and Parkin 1975). An additional principal mechanism through which inflation fosters the redistribution of income and wealth is the debtor-creditor hypothesis. This redistribution occurs from nominal creditors to nominal debtors when interest rates on assets are denominated in terms of currency and do not fully adjust to the prevailing inflation rate. However, inflation is also found to have mixed and opposite effects on income distribution in several studies (e.g., Berisha et al. 2023; Monnin 2014).

Trade openness is used as a proxy for globalisation, which is a very crucial determinant of income inequality. On one hand, globalisation is considered to stimulate economic growth and social welfare, where developing countries have a chance to trim down the gap with the world economy. Others maintain globalisation as the reason behind worsening income distribution and environmental degradation, causing social degeneration and difficulty in competition. The pro-globalist commentators insist that globalisation has disintegrated national borders and has brought about economic integration, lifting millions out of poverty, promoting economic growth, and closing the inequality gap (Bhagwati 2004; Dollar and Kraay 2002; Zhou et al. 2011). Whereas the anti-globalist commentators assert that globalisation has adverse impacts on particularly the developing economies due to the accentuating within and between countries income inequality (Firebaugh 2003; Stiglitz 2002; Wade 2004).

Unemployment, a key driver of income inequality (e.g., Saunders 2002), is included as a control for labor market policies and conditions. Unemployment forces labours out of income sources, and consequently, increases economic inequality.

Population size is an important factor in income inequality and can have varying effects depending on factors like the level of development, composition, policies, resource availability, and social norms. For instance, in larger populations, there may be opportunities for economies of scale in production and distribution, potentially leading to lower prices for goods and services. This could benefit lower-income individuals by improving their purchasing power and reducing relative income inequality. Larger populations may also offer a broader and more diverse labour force. This can lead to greater wage disparities as competition for certain skilled jobs intensifies, potentially increasing income inequality.

Technological advancements, such as artificial intelligence and advanced machinery, can boost productivity, reduce production costs, and decrease dependence on human labour, potentially widening income disparities. Conversely, technological progress can create new industries and employment opportunities, reducing income inequality. A recent study by Poliquin (2021) illustrates how technology, including broadband adoption, affects wages, leading to disparities between different job positions. The research investigates the introduction of something as relatively mundane as broadband in Brazil between 2000 and 2009. It is revealed that the technology coincided with an increase in wages across the labour market. The average employee saw a wage rise of just 2.3%, whereas those in managerial positions and boardrooms saw a 9% and 19% boost in income, respectively. It is hypothesised that the new technology allowed the more productive workers to be further productive, thus widening the income gap. On the other hand, in a study of country panel data for 29 countries, it is demonstrated that innovation activities reduce personal income inequality by matching patents from the European Patent Office with their inventors (Benos and Tsiachtsiras 2019). Following Baek and Shi (2016), this study introduces internet users as a proxy for technological innovation, a critical factor for both exacerbating and mitigating income inequality.

Wan et al. (2022) note that income inequality in Less Developed Countries (LDCs) is significantly associated with the urban–rural gap. Urbanization may exacerbate income inequality due to higher urban wages compared to rural areas. However, extensive urbanisation can mitigate income inequality through trickle-down effects (Ha et al. 2019).

Lastly, we incorporate institutional quality. Good governance can reduce income inequality via several channels, such as ensuring equitable access to resources, labour market regulations, focusing on progressive taxation and social welfare policies, ensuring political stability and rule of law that can create an environment conducive to prosperity. However, empirical evidence does not find such a straightforward effect. Asamoah (2021), when institutional quality is measured using the World Governance Indicators, finds a quadratic effect for advanced countries but a monotonic negative impact for developing countries. When institutional quality measure derived from the International Country Risk Guide is used as the threshold variable, an inverted U-shaped Kuznets relationship between institutions and income

inequality in both advanced and developing countries is identified. Regardless, institutional quality indeed determines income inequality levels.

For panel data, basic estimation methods such as OLS are prone to inefficiency because they do not discriminate between various cross-sectional units and, thus, may be blamed for camouflaging the heterogeneity existing within each cross-sectional unit. Hence, more sophisticated estimators like the Fixed Effects (FE) or Random Effects (RE) estimators are suitable. The idea behind the RE model is that the variation across the entities is assumed to be random and uncorrelated with the covariates used in the model ($Cov(\alpha_i, Covariates_{it}) = 0$). However, this assumption is potentially impractical in many applications. On the other hand, in the FE model, the intercept varies across individuals (countries in this case) and hence, it relies on the variation within individuals and not between them. It is assumed that, if not controlled for, something with the individual may bias the outcome variables, which is the justification of the assumption of the correlation between the predictor variables and the entity's error term. In simpler terms, the consistent estimation in the FE model does not impose that the unobserved heterogeneity is uncorrelated with the explanatory variables ($Cov(\alpha_i, Covariates_{it}) \neq 0$). We run the Hausman test to decide between fixed or random effects model. The null hypothesis of the Hausman test is that the preferred model is random effects. It tests whether the unique errors are correlated with the regressors and the null hypothesis is they are not. We cluster robust standard errors at the country level to control for heteroskedasticity, cross-sectional dependence, and any potential correlation of standard errors among countries.⁷ We also test for suitability of time effects using the testparm i.year command. If the test statistic is significant, we reject the null that the coefficients for all years are jointly equal to zero, therefore time fixed effects are necessary. Since the climate change vulnerability index tends to be strongly correlated with macroeconomic variables, such as GDP per capita, we adjust the index for the level of income.

India model specification

We model the climate change and income inequality relationship for the Indian context in the following form:

$$NetGini = f(\text{Surface Temperature Change}, Z) \quad (2)$$

where Z is a set of income inequality determinants of India consisting of government consumption, PCA of strongly correlated fertility rate and age dependency ratio to quantify population characteristics, consumer price inflation, gross secondary school enrollment, globalization index, log of GDP per capita, and square of the log of GDP per capita. We only use annual surface temperature change as a climate change indicator for India because data for other indicators are available for shorter periods, which would make the number of observations even smaller and that would consequently make having meaningful and reliable inferences tougher. Due to the

⁷ We also checked with Heteroscedasticity and Autocorrelation Consistent (HAC) standard errors and the results are same.

strong correlation between the climate change variable and other regressors, we create a GDP per capita adjusted index following the same steps as earlier. We only include net Gini in this model because, attributing the complex Indian tax structures to a significantly large informal economy, disposable income is more intuitive and informative for the income distribution context. Additionally, in the related literature, net Gini is most preferred as it accounts for the fiscal policies implemented in a given year. We also linearly interpolate the few missing observations for the secondary school enrollment variable. As a measure of fiscal policy, we include government consumption because it is a crucial determinant of income inequality in India (Munir and Sultan 2017). It can have both positive and negative impacts. For instance, if the government chooses to spend more on welfare benefits, that would most certainly reduce the level of income inequalities since the workforce gets a shot at improving their skills. However, unrestrained government expenditure is known to crowd out private investments, which might stagnate employment conditions and thus, increase income disparity. Also, if government expenditure is concentrated on fields like the military, that might repel foreign investors because they deem such settings hostile (Wisniewski and Pathan 2014). We carefully chose the control variables and kept their numbers limited to avoid overfitting and reducing degrees of freedom.

For estimating the relationship in the Indian context, we adopt the ARDL bounds testing approach. The ARDL approach to cointegration was first developed by Pesaran and Shin (1997). Pesaran et al. (2001) subsequently redeveloped the bounds testing approach. We chose this particular model due to its five comparative advantages over earlier and more cointegration techniques and simple regression techniques. First, the ARDL model does not require all variables to be in the same order of integration; it can be deployed even when the included series have both $I(0)$ and $I(1)$ integrations. Second, ARDL circumvents the assumption of equal lag length, unlike the traditional cointegration models. Third, one of the main advantages of using the ARDL approach to cointegration is that the power of this test does not suffer in finite samples when invalid restrictions are imposed. For its finite sample properties, the ARDL bounds test approach to cointegration is robust and performs better even in smaller samples (Mah 2000; Pattichis 1999; Tang and Nair 2002). Fourth, the ARDL approach can generate non-biased long-run model estimates (Harris and Sollis 2003). Fifth, a bound testing approach is possible even when the explanatory variables are endogenous (Alam and Quazi 2003; Tang 2004).

In accordance with Pesaran et al. (2001), the ARDL model of this study is specified as follows:

$$\begin{aligned}
\Delta gini_disp = & \alpha_0 + \sum_{i=1}^n \alpha_{1i} \Delta gini_disp_{t-i} + \sum_{i=1}^n \alpha_{2i} \Delta annual_surface_temp_{t-i} + \sum_{i=1}^n \alpha_{3i} \Delta pop_stat_{t-i} \\
& + \sum_{i=1}^n \alpha_{4i} \Delta gov_con_{t-i} + \sum_{i=1}^n \alpha_{5i} \Delta inf_{t-i} \\
& + \sum_{i=1}^n \alpha_{6i} \Delta sec_school_{t-i} + \sum_{i=1}^n \alpha_{7i} \Delta kof_{t-i} + \sum_{i=1}^n \alpha_{8i} \Delta lgdp_{t-i} \\
& + \sum_{i=1}^n \alpha_{9i} \Delta lgdp_{t-i} + \beta_1 gini_disp_{t-1} \\
& + \beta_2 annual_surface_temp_{t-1} + \beta_3 pop_stat_{t-1} + \beta_4 gov_con_{t-1} + \beta_5 inf_{t-1} \\
& + \beta_6 sec_school_{t-1} + \beta_7 kof_{t-1} + \beta_8 lgdp_{t-1} \\
& + \beta_9 lgdp_{t-1} + \varepsilon_t
\end{aligned} \tag{3}$$

where Δ is the first difference operator, n is the lag length, α_1 - α_9 denote the dynamic short-run coefficients, β_1 - β_9 are the long-run multipliers and ε_t is the error term.

To carry out the ARDL bounds testing procedure, there are two stages. The first stage involves testing for a cointegrating relationship to establish whether there is a linear combination for nonstationary processes and determines the long-run level relationship between variables. From Eq. (3), the null hypothesis for testing no cointegration is given by:

$$H_0 : \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = \beta_8 = \beta_9 = 0$$

The f-statistic of the joint significance test (Wald test) is used to determine whether the lagged level of the variables is significant and cointegrated in the Conditional Error Correction model. The F-statistic is compared with the two asymptotical critical value sets developed by Pesaran et al. (2001), suitable for large sample studies, and further developed by Narayan (2004, 2005) to accommodate smaller sample studies ranging between 30 and 80 observations. The first set assumes that all the variables are $I(0)$, while the other assumes all the variables are $I(1)$. The decision to reject the null hypothesis of no cointegration depends on whether the F-statistic is greater than the $I(1)$ bound. If the F-statistic falls above the $I(1)$ bounds, a long-run level relationship exists; if it falls below the $I(0)$ bound, there is no existence of a long-run cointegrating relationship; the outcome remains inconclusive if the F-statistic falls between the bounds. It is to be noted that before testing for the cointegrating relationship, the variables are to be first tested for the presence of unit roots to determine stationarity. This is necessary to confirm whether all series are either $I(0)$ or $I(1)$. $I(2)$ series may lead to biased F-test results. The second stage of ARDL modelling deals with the estimation of the coefficients of the long-run relationships as well as interpreting the values of the estimated coefficients. Using the Akaike Information Criterion (AIC), the optimal lag length of the ARDL model is determined.

On confirmation of cointegration, the error correction model (ECM) is specified as follows:

$$\begin{aligned}
\Delta gini_disp = & \theta_0 + \sum_{i=1}^n \theta_{1i} \Delta gini_disp_{t-i} + \sum_{i=1}^n \theta_{2i} \Delta annual_surface_temp_{t-i} \\
& + \sum_{i=1}^n \theta_{3i} \Delta pop_stat_{t-i} + \sum_{i=1}^n \theta_{4i} \Delta gov_con_{t-i} + \sum_{i=1}^n \theta_{5i} \Delta inf_{t-i} \\
& + \sum_{i=1}^n \theta_{6i} \Delta sec_school_{t-i} + \sum_{i=1}^n \theta_{7i} \Delta kof_{t-i} \\
& + \sum_{i=1}^n \theta_{8i} \Delta lgdppc_{t-i} + \sum_{i=1}^n \theta_{9i} \Delta lgdppc_sq_{t-i} + \varphi ECT_{t-1} \\
& + \mu_t
\end{aligned} \tag{4}$$

In Eq. (4), $\theta_1 - \theta_9$ are the short-run coefficients, φ is the coefficient of the error correction term (*ECT*) which captures the long-run dynamics and μ_t is the residual error term. The validity of the error correction mechanism depends on the size and sign of the coefficient representing the speed of adjustment. φ is expected to have a negative value and be statistically significant.

Data type and source

The study involves annual data ranging from 1971 to 2021. We incorporate two different panel datasets (unbalanced): (i) 43 countries most vulnerable to climate change (compiled using reports from Germanwatch's Global Climate Risk Index 2021, INFORM Climate Change Risk Index, and IPCC 2022), and (ii) 39 most unequal countries in terms of income (compiled from World Inequality Lab's Top 10% Income data and SWIID database). For India, we prepared a time series dataset. We collect data from various sources, namely, UN World Population Prospects, World Development Indicators-World Bank, Worldwide Governance Indicators-World Bank, ND-GAIN, Emergency Events Database (EM-DAT) World Bank Education Statistics, Food and Agriculture Organization (FAO), SWIID, KOF, and International Financial Statistics (IFS) by the IMF. For detailed variable information, summary statistics, and source links, refer to Online Appendix II, III and XXII.

Results and discussion

Panel analysis

Tables 1 and 2 display our baseline estimation results of Eq. (1) where fixed effects-regression is estimated. The highly significant test statistics confirm the suitability of the fixed effects model, including time fixed-effects across all specifications. We find that an increase in all three climate change indices worsens gross income inequality in unequal countries (Table 1). The impact of climate change vulnerability is most profound on income distribution. A one-unit increase in vulnerability, surface temperature, and climate-related disasters leads to approximately 59, 0.67, and 0.05 unit increases in gross income inequality, respectively, and the coefficients are significant

Table 1 Fixed effects estimation (Climate Change and Gross Gini)

Dependent Variable: <i>gini_mkt</i>	(1)	(2)	(3)	(4)	(5)	(6)
	Unequal Countries			Vulnerable Countries		
<i>vulnerability</i>	58.563** (26.142)	0.667** (0.243)	0.050** (0.024)	29.617 (17.666)	0.274 (0.171)	− 0.002 (0.024)
<i>annual_surface_temp</i>						6.563** (2.997)
<i>climate_disaster</i>						− 0.565*** (0.178)
<i>lgdppc</i>	− 2.146 (5.085)	2.828 (4.644)	2.592 (5.046)	3.733 (2.918)	3.924 (3.232)	0.074 (0.064)
<i>lgdppc_sq</i>	0.056 (0.273)	− 0.088 (0.287)	− 0.089 (0.298)	− 0.425** (0.190)	− 0.383* (0.207)	0.005 (0.016)
<i>age_dep</i>	− 0.010 (0.078)	0.004 (0.068)	0.013 (0.085)	0.063 (0.058)	0.068 (0.063)	0.003 (0.002)
<i>gdp_growth</i>	− 0.017 (0.020)	− 0.042* (0.024)	− 0.018 (0.029)	− 0.009 (0.013)	− 0.009 (0.015)	− 0.012 (0.014)
<i>inf</i>	0.012* (0.007)	0.012* (0.007)	0.010* (0.006)	0.002 (0.002)	0.001 (0.002)	− 0.050 (0.050)
<i>trade</i>	0.000 (0.015)	− 0.008 (0.013)	− 0.001 (0.015)	− 0.007 (0.012)	− 0.008 (0.012)	− 0.307 (0.343)
<i>unemployment</i>	− 0.001 (0.116)	− 0.133 (0.125)	− 0.059 (0.137)	− 0.030 (0.041)	− 0.043 (0.046)	− 0.039 (0.082)
<i>pop_gr</i>	0.031 (0.561)	0.319 (0.527)	0.489 (0.623)	− 0.251 (0.259)	− 0.086 (0.314)	0.002 (0.018)
<i>urb</i>	0.239 (0.123)	0.231* (0.130)	0.309** (0.136)	− 0.074 (0.074)	− 0.077 (0.079)	1.529** (0.686)
<i>internet</i>	− 0.049 (0.031)	− 0.055* (0.031)	− 0.040 (0.033)	0.002 (0.018)	− 0.001 (0.020)	532
<i>inst_qual</i>	1.057 (0.989)	1.220 (1.002)	1.094 (1.116)	1.373* (0.694)	1.499** (0.713)	0.5717
Observations	778	736	638	660	629	82.42***
R ²	0.4771	0.5027	0.4561	0.5643	0.5601	8.67***
Hausman Test statistic	57.02***	81.99***	64.53***	105.20***	99.13***	
testparm i:year	2.97***	6.17***	4.32***	3.02***	3.15***	

***, **, and * represent significance at 1%, 5%, and 10% levels, respectively

Robust standard errors are mentioned in the parenthesis

Table 2 Fixed effects estimation (Climate Change and Net Gini)

Dependent Variable: <i>gini_disp</i>	(1)	(2)	(3)	(4)	(5)	(6)
	Unequal Countries			Vulnerable Countries		
<i>vulnerability</i>	51.251* (25.404)	0.736*** (0.213)		33.934* (17.614)		
<i>annual_surface_temp</i>			0.056* (0.031)		0.324* (0.162)	− 0.018 (0.025)
<i>climate_disaster</i>			3.289 (4.905)			6.733** (2.899)
<i>lgdppc</i>	− 1.071 (5.205)	3.603 (4.702)	− 0.187 (0.295)	3.703 (2.851)	3.551 (3.156)	− 0.563*** (0.176)
<i>lgdppc_sq</i>	− 0.040 (0.279)	− 0.188 (0.286)	0.040 (0.079)	− 0.423** (0.186)	− 0.349* (0.204)	0.062 (0.059)
<i>age_dep</i>	0.007 (0.076)	0.022 (0.065)	0.007 (0.026)	0.051 (0.054)	0.060 (0.058)	0.002 (0.018)
<i>gdp_growth</i>	0.004 (0.019)	− 0.018 (0.021)	0.010** (0.005)	− 0.011 (0.014)	− 0.008 (0.015)	0.003 (0.002)
<i>inf</i>	0.011* (0.006)	0.012* (0.006)	− 0.009 (0.012)	0.002 (0.002)	0.002 (0.002)	− 0.012 (0.014)
<i>trade</i>	− 0.009 (0.013)	− 0.016 (0.013)	− 0.065 (0.132)	− 0.005 (0.011)	− 0.007 (0.012)	− 0.021 (0.057)
<i>unemployment</i>	− 0.008 (0.114)	− 0.141 (0.119)	0.567 (0.636)	− 0.000 (0.052)	− 0.168 (0.343)	− 0.385 (0.349)
<i>pop_gr</i>	− 0.327 (0.579)	− 0.071 (0.561)	0.281** (0.110)	− 0.319 (0.280)	− 0.069 (0.084)	− 0.027 (0.085)
<i>urb</i>	0.217** (0.107)	0.203* (0.102)	− 0.055* (0.032)	− 0.068 (0.078)	− 0.021 (0.020)	− 0.018 (0.020)
<i>internet</i>	− 0.063** (0.031)	− 0.068** (0.030)	1.336 (1.127)	− 0.016 (0.018)	1.346* (0.782)	1.430* (0.776)
<i>inst_qual</i>	1.307 (1.022)	1.454 (1.034)	638	1.236 (0.752)	629	532
Observations	778	736	0.5231	660		0.5974
R ²	0.5317	0.5636	75.27***	0.5829	0.5802	
Hausman Test statistic	60.95***	96.05***	5.57***	64.86***	60.24***	49.10***
testparm i:year	1.94**	9.03***		3.62***	7.47***	4.45***

***, **, and * represent significance at 1%, 5%, and 10% levels, respectively
Robust standard errors are mentioned in the parenthesis

Table 3 Heteroskedasticity and slope heterogeneity tests

	Modified Wald Test for group-wise Heteroskedasticity	Slope Heterogeneity Test	
		Delta	Adj. Delta
Table 1 (1)	43,386.6***	7.64***	12.87***
Table 1 (2)	23,981.5***	6.92***	11.65***
Table 1 (3)	0.0***	3.43***	7.49***
Table 1 (4)	12,703.2***	2.11**	4.55***
Table 1 (5)	6618.5***	1.68*	3.56***
Table 1 (6)	54,228.0***	− 1.99**	− 8.66**
Table 2 (1)	42,487.6***	6.73***	11.34***
Table 2 (2)	11,748.9***	5.97***	10.05***
Table 2 (3)	0.0***	2.71***	5.91***
Table 2 (4)	24,691.7***	2.67***	5.76***
Table 2 (5)	13,386.2***	2.42***	5.14***
Table 2 (6)	21,042.3***	− 0.95	− 4.14***

***, **, and * represent significance at 1%, 5%, and 10% levels, respectively

at a 5% level. For vulnerable nations, though we find positive and economically significant coefficients for vulnerability and surface temperature change, they are statistically insignificant. We find no impact of climate-related disasters on gross income inequality in vulnerable countries. This is possible if disasters affect middle-income groups, thereby leaving income inequality levels unaltered (Pleninger 2022). We find negative and statistically significant coefficients of the squared log of GDP per capita in the panel of vulnerable countries, which suggests that gross income inequality decreases with prolonged economic growth.

In Table 2, we plot the empirical outcomes of the climate change and net income inequality relationship. We find that the coefficient of climate change indices is positive and significant across all specifications, except for specification (6). A unit increase in vulnerability worsens income inequality in both unequal and vulnerable countries by approximately 51 and 34 units, respectively. Surface temperature change by a unit leads to an approximately 0.74 unit increase in the net Gini in the unequal countries, and the coefficient is significant at a 1% level whereas it has a comparatively smaller impact for the vulnerable countries. Climate-related disaster is found to slightly increase net income inequality, with a statistically significant relationship at a 10% level for the unequal countries, while no relationship is found for the vulnerable nations. Technical innovation (proxied by share of internet users in our case) reduces net income inequality in the group of unequal countries, and the coefficients are significant at 5 and 10 percent level.

In general, our findings in Tables 1 and 2 are in line with existing literature that unanimously agrees on the aggravating effects of climate change on income inequality (for instance, see, Cevik and Jalles 2023; Paglialunga et al. 2020).

Table 3 presents the diagnostic test results for heteroskedasticity and slope heterogeneity (Pesaran and Yamagata 2008) for all the specifications. The significant

Table 4 Multicollinearity Tests

Corresponding Equations (For both Table 1 and 2) →	Unequal countries			Vulnerable countries		
	(1)	(2)	(3)	(4)	(5)	(6)
<i>vulnerability</i>	1.68			2.47		
<i>annual_surface_temp</i>		1.33			1.22	
<i>climate_disaster</i>			1.75			1.33
<i>lgdppc</i>	6.85	5.53	5.77	9.45	6.77	7.52
<i>age_dep</i>	6.34	6.07	7.91	4.44	4.37	4.83
<i>gdp_growth</i>	1.13	1.16	1.16	1.15	1.18	1.23
<i>inf</i>	1.10	1.10	1.09	1.09	1.08	1.10
<i>trade</i>	1.29	1.34	1.51	1.18	1.20	1.17
<i>unemployment</i>	1.41	1.42	1.32	1.52	1.57	1.38
<i>pop_gr</i>	4.20	4.07	4.78	3.30	3.39	3.62
<i>urb</i>	3.86	3.14	3.63	7.45	5.65	5.87
<i>internet</i>	2.31	2.66	2.27	2.30	2.61	2.48
<i>inst_qual</i>	1.40	1.38	1.40	1.72	1.69	1.76
Mean VIF	2.87	2.65	2.96	3.28	2.79	2.94

Table 5 Pesaran (2015) Cross-sectional dependence test

	Unequal countries	Vulnerable countries
<i>gini_mkt</i>	86.89***	71.85***
<i>gini_disp</i>	86.09***	72.26***
<i>vulnerability</i>	53.01***	30.94***
<i>annual_surface_temp</i>	91.22***	79.12***
<i>climate_disaster</i>	42.66***	40.99***
<i>lgdppc</i>	106.34***	89.40***
<i>age_dep</i>	33.48***	44.91***
<i>gdp_growth</i>	37.68***	28.34***
<i>inf</i>	22.37***	28.22***
<i>trade</i>	98.35***	79.25***
<i>unemployment</i>	20.17***	32.14***
<i>pop_gr</i>	26.60***	27.70***
<i>urb</i>	107.63***	93.23***
<i>internet</i>	71.63***	42.00***
<i>inst_qual</i>	3.28***	3.88***

***, **, and * represent significance at 1%, 5%, and 10% levels, respectively

test statistics indicate the presence of heteroskedasticity and slope heterogeneity. In Table 4, we show the VIF to examine multicollinearity issues in our specifications. The values are all below 10, with the means less than 4. Hence, we can safely conclude there are no multicollinearity issues. In Table 5, the test statistics of the

Table 6 Unit root tests

H_0 : Unit Root					
Variables	Augmented Dickey-Fuller		Phillips-Perron		Decision
	Stationarity in Levels	Stationarity in First Difference	Stationarity in Levels	Stationarity in First Difference	
<i>gini_disp</i>	– 1.782	– 4.001***	– 1.345	– 3.765***	I(1)
<i>annual_surface_temp</i>	– 5.746***	–	– 5.703***	–	I(0)
<i>pop_stat</i>	– 4.132**	–	– 4.132**	–	I(0)
<i>gov_con</i>	– 2.851	– 5.109***	– 1.986	– 4.992***	I(1)
<i>inf</i>	– 3.504**	–	– 4.969***	–	I(0)
<i>sec_school</i>	– 2.382	– 3.545**	– 1.915	– 6.329***	I(1)
<i>kof</i>	2.072	– 1.814*	2.947	– 2.563**	I(1)
<i>lgdppc</i>	– 1.402	– 6.048***	– 1.615	– 6.089***	I(1)
<i>lgdppc_sq</i>	– 1.179	– 5.924***	– 1.361	– 5.965***	I(1)

***, **, and * represent significance at 1%, 5%, and 10% levels, respectively

Pesaran (2015) cross-sectional dependence test are highly significant at 1% level, which confirms the presence of strong cross-sectional dependence for all variables.⁸

India analysis

We start our analysis for India by performing the Augmented Dickey-Fuller and the Phillips-Perron tests to ensure that no variables included in our model are integrated into order 2. Based on the results in Table 6, we confirm that none of the series are I(2).

Subsequently, we perform the ARDL bounds test for cointegration. We find that the F-statistic is higher than the critical value bounds at all significance levels. Consequently, the null hypothesis of no cointegration is rejected, and we conclude that there is a long-term relationship among the variables (see Table 7).

After confirming cointegration, we estimate the ARDL ECM model. The optimal lag length is determined using the AIC criterion. The AIC selected ARDL (1, 1, 2, 2, 2, 3, 2, 0, 2) for the model. The short- and long-run estimations are reported in Table 8. We find that in the long-run, a unit-positive change in annual surface temperature leads to a 1.57 unit increase in income inequality in India. The coefficient is statistically significant at the 10% level. In the short run, we find an economically and statistically significant (5% level) coefficient of climate change that indicates an income inequality worsening impact of climate change. This finding is similar to Aggarwal (2021) who concludes that climate shocks are responsible for worsening consumption inequality among Indian sectors. Most importantly, the coefficient of the lagged error correction term is highly significant at a 1% level and negative,

⁸ The cross-sectional dependence test has been performed prior to the estimations.

Table 7 Bounds test

Dependent Variable	Function	F-Statistic
<i>gini_disp</i>	$f(gini_disp annual_surface_temp, pop_stat, gov_con, inf, lgdppc, sec_school, lgddpc_sq)$	8.0384****
Critical Values		
1%	2.5%	5%
I(0)	I(0)	I(0)
	I(1)	I(1)
2.45	3.79	3.4
	2.15	1.91
		3.11
		1.66
		2.79

****, ***, **, and * represent significance at 1%, 2.5%, 5% and 10% level, respectively

Table 8 Long- and short-run estimates: ARDL-ECM model

Long-Run Estimates		
Dep. Variable: <i>gini_disp</i>		
	Coefficient	Std. Errors
<i>annual_surface_temp</i>	1.572*	0.924
<i>pop_stat</i>	7.507***	1.868
<i>gov_con</i>	1.424***	0.264
<i>inf</i>	0.044*	0.022
<i>sec_school</i>	0.117*	0.060
<i>kof</i>	0.527***	0.069
<i>lgdppc</i>	1.285	2.287
<i>lgdppc_sq</i>	-0.211	0.231
Short-Run Estimates		
Dep. Variable: $\Delta gini_disp$		
	Coefficient	Std. Errors
<i>ECT</i> (-1)	- 0.649***	0.066
$\Delta annual_surface_temp$	0.452**	0.191
Δpop_stat	- 23.526*	12.941
Δpop_stat (-1)	41.290***	13.032
Δkof	0.208***	0.064
Δkof (-1)	0.039	0.068
Δkof (-2)	0.175**	0.064
Δgov_con	0.461***	0.117
Δgov_con (-1)	- 0.490***	0.155
Δsec_school	0.145***	0.037
Δsec_school (-1)	0.170***	0.038
$\Delta lgdppc$	- 17.145***	4.628
$\Delta lgdppc$ (-1)	- 18.541***	4.776
$\Delta lgdppc_sq$	1.356***	0.363
$\Delta lgdppc_sq$ (-1)	1.528***	0.393
R^2	0.8238	
Adj. R^2	0.7468	
Ramsey RESET t-statistic	1.120 (0.2741)	
Jarque-Bera test statistic	3.109 (0.2113)	
Breusch-Godfrey F-statistic	0.596 (0.5595)	
Breusch-Pagan-Godfrey F-statistic	0.860 (0.6401)	

***, **, and * represent significance at 1%, 5%, and 10% levels, respectively

The p-values of the test statistics are mentioned in the parentheses

supporting the evidence of a stable long-run relationship among the variables. This coefficient denotes that a deviation from the long-run equilibrium level is corrected

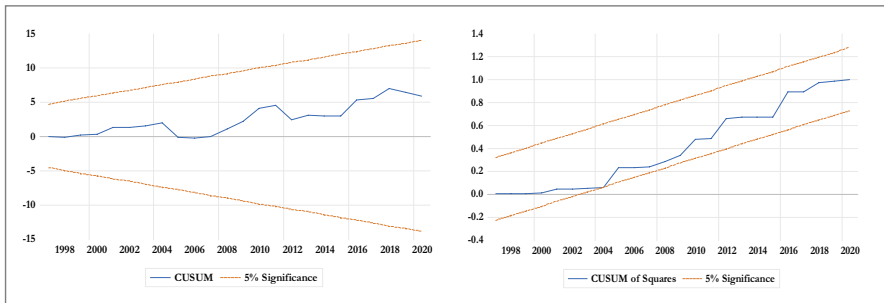


Fig. 6 Parameter Stability Tests

by approximately 65% over the following year. In other words, there is long-run convergence toward equilibrium. Apart from the central findings, we also present some insightful and interesting results. We find that lagged population characteristics, that include fertility rate and age dependency ratio worsen the income distribution situation in India the most. Globalisation is found to have a significant income inequality worsening effect, in line with several studies (e.g., Munir and Bukhari 2020; Sethi et al. 2021). Government consumption in the previous period is effective in reducing income inequality, though worsens the income inequality in the contemporary period. Though not significant, the long-run estimates of per capita GDP conform to the Kuznets Curve hypothesis (Kuznets 1955). However, we find exactly opposite and significant outcomes in the short-run. The most interesting of all is that we find gross enrollment ratio in secondary schools increases income inequality, contrary to our expectations. There can be a few explanations for this counterintuitive finding: maybe secondary education isn't enough to have sufficient earnings; merely an increase in enrollment does not paint the bigger picture, as the quality of skills and standard of education imparted are more important; enrollment statistics do not shed light on the drop-out figures, and more drop-outs lead to a worse-off population.

Our model is subjected to and passes a battery of diagnostic tests, which are reported in Table 8 and Fig. 6. The insignificant Ramsey RESET, Jarque–Bera, Breusch–Godfrey, and Breusch–Pagan–Godfrey test statistics reveal that our model does not suffer from any misspecification, non-normal distribution of the error term with non-zero mean, autocorrelation, and heteroskedasticity problems, respectively. Lastly, Fig. 6 shows that the CUSUM and CUSUM of squares tests confirm the parameter stability (CUSUM lines fall within the 5% significance boundary).

Robustness check

To confirm the soundness of the findings, we follow a few steps. First, we merge the two panels and run the same panel estimation technique. Second, we introduce three new control variables: agriculture value addition, financial development

index, and government consumption⁹, and employ different combinations of control variables.¹⁰ Lastly, to check for any spillover effect from the previous period, we introduce regressors lagged by a period. We incorporate the second and third steps mentioned above for the merged panel and the two separate panels. We resort to fixed effects estimation with time-fixed effects. The findings are consistent with our main empirical results. We find that climate change indices, both contemporary and lagged, increase income inequality in the merged panel, the vulnerable and unequal countries and the coefficients are mostly statistically significant. We do not find any considerable deviations (see Online Appendix VII—XXI). Hence, we conclude that our findings are robust to different specifications.

Conclusion

Climate change presents a unique and ever-evolving challenge to the global economy. Building on the previous contributions to climate change and income inequality literature, we focus on the impacts of climate change on income distribution in a set of 39 highly unequal countries in terms of income distributions, a set of 43 countries highly vulnerable to climate change, and India, spanning from 1971 to 2021. We employ the fixed effects estimation technique for the panel datasets and the ARDL bounds test approach to estimate the relationship for India. In general, our empirical analysis concludes that climate change, quantified by three different indices, has deleterious effects on income distribution in both groups and India, after controlling for conventional determinants of income inequality, in line with existing theory and related studies.

We find that for unequal and vulnerable countries, climate change indices have a statistically significant impact on income inequality (both gross and net) in unequal countries, with vulnerability having the most profound effect. In unequal countries, a one-unit increase in vulnerability, surface temperature, and climate-related disasters leads to 59, 0.7, and 0.06 units of increase in gross income inequality. However, in vulnerable countries, the impact of vulnerability and surface temperature change is positive but statistically insignificant, and climate-related disasters have no significant impact. The coefficients of climate change indices are positive and significant (except for climate disasters) when analysing their impacts on net Gini. An increase in vulnerability worsens income inequality in both unequal and vulnerable countries, with a more pronounced effect in unequal countries. Surface temperature change has a highly

⁹ Agriculture has significantly large contributions to the economies in the developing nations; Financial development is an established determinant of income inequality that has range of impacts (Asamoah 2021; Vo et al. 2023).

¹⁰ We first run the regression including only the climate change index. Subsequently, we keep on adding one variable at a time and note the outcomes. We ensure that we test combinations of control variables as used in different literature. We decide the priority of the control variables to add first based on the importance laid on them in the existing literature. We keep the order of control variables as shown in Appendix VIII consistent for the subsequent robustness checks (online Appendix IX—XIX). Of course, deciding the priority of the control variables can be subjective and the order can be altered but it is unlikely to obtain significantly deviated estimates of climate change impacts.

significant impact on net Gini in unequal countries but a smaller impact in vulnerable countries. Climate-related disasters increase net income inequality in unequal countries, while no significant relationship is found for vulnerable nations. Our findings are robust to different specifications. In India, we find that in the long run, income inequality is worsened by 1.57 units with each unit increase in surface temperature, and the coefficient is marginally significant at the 10% level. In the short run, we conclude that a unit increase in surface temperature leads to approximately 0.45 units increase in net income inequality, and the coefficient is statistically significant at 5% level.

Policy implications

Our empirical findings have several direct policy implications. Climate change is already an inevitable reality, and its detrimental impacts on income inequality, among many other aspects, are more ascertained than before. In line with our findings and existing literature, we present the following policy recommendations:

- i. Since the less developed and emerging market economies have barely contributed to stocks of greenhouse gases and have comparatively low energy consumption per capita, which are key drivers of climate change, imposing emissions reduction obligations on them can be unfair and inconsistent with their development goals. That being acknowledged, they have emerged to be on the frontlines of the climate crisis. Hence, it will be prudent for policymakers to implement inclusive development policies that are consistent with climate adaptation and mitigation goals. In other words, green growth and sustainable development are the way ahead.
- ii. The impacts of climate change are unequal on various economic sections of society, with poorer populations being more vulnerable to them. Hence, social safety nets and facilities for underprivileged sections should be improved to enhance their ability to cope with climate shocks.
- iii. To tackle the threat of climate change on income inequality, physical and financial resilience should be enhanced.
- iv. Not only does climate change amplify income inequality, but there is also a growing body of literature that substantiates the reciprocal relationship wherein income inequality contributes to climate change (e.g., Ali 2022; Oanh and Ha 2023). Thus, there is a potential vicious cycle. We propose targeted intervention toward tackling them at the same time. For instance, climate change mitigation policies, such as implementing a carbon tax and eliminating fossil fuel subsidies, should be crafted to ensure fairness and include provisions for providing direct cash transfers to compensate low-income households for any increases in energy costs; increasing access to education, heavily subsidised green energy, raising environmental awareness, implementing behavioural nudges and incentivisation of sustainable practices among the poorer sections at the cost of green taxation for the financially affluent sections might prove beneficial in curbing income inequality and climate change simultaneously.

Limitations and recommendations

We suggest future studies be carried out, considering several other avenues that will further enrich the literature. There is an obvious call for empirical analysis using dynamic panel estimation techniques to capture the evolution of the relationship more extensively. Given the simultaneity and reverse causation in the climate change-inequality relationship, efforts should be directed toward finding suitable instruments for climate change to facilitate IV-2SLS estimation. Data availability was an issue for the panel analyses that proved to be restrictive. For example, due to the lack of and missing observations, we could not employ more sophisticated dynamic estimation techniques like the CCE-GMM estimation that controls for endogeneity and cross-sectional dependence more robustly. Another recommendation is to use monthly or quarterly data for single-country analyses, as they can provide better insights. Limiting a study to only annual data can be prohibitive for single-country analyses in the sense that a smaller dataset limits the number of options for estimation techniques and, of course, biased results. The literature is extremely thin for India, and given how precariously India is placed in terms of income distributions and climate change, more research should be targeted in this direction. Using IHDS datasets to create an income inequality index will most certainly enlarge the Indian dataset, facilitating state-wise analysis, and prove to be a great next step.

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1007/s43546-024-00685-8>.

Author contributions Swapnanil SenGupta, the first author, conceived the idea for the paper and designed the analysis. He also collected the data and performed the data analysis. The second author, Aakansha Atal, prepared the literature review and the theoretical framework. She also prepared the charts and the tables. Both authors discussed the results and contributed to the final manuscript.

Funding Open Access funding enabled and organized by Projekt DEAL.

Data availability All data sources are provided in the article along with links. The compiled datasets and the regression codes for replication are available on request.

Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

Open Access This article is licensed under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License, which permits any non-commercial use, sharing, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if you modified the licensed material. You do not have permission under this licence to share adapted material derived from this article or parts of it. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by-nc-nd/4.0/>.

References

- Abdullah AN, Mohammad KK, Zander BM, Stacey N, Garnett ST (2016) A short-term decrease in household income inequality in the Sundarbans, Bangladesh, following cyclone Aila. *Nat Hazards* 83(2):1103–1123. <https://doi.org/10.1007/s11069-016-2358-1>
- Aggarwal R (2021) Impacts of climate shocks on household consumption and inequality in India. *Environ Dev Econ* 26(5–6):488–511. <https://doi.org/10.1017/S1355770X20000388>
- Alam I, Quazi R (2003) Determinants of capital flight: an econometric case study of Bangladesh. *Int Rev Appl Econ* 17(1):85–103. <https://doi.org/10.1080/713673164>
- Ali IMA (2022) Income inequality and environmental degradation in Egypt: evidence from dynamic ARDL approach. *Environ Sci Pollut Res* 29(6):8408–8422. <https://doi.org/10.1007/s11356-021-16275-2>
- Asamoah LA (2021) Institutional quality and income inequality in developing countries: a dynamic panel threshold analysis. *Prog Dev Stud* 21(2):123–143. <https://doi.org/10.1177/14649934211016715>
- Baek I, Shi Q (2016) Impact of economic globalization on income inequality: developed economies vs emerging economies. *Glob Econ J* 16(1):49–61
- Benos N, Tsiachtsiras G (2019) Innovation and income inequality: world evidence. MPRA Paper No. 92050
- Berisha E, Dubey RS, Gharehgozli O (2023) Inflation and income inequality: does the level of income inequality matter? SSRN Electron J. <https://doi.org/10.2139/ssrn.4317185>
- Bhagwati J (2004) In defense of globalization. Oxford University Press, New York
- Birkmann J, Jamshed A, McMillan JM, Feldmeyer D, Totin E, Solecki W, Ibrahim ZZ, Roberts D, Kerr RB, Poertner H-O, Pelling M, Djalante R, Garschagen M, Filho WL, Guha-Sapir D, Alegria A (2022) Understanding human vulnerability to climate change: a global perspective on index validation for adaptation planning. *Sci Total Environ* 803:150065. <https://doi.org/10.1016/j.scitotenv.2021.150065>
- Bui AT, Dungey M, Nguyen CV, Pham TP (2014) The impact of natural disasters on household income, expenditure, poverty and inequality: evidence from Vietnam. *Appl Econ* 46(15):1751–1766. <https://doi.org/10.1080/00036846.2014.884706>
- Cevik S, Jalles JT (2023) For whom the bell tolls: climate change and income inequality. *Energy Policy* 174:113475. <https://doi.org/10.1016/j.enpol.2023.113475>
- Chisadza C, Clance M, Sheng X, Gupta R (2023) Climate change and inequality: evidence from the United States. *Sustainability* 15(6):5322. <https://doi.org/10.3390/su15065322>
- Dang HH, Nguyen MC, Trinh TA (2023) Does hotter temperature increase poverty and inequality? Global evidence from subnational data analysis. 104. London
- Deyshappriya NPR (2017) Impact of macroeconomic factors on income inequality and income distribution in Asian countries. ADBI Working Paper Series, 696. <https://www.adb.org/publications/impact-macroeconomic-factors-income-inequality-distribution>
- Di Falco S, Chavas J-P (2009) On crop biodiversity, risk exposure, and food security in the highlands of Ethiopia. *Ame J Agric Econ* 91(3):599–611. <https://doi.org/10.1111/j.1467-8276.2009.01265.x>
- Diffenbaugh NS, Burke M (2019) Global warming has increased global economic inequality. *Proc Natl Acad Sci* 116(20):9808–9813. <https://doi.org/10.1073/pnas.1816020116>
- Dollar D, Kraay A (2002) Spreading the wealth. *Foreign Aff* 81(1):120–133
- Dong Z, Tang C, Wei X (2018) Does population aging intensify income inequality? Evidence from China. *J Asia Pac Econ* 23(1):66–77. <https://doi.org/10.1080/13547860.2017.1354270>
- Evers J, Pathirana A (2018) Adaptation to climate change in the Mekong River Basin: introduction to the special issue. *Clim Change* 149(1):1–11. <https://doi.org/10.1007/s10584-018-2242-y>
- Firebaugh G (2003) The new geography of global income inequality. Harvard University Press, Cambridge
- Fischer S, Modigliani F (1978) Towards an understanding of the real effects and costs of inflation. *Rev World Econ* 114(4):810–833. <https://doi.org/10.1007/BF02696381>
- Ghosh A (2018) Recipe of a disaster: peripheral lives in the epicentre of changing climate. In: Sustainability conflicts in coastal India: hazards, changing climate and development discourses in the Sundarbans. Springer, Cham, pp 35–66
- Ha NM, Le ND, Trung-Kien P (2019) The impact of urbanization on income inequality: a study in Vietnam. *J Risk Financ Manag* 12(3):1–14

- Hallegatte S, Bangalore M, Bonzanigo L, Fay M, Kane T, Narloch U, Rozenberg J, Treguer D, Vogt-Schilb A (2016) Shock waves managing the impacts of climate change on poverty
- Harris R, Sollis R (2003) Applied time series modelling and forecasting. MIT Press, Cambridge
- IPCC (2012) Managing the risks of extreme events and disasters to advance climate change adaptation
- IPCC (2014) Climate change 2014: mitigation of climate change
- IPCC (2018) Global Warming of 1.5°C. An IPCC Special Report
- IPCC (2021) Climate change 2021: the physical science basis
- Islam SN, Winkel J (2017) Climate change and social inequality. 152
- Jaumotte F, Lall S, Papageorgiou C (2008) Rising income inequality: technology, or trade and financial globalization? WP/08/185.
- Keerthirathne S, Tol RSJ (2018) Impact of Natural Disasters on Income Inequality in Sri Lanka. *World Dev* 105:217–230. <https://doi.org/10.1016/j.worlddev.2018.01.001>
- Kuznets S (1955) Economic growth and income inequality. *Am Econ Rev* 45(1):1–28
- Laidler D, Parkin M (1975) Inflation: a survey. *Econ J* 85(340):741. <https://doi.org/10.2307/2230624>
- Lindsey R, Dahlman L (2023) Climate change: global temperature. Retrieved October 31, 2023 [https://www.climate.gov/news-features/understanding-climate/climate-change-global-temperature#:~:text=Earth's%20temperature%20has%20risen%20by,0.18%C2%B0%20C\)%20per%20decade](https://www.climate.gov/news-features/understanding-climate/climate-change-global-temperature#:~:text=Earth's%20temperature%20has%20risen%20by,0.18%C2%B0%20C)%20per%20decade)
- Mah JS (2000) An empirical examination of the disaggregated import demand of Korea—the case of information technology products. *J Asian Econ* 11(2):237–244. [https://doi.org/10.1016/S1049-0078\(00\)00053-1](https://doi.org/10.1016/S1049-0078(00)00053-1)
- Miljkovic T, Miljkovic D (2014) Modeling impact of hurricane damages on income distribution in the coastal U.S. *Int J Disaster Risk Sci* 5(4):265–273. <https://doi.org/10.1007/s13753-014-0030-5>
- Ministry of Environment Forest and Climate Change (2022) India's Long-Term Low-Carbon Development Strategy
- Monnin P (2014) Inflation and Income Inequality in Developed Economies. 2014/1.
- Munir K, Bukhari M (2020) Impact of globalization on income inequality in asian emerging economies. *Int J Sociol Soc Policy* 40(1/2):44–57. <https://doi.org/10.1108/IJSSP-08-2019-0167>
- Munir K, Sultan M (2017) Macroeconomic Determinants of Income Inequality in India and Pakistan. *Theoretical and Applied Economics* 1(4):109–120
- Narayan P (2004) Reformulating critical values for the bounds F- statistics approach to cointegration: an application to the tourism demand model for Fiji. 02/04
- Narayan PK (2005) The Saving and Investment Nexus for China: Evidence from Cointegration Tests. *Appl Econ* 37(17):1979–1990. <https://doi.org/10.1080/00036840500278103>
- Nishio A (2021) When poverty meets climate change: a critical challenge that demands cross-cutting solutions
- Oanh TTK, Ha NTH (2023) Impact of income inequality on climate change in Asia: the role of human capital. *Hum Soc Sci Commun* 10(1):461. <https://doi.org/10.1057/s41599-023-01963-w>
- Odedokun MO, Round JI (2001) Determinants of income inequality and its effects on economic growth: evidence from African Countries. 103/2001
- Paglialunga E, Coveri A, Zanfei A (2020) Climate change and inequality in a global context. Exploring climate induced disparities and the reaction of economic systems. 2020/03
- Pattichis C (1999) Price and income elasticities of disaggregated import demand: results from UECMs and an application. *Appl Econ* 31(9):1061–1071. <https://doi.org/10.1080/000368499323544>
- Pesaran MH (2015) Testing weak cross-sectional dependence in large panels. *Economet Rev* 34(6–10):1089–1117
- Pesaran MH, Shin Y (1997) An autoregressive distributed-lag modelling approach to cointegration analysis. In: Strom S (ed) *Econometrics and economic theory in the 20th century*. Cambridge University Press, Cambridge, pp 371–413
- Pesaran MH, Yamagata T (2008) Testing slope homogeneity in large panels. *J Economet* 142(1):50–93. <https://doi.org/10.1016/j.jeconom.2007.05.010>
- Pesaran MH, Shin Y, Smith RJ (2001) Bounds Testing Approaches to the Analysis of Level Relationships. *J Appl Economet* 16(3):289–326. <https://doi.org/10.1002/jae.616>
- Pleninger R (2022) Impact of natural disasters on the income distribution. *World Dev* 157:105936. <https://doi.org/10.1016/j.worlddev.2022.105936>
- Poliquin CW (2021) The wage and inequality impacts of broadband Internet. Los Angeles.
- Randolph SM, Lott WF (1993) Can the Kuznets Effect Be Relied on to Induce Equalizing Growth? *World Dev* 21(5):829–840. [https://doi.org/10.1016/0305-750X\(93\)90036-9](https://doi.org/10.1016/0305-750X(93)90036-9)

- Saunders P (2002) The direct and indirect effects of unemployment on poverty and inequality. SPRC Discussion Paper No. 118
- Sethi P, Bhattacharjee S, Chakrabarti D, Tiwari C (2021) The impact of globalization and financial development on India's income inequality. *J Policy Model* 43(3):639–656. <https://doi.org/10.1016/j.jpolm.2021.01.002>
- Skare M, Stjepanović S (2014) Income distribution determinants and inequality—international comparison. *Amfiteatru Econ* 16(37):980–993
- Stiglitz J (2002) Globalization and its discontents. W.W. Norton and Company
- Tang T (2004) A reassessment of aggregate import demand function in the ASEAN-5: a cointegration analysis. *The International Trade Journal* 18(3):239–268. <https://doi.org/10.1080/08853900490478131>
- Tang TC, Nair M (2002) A cointegration analysis of Malaysian import demand function: reassessment from the bounds test. *Appl Econ Lett* 9(5):293–296. <https://doi.org/10.1080/13504850110073471>
- Tanzi V (1998) Fundamental determinants of inequality and the role of government. WP 1998/178.
- Tongia R (2022) It is unfair to push poor countries to reach zero carbon emissions too early. Brookings. Retrieved December 22, 2023. <https://www.brookings.edu/articles/it-is-unfair-to-push-poor-countries-to-reach-zero-carbon-emissions-too-early/>
- UNDESA (2016) Climate Change and Inequality Nexus, pp 21–46 in
- Vo DH, Pham AT, Tran Q, Nam Thanh Vu (2023) The long-run effects of financial development on income inequality: evidence from the Asia-Pacific countries. *Heliyon* 9(8):e19000. <https://doi.org/10.1016/j.heliyon.2023.e19000>
- Wade RH (2004) Is globalization reducing poverty and inequality? *World Dev* 32(4):567–589. <https://doi.org/10.1016/j.worlddev.2003.10.007>
- Wan G, Zhang X, Zhao M (2022) Urbanization can help reduce income inequality. *Npj Urban Sustain* 2(1):1. <https://doi.org/10.1038/s42949-021-00040-y>
- Wisniewski TP, Pathan SK (2014) Political environment and foreign direct investment: evidence from OECD countries. *Eur J Polit Econ* 36:13–23
- WMO (2021) WMO Atlas of Mortality and Economic Losses from Weather, Climate and Water Extremes (1970–2019)
- WMO (2023) Global temperatures set to reach new records in next five years
- World Bank (2020) Poverty and Shared Prosperity 2020: Reversals of Fortune.
- Yamamura E (2015) The impact of natural disasters on income inequality: analysis using panel data during the period 1970 to 2004. *Int Econ J* 29(3):359–374. <https://doi.org/10.1080/10168737.2015.1020323>
- Zhou L, Bowels T, Biswas B, Saunders PJ (2011) Impact of globalization on income distribution inequality in 60 countries. *Glob Econ J* 11(1):1–18. <https://doi.org/10.1515/1524-5861.1845>