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Original Research Article

Income Inequality and its Important Determinants in India

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Abstract

Income inequality is considerably high and still growing, which may cause a significant loss of India's human development and economic performance in the post-pandemic period. Thus, using cointegrating models viz; FMOLS, DOLS, CCR, and ARDL models, we scrutinize short-run as well as long-run impact of natural disaster, economic development, technological innovation, and human capital on income inequality in India. Results show that the natural disasters and economic development worsen income inequality in both short- and long-run. Further, India's human capital also aggravates income inequality in the short run. In contrast, India's technological innovation and human capital in the long run improve income distribution significantly. Finally, the policy suggestions are mentioned in the conclusion section. Our results are consistent and robust with alternative modelling.

Keywords: FMOLS, DOLS, CCR, ARDL model; Economic development; Human capital, Natural Disaster; Technological Innovation.

JEL Classification: *C22, D31, E60, I24, O33, O40*.

1. INTRODUCTION

In India, income inequality is continuously increasing since the 1980s. The top 1% population seized 11% of total earnings in 1990 and 21% in 2019. Earning share of top 10% raised from 30% to more than 56% between 1980 and 2019 (WIL, 2020 [[1]]). With this fact, India is the most unequal nation on the earth. In addition, the lengthy pernicious impact of the covid-19 pandemic added some fuel to the existing fire. It causes a reduction in the share of income held by a marginalized section of society. With the widespread negative economic outcome due to pandemics, the poor and middle class are likely to be hit severely. Nevertheless, the working structure changed radically that some can work from home and others have to sit idly in the home during pandemics. The pandemic has threatened the lives and livelihood of less educated and less-well paid people severely than more educated and better paid, many of whom can work from home safely (Deaton, 2021). The unexpected outcome of the pandemic aggravates inequality in India.

The strong prediction that pandemic deteriorate income distribution, reinforced by recent reports by Oxfam (2021) and Forbeas (2021). Oxfam (2021) expresses that "billionaire fortunes coming back to their pre-pandemic highs in just nine months while regaining for the world's poorest people could take over a decade". Forbeas (2021) demonstrate that in spite of covid-19 negative impact, 2020 was a dramatic year for super rich. In 2020, 5 trillion dollars shoot up in terms of wealth. A substantial number of new billionaires came into the limelight. India has the third-highest number of billionaires. They demonstrate that supper rich came to normal soon and will come out soon after the pandemic's second wave. Only the majority of marginalized sections of society suffer severely. Thus, many international organizations [[2]] such as IMF, WB, ILO, OECD, and ADB are expressing deep concern that pandemic will further drive-up inequality with deeply harmful effects. High inequality is morally wrong and

[1] World Inequality Lab (WIL) 2020 report.

[2] International Monetary Fund (IMF), World Bank (WB), International Labour Organization (ILO), Organization for Economic Cooperation and Development (OECD) and Asian Development Bank (ADB)

economically harmful, and finally, it divides our society over time. This substantially high-income inequality may cause a significant loss of India's human development and economic performance in the post-pandemic period. With this backdrop, we attempt to understand the impact of natural disasters, economic development, technological innovation, and human capital on income distribution over four decades (1980 to 2019) in India.

Why natural disaster (ND)? The natural disaster characterized as meteorological (storm; the tropical cyclone, hot wave, cold wave), hydrological (flood; riverine flood and flash flood, landslide), geophysical (i.e., earthquake), climatological (drought) and biological (epidemic). ND is a paramount unfavorable incident out of natural processes of the earth. It may cause consequential life or property loss. Typically, it leaves some economic impairment in its wake. The severity of ND rests on the affected population's resilience as well the infrastructure available. India is highly exposed to natural disasters affecting millions, killing thousands of people, and destroying a significant amount of assets annually. For example, Odisha and West Bengal are exposed to severe cyclones and droughts in the North-West. The coastal regions are exceptionally likely to get cyclones, floods, droughts as well as heatwaves owing to their terrestrial site. Statistically, between 1980 and 2019, the average number of death due to natural disasters is 4,037, while 4,97,67,655 (near to 50 million) people are affected annually (on average). The annual average economic loss is 27,42,177,000 dollars (2 billion 742 million 1lakh 77 thousand) between 1980 and 2019. The natural disaster figures are presented in Fig.1. The loss of lives and significantly affected people and economic loss from the natural disaster is considerably high in India. This substantial impact of natural disasters generously motivates us to consider how ND affect income inequality in India.

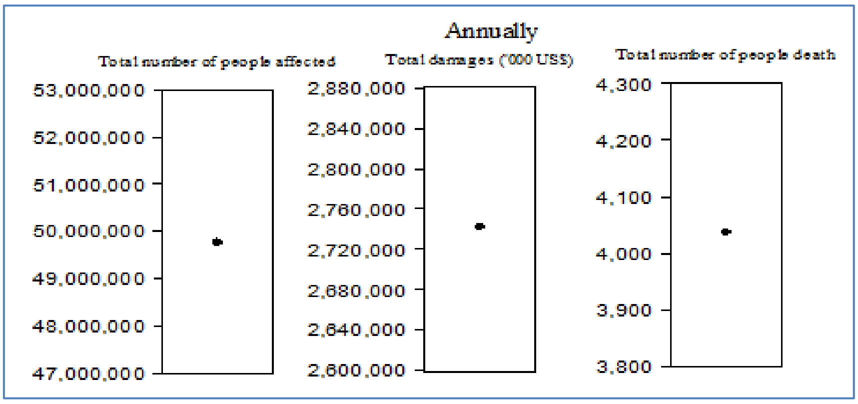

Fig-1: Average number of people affected, death as well as property damages due to natural disaster between 1980 and 2019 in India

Source: Author's plotting; Data is taken from EM-DAT.

Note: black dots indicate the annual average number of people affected and death as well as the average value of property damages due to different kinds of natural disasters between 1980 and 2019 in India.

Theoretically, ND may destructively affect the income of poor, directing to an amplified inequality. ND affected regions largely suffer from economic impairment through Physical as well as human capital waste. In turn, typically cause drops in average incomes. Impoverished households are more vulnerable. They bear substantial cost due to ND and vanishes higher shares of their household's income relative to affluent families (Kim, 2012; Toya and Skidmore, 2007; Datt and Hoogeveen, 2003; Masozera *et al.*, 2002). People as a community constantly challenge with the likelihood of ND. ND is the exogenous shocks that sway socio-economic surroundings. For instance, Odisha cyclone in 1999 killed more than 10,000 people and devasted notable properties. Tsunami in Indonesia (2004), as well as 2008 Sichuan earthquake in China, triggered a sizable quantity of property impairment. Nevertheless, the Great East Japan earthquake (2012) and 2005 Hurricane Katrina in the United States, hindered economic activities, even in these advanced nations. These NDs shattered extensive economic and human losses, regardless of the economy's stage of economic prosperity. From a theoretical perspective, we conclude that natural disaster deteriorates income distribution affecting the poor and their income/properties severely.

Why economic development (ED)? India's economic development measured by GDP per capita has increased many folds between 1980 and 2019. The trend of GDP per capita (constant 2010, $ US) is displayed in Fig. 2 (c). Theoretically, Kuznets (1955) predicted that income inequality increases with initial economic development, and after reaching a point, inequality falls with further economic development. This pattern of income inequality concerning economic development over time gives rise to an Inverted-U hypothesis. Ahluwahli (1976) found strong support for the notion that inequality increases in the initial phase of development and then, decay as development occurs continuously. However, this study does not deal with the Kuznets hypothesis. As India's per capita income is low thus, we predict that a low level of per capita income may worsen income inequality in India. The drastic structural changes of the Indian economy and theoretical interpretation of Kuznets hypothesis motivates us to consider economic development in our specification.

Why technological innovation (TI)? India is experiencing and potentially competent to command the introduction of advanced technology after the introduction of new economic policy in the 1990s. Fig 2 (e) shows the development of technological innovation measured by the number of patent applications issued by residents between 1980 and 2019. Annual technological innovation has increased significantly, as shown in Fig.2(e). Technology is a crucial parameter that stimulates economic growth via productivity raising significantly. Technology can also stimulate income and wealth distribution, increasing the income of skilled workers, at the cost of unskilled workers. Via technology, innovators can consume high rents. Greenwood (1997) and Acemoglu (1998 and 2003) asserted that technological progress is complementary to skilled workers by its nature, and thus, unskilled workers are left behind. In turn, it paves to generate a hole between skilled and unskilled workers' income. Interestingly, Culpeper (2005) argued that technological progress impact income distribution based on how it uses productive factors. Capital intensive technology reduces labour employment and income while labour-intensive technology increases labour employment and income. The former increases income concentration but later reduces income concentration in an economy. Therefore, the actual impact on income concentration depends on the factor bias of technology. If technological progress is exogenous and universally towards capital intensive, then universally it raises income inequality within countries, while if technological progress is exogenous and universally towards labour intensive, then universally it declines income inequality within the countries.

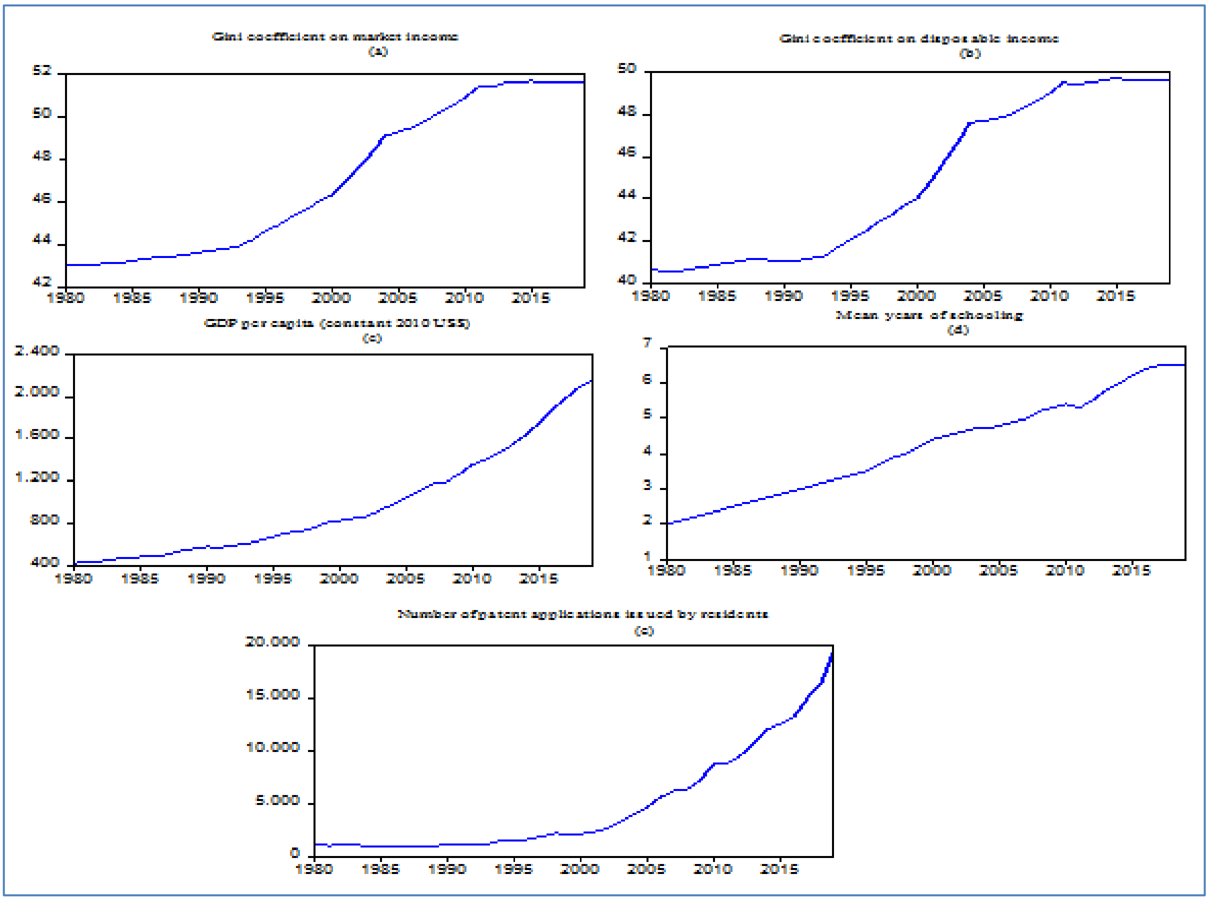

Fig-2: Trend of income inequality, economic development, human capital, and technological innovation.

Source: Author's Plotting, collecting data set from SWIID (for Gini coefficients), UNDP (for mean years of schooling), and WDI (for GDP per capita and number of patent applications issued by residents)

Note: vertical axis indicates the value of variable and horizontal axis is the years from 1980 to 2019

Why human capital (HC)? Commonly, inequalities of any sort are unwelcome. Often stated income disparity is an exhibition of inequality in other capabilities areas. Given the hostile consequence of inequality upon economic and political atmospheres, many would reach a unanimity that prefers from a less income dispersion to a more dispersion. In the domain of capabilities, human capital captured by different educational attainment indicators is realized as a potential commanding income equalizer. The policy of any government for equal access to schooling is backed and reinforced if it improves income distribution. Specifically, according to human capital theory, variation in characteristics of workers such as gender, race, and religion (Azzoni and Servo, 2002). As wage income constitutes a substantial share of the total income of individuals, dispersion in wage income among individuals burgeon income inequality within countries. Fig.2 (d) explains the trend of human capital measured by mean years of schooling in India. Fig.2 (d) shows the continuous increase in the level of human capital. Therefore, it essential to consider human capital in explaining income inequality in India.

With this background, our objective is to explore the impact of ND, ED, TI, and HC on income inequality in India. To the best of our knowledge, little or no study in India examines the impact of ND, ED, TI, and HC on income inequality in India. This gap constitutes a substantial barricade to identifying the most potential domestic policies for reducing inequality. Therefore, this gap motivates us to empirically investigate the role of these factors under consideration affecting income inequality from a policy perspective in India.

Using FMOLS, DOLS, CCR, and Bounded ARDL models, results show the natural disaster and economic development worsen income inequality. In contrast, technological innovation and human capital improve income distribution significantly, at least in the long run in India. Further, it shows the natural disaster, economic development, and human capital worsen income inequality in the short run. Our results are robust with alternative modelling and alternative measurement of the dependent variable.

With these outcomes from empirical exercises, our study contributes significantly to the existing literature in different ways. First, we are the first to scrutinise the impact of ND, ED, TI, and HC on income inequality in India under a time series framework for the period 1980 to 2019. Second, if series are stationary at the difference, then variables are cointegrated in the model. The fundamental issues that concern non-stationarity in data series produce potential spurious correlation and endogeneity problems (Engle and Granger, 1987). Using conventional methods, in this case, may provide misleading and unreliable results. Therefore, to circumvent misleading results, we used sophisticated time series techniques (i.e., FMOLS, DOLS, CCR, and ARDL) that take care of small sample bias, spurious correlation, endogeneity problems, thus producing reliable results. Finally, our results are consistent with the alternative modelling and consistent with the analysis's alternative dependent variable.

Section 2 discusses concomitant literature with various subsections, whereas section 3 presents data descriptions as well as empirical investigation methods. Discussions based on results are portrayed in Section 4. Section 5 briefly describes the consistency and robustness of findings, whereas section 6 concludes.

2. LITERATURE SURVEY

This section demonstrates associated literature involving the interest of analysis and segregated into five sub-sections. The studies involving economic inequality in India are presented in Section 2.1, whereas literature on how natural disaster affects income inequality is portrayed in Section 2.2. Section 2.3 includes studies that described the rapport between economic development as well as income disparity. The impact of technological innovation and human capital on income disparity is considered in Section 2.4 and Section 2.5, respectively.

2.1 Economic inequality related literature in India

In India, literature involving economic inequality hinge on the trend and pattern of income, consumption, and wealth inequality. For instance, Banerjee and Piketty (2005) and Chancel and Piketty (2017) developed an income inequality trend based on India's income tax data since 1922. Chakravorty, Chandrasekhar, and Noraparaju (2016) have estimated income inequality in the agricultural sector using data from NSSO for the period 2003 to 2013. Subramanian and Jayaraj (2006) analyzed the distribution of wealth using a five-wealth survey of NSSO. Jayadev, Motiram, and Vakulabharanam (2007) and Anand and Thampi (2016) used All-India Debt and Investment Survey (AIDIS) data and examined the pattern of wealth distribution in India. Further, Zacharias and Vakulabharanam (2011) investigated the relationship between wealth distribution and caste division in India during 1991 and 2003.

Analyzing the pattern of poverty and inequality, Himanshu (2007) showed that faster post-reform economic growth had not been accompanied by more rapid poverty reduction; instead accompanied by rising inequality. Chandrasekhar and Ghosh (2015) directed that economic inequality is driven by employment patterns and changes in the labour market, which have been impacted by macroeconomic policies and processes and the practice of social discrimination and exclusion. Employing NSSO data, Sarkar and Mehta (2010) showed that inequality in rural and urban areas increases vastly. Finally, reviewing many studies, Dev (2018) examined the different dimensions of inequality and discussed public policies for reducing high inequality in India. Note that all these studies deal with consumption, income, and wealth distributions trends in India.

2.2 Natural disaster and income inequality

Tripathy (2019) explored the economic effect of ND on poverty and inequality in India. He found that ND has been growing over time in India. W.J. Wouter Botzen (2019) studied the direct/indirect economic impact of ND and shows that ND has momentous undesirable direct economic costs, like significant property damages and casualties in both advanced and developing nations. Eduardo (2010) maintained that large disasters affect the output negatively, regardless of time horizons. Anh Tuan (2014) observes the effect of ND on household income, expenditure, poverty and inequality. He discovered that ND led to a substantial reduction of household's income and expenditure in Vietnam.

Some other studies provide excellent outcomes regarding the connection between ND and income disparity. For instance, Abdullah *et al*. (2016) examine Cyclone Aila's impact in the Sundarbans region in Bangladesh and shows income inequality decreased after Cyclone Aila. Feng *et al.* (2016) illustrate that household income cut down by 14 % because of Sichuan earthquake (2008) in China. They, however, confirmed that income disparity did not alter. Keerthiratne and Tol (2018) discover the effect of ND on income disparity at the district level in Sri Lanka from 1985 to 2013. They represented that ND does not sway household's expenditure disparity. These results are providing somewhat surprising as people assume ND to worsen income inequality.

Another strand of literature claimed that natural disaster aggravates income distribution. For example, Bui *et al*. (2014) discovered that ND amplified inequality in Vietnam. When ND occur, households can confront significant devastation in assets and income. Nevertheless, the marginalized section may be more exposed to the devastation of income because they fail to participate in work. Similarly, Yamamura (2015) findings that although ND increases income disparity over a short span, it vanishes in long run. However, Karim and Noy (2016) suggested that "the direct impact of disasters on poor cannot be answered abundantly by simply examining the cross-country distribution of costs and economic activity. The evidence on the distribution of the direct impact of disaster within a country on households in various income levels is less well understood" as it rests on nation characteristics. Thus, the country-wise study is the need of the hour.

2.3 Economic development and income inequality

Kuznets (1955), in his seminal work, describes the association between economic development and income distribution. Kuznets hypothesis maintained that income disparity intensifies with income growth up to a critical point, and then inequality lessens with further economic development. However, his presumption has been increasingly criticized over the last three decades. Considering the heterogeneity of income and wealth, Stiglitz (1969) maintained that it needs to validate that inequality surges during the initial times of development and then cuts when a critical point is reached. Ahluwalia (1976) directed an empirical analysis over sixty countries and provided evidence of the Kuznets hypothesis. Fielding and Torres (2006) show a correlation between lessening in inequality and progresses in development indicators viz; income, literacy, and life expectancy. This correlation results from a causal link running from inequality to average earning and lifespan. Shari (2000) investigates the trends of income disparity in Malaysia for the period 1970–1995. He started that universal growth policies executed underneath the New-Economic-Policy have significantly impacted reducing income inequality in Malaysia. Wahiba and El Weriemmi (2014) considered the connection between income inequality as well as income growth in Tunisia. The core results demonstrate that growth and openness are accelerating inequalities. However, under the Kuznets framework, Ram (1997) shows that income disparity unable to weakening with an increased income, even at a considerable level of development. However, it characterized by an early decay and then, a successive rise in income disparity.

Some others documented no significant relation between economic development and income disparity. For instance, Law and Tan (2009) inspect the role of financial progress in influencing income disparity in Malaysia. The empirical results specify that financial market expansion is statistically irrelevant in dropping inequality in Malaysia. Kavya and Shijin (2020) observe the impact of interlinkage between income growth and financial market on inequality. They reveal no evidence to back the assumption of income growth and financial development under Kuznets hypothesis. Dion and Birchfield (2010) show that individual income unable to elucidate steadily the provision for redistribution in low-income countries.

2.4 Technology innovation (TI) and income inequality

A significant strand of literature advanced that technological innovation worsens income distribution across the countries. For example, Krussel *et al*. (2000) observed that skill premium has increased due to the consequence of capital-skill complementarity enhanced by ICT via higher productivity and higher-skilled labour demand; capital-skill complementarily boosted skilled workers wages. Higher wage income, in turn, led to higher income inequality. Serven (2004), Atkinson *et al.* (2011), Prasetyo (2013), Santos, Sequeira, and Ferreira-Lopes (2017) and Untari, Priyarsono, and Novianti (2019) explained that the quantity and quality of ICT infrastructure has a positive consequence on growth and negative consequence on income inequality. Mohd Daud *et al*. (2020) also found that digital knowhow amplifies income disparity.

Further, Jaumotte *et al*. (2013) reported that the technological progress effects on inequality are larger relative to globalization. Considering increasing agricultural technology, Ding *et al*. (2011) maintained that agriculturalists who implemented modern technologies earn nearly 15% higher compared to those who do not use technology, worsening income disparity in rural China.

However, Kudasheva, Kunitsa, and Mukhamediyev (2015) examine the influence of education and ICT on income distribution. They suggest that the blend of education and ICT can improve income inequality. In the context of India, Giri, Pandey, and Mohapatra (2021) evaluate trade and financial globalization, and technological progress impact on inequality for the period 1982 to 2018. They claimed that there is a positive and substantial impact of technological progress on income inequality.

2.5 Human capital (HC) and income inequality

Becker and Tomes (1979) raised a rudimentary theoretical framework of intergenerational mobility to elucidate educational impact on income disparity as well as intergenerational income mobility. Considering such a framework, several intellectuals resorted to empirical evidence to analyze the rapport among educational development, income variation, and intergenerational mobility. The higher inequality infers larger HC growth and macroeconomic activity under the overlapping-generations model with heterogeneity in income and talent (Chiu, 1998). Checchi *et al*. (1999) showed that family background is an indispensable parameter affecting labour market performance. In this context, the equal opportunity to access higher education may assist children from marginalized sections of society. Zhang (2005) express that accelerating income disparity hinders economic development by straight impairing capital accumulation and indirectly hovering the physical to human capital ratio. However, according to Castelló-Climent and Doménech (2014), most economies have realized a strong decrease in educational inequality, mainly because of the unparalleled decline of illiterates. However, a similar decrease in inequality has not been accompanied.

Significant literature powerfully demonstrates that human capital improves income distribution. For instance, Gregorio and Lee (2002), Shahpari and Davoudi (2014), Abdullah, Doucouliagos, and Manning (2015), Lee and Lee (2018), Lee and Vu (2019), and Sehrawat and Singh (2019) used different educational parameters such as enrolment rate, expenditure on education, and average years schooling as proxies for human capital. They conclude that increases in human capital can reduce income inequality and hence, improves income distribution. However, Glomm and Ravikumar (2003) illustrate that income gap between rich and poor may broaden even when all individuals access the same quality of public education. Hence, public education may not reduce income disparity, at least in the short run. Conversely, some other literature documents document that human capital does not improve income distribution significantly (Sylwester, 2002; Restuccia and Urrutia, 2004; Duman, 2008; and Battistón, García-Domench, and Gasparini, 2014).

Reviewing a large number of concomitant literatures, we confirmed that no single study has examined the effect of ND, ED, TI, and HC on income inequality in a single framework in the context of India. Therefore, the present study attempt to fill this gap by analyzing the relationship between these independent variables and income inequality (dependent variable) in India.

3. DATA AND METHODOLOGY

3.1 Data

Data on household's or individual's income distribution is a significant problem in India, which stands as a barrier for comprehensive research involving income distribution and its impact on various macroeconomic factors. Mainly, few observations involving consumption data in different surveys of National Sample Survey Organization (NSSO) and two observations associated with income in India Human Development Survey (IHDS) are available. Therefore, analysis using extremely few observations of income and consumption may not be possible under the time series framework. However, recently income inequality trend based on India's individual tax returns data has been established by Banerjee and Piketty (2005) and Chancel and Piketty (2017). Although there are limitations in using income tax returns data to measure income inequality, it fills the gap of lack of data comprehensively.

First, we used income inequality data measured by the Standardized Gini coefficient of household disposable (post-tax, post-transfer) and household market (pre-tax, pre-transfer) income (for robustness check). Data were drawn from SWIID, version 9.0, created by Solt (2016). SWIID database collects data from different individual studies and used different statistical tools to standardized data across countries and time. This data is more reliable (Santiago *et al.*, 2019; Cevik and Correa-Caro, 2015; Jaumotte *et al.*, 2008) than any other international database such as WDI, WIID, etc., provides time-series data without missing observations up to 2015. Further, we generated data from 2015 to 2019 using three years moving averages due to two reasons; unavailability of data and to avoid small sample bias. Two Gini coefficients based on market and disposable income used as the dependent variable. One for baseline regression and the second one for robustness check.

Second, we use the mean year of schooling as a proxy for human capital. Data were taken from the Barro-Lee database (http://www.barrolee.com/) for the period 1980 to 1990. The missing value during this period filled with three years moving average. From 1990 to 2019, data were drawn from the United Nations Development Programme (UNDP). UNDP provides data from 1990 onwards without any missing value for India. We collected data from two sources owing to the unavailability of data from one source. Following many other studies such as Figini and Gorg (2006 and 2011), Asteriou *et al*. (2014), Meschi and Vivarelli (2009), and Herzer and Nunnenkamp (2013), we consider human capital as an important variable affecting inequality significantly.

Third, technological innovation is another vital factor that affects inequality. Following the studies by Antonelli and Gehringer (2016), Chu and Cozzi (2018) and Mnif (2016), we used the number of patent applications issued by the residents as a proxy for technological innovation. Data is taken from World Development Indicators (WDI).

Fourth, we use economic development measured by GDP per capita (constant 2010 $US) following many empirical studies (Kuznets, 1955; Ahluwalia, 1976; Fielding and Torres, 2006; Kavya and Shijin, 2020). They claimed that economic development is one of the significant factors that derive income inequality depending on its distributive effects. GDP per capita data were drawn from WDI. Lastly, we use the number of death and number of people affected because of various forms of natural disasters [[3]] annually as proxy for natural disasters (ND). We have not considered total assets damage due to ND for analysis as it undermines the actual impact of ND on income inequality. Several studies pointed out those economic losses due to ND are compensated by government provision immediately after a natural disaster occurrence. Thus, the total number of people affected and number of deaths are possibly better indicators to capture ND in India. Natural disaster data collected from the EM-DAT (Emergency Events Database). This study considers data from 1980 to 2019. During this period, the structure of the Indian economy transformed drastically and, therefore, an appropriate period for investigation.

3.2 Model specification

3.2.1 Time series characteristics

We consider the Augmented Dickey-Fuller (ADF) unit root test to corroborate stationarity features of data. Unit root test helps us to apply appropriate econometrics tools as well. Table 1 shows there is unit root problem in data set. Specifically, the ADF test suggests that our data set are non-stationary at level but stationary at the first difference, except ND series. ND series is stationary at level. Table 1 also hints at the possible existence of a significant cointegrating relationship between variables. Therefore, we used the Johansen cointegration test to corroborate the cointegrating characteristic of the model. Johansen (1988) model is widely used for the cointegration test. It involves a rank matrix and characteristic roots.

Table-1: Unit root test results

Variable	ADF TEST	
	C	**C+T**
lnGDPPC	3.062	-1.288
ΔlnGDPPC	-4.816***	-6.038***
lnGini_disp_se	-1.577	-1.291
ΔlnGini_disp_se	-5.896***	-6.211***
lnTP	2.368	-3.108
ΔlnTP	-5.129***	-5.997***
lnMYS	-3.989***	-1.042
ΔlnMYS		-4.317***
lnTotal affected	-3.897***	-3.838**
lnTotal Death	-6.263***	-6.275***

Source: Author's estimation.

Note: C indicates constant, and C+T indicates constant plus time trend, ln indicates natural logarithm, Δ denotes first difference series. GDP pc, Gini_disp_se, TI, MYS, and ND indicate GDP per capita, standardized Gini coefficient of household disposable income, Technological innovation, mean year of schooling, and natural disaster, respectively. Also, follow these abbreviations in the rest of the analysis.

Table-2: Johansen System Cointegration Test

[3] Various forms of natural disasters such as cyclones, droughts, epidemics, floods, heavy rains, landslides, storms, strong winds, tsunami, etc.

Table-2 (a): Unrestricted Cointegration Rank Test (Trace)

Hypothesized		**Trace**	**0.05**	
No. of CE(s)	Eigenvalue	Statistic	Critical Value	Prob.**
None *	0.482224	58.08855	55.24578	0.0275
At most 1	0.365355	33.73468	35.01090	0.0681
At most 2	0.289722	16.91115	18.39771	0.0797
At most 3 *	0.108597	4.253476	3.841466	0.0392
Trace test indicates 1 cointegrating eq. (s) at the 0.05 level				
* Denotes rejection of the hypothesis at the 0.05 level				

Table-2 (b): Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized		**Max-Eigen**	**0.05**	
No. of CE(s)	Eigenvalue	Statistic	Critical Value	Prob.**
None	0.482224	24.35387	30.81507	0.2505
At most 1	0.365355	16.82352	24.25202	0.3496
At most 2	0.289722	12.65768	17.14769	0.2003
At most 3 *	0.108597	4.253476	3.841466	0.0392
Max-eigenvalue test indicates no cointegration at the 0.05 level				
* denotes rejection of the hypothesis at the 0.05 level				

Table 2 (include Table 2(a), and Table 2(b) shows the cointegrating relationship between variables under consideration. Both Trace statistics (Table 2.a) and maximum eigenvalue (Table2.b) reject the null hypothesis - no cointegration against the alternative hypothesis - the presence of cointegration among variables under study. Hence, in the long run, these variables are cointegrated. Therefore, using OLS and other similar econometrics tools for non-stationary time series and cointegrating variables may yield biased and inconsistent estimators. Hence, ADF and Johansen cointegration test suggested using cointegrating models.

3.2.2 Empirical methods

Getting the guidance from the unit root and cointegration tests, we use sophisticated estimation techniques to circumvent problems of omitted variables, unit root, endogeneity, and reverse causality by employing FMOLS (Phillips and Hansen, 1990), DOLS (Stock and Watson, 1993) and CCR (Park, 1992) models. FMOLS, DOLS, and CCR [4] are widely known for their power to deal with small sample bias, simultaneity bias, endogeneity problem and serial correlation in the model. The final estimation equation as follow.

$$lnGin\ disp\ se_t = f(lnND_t, lnGDPpc_t, lnTI_t, lnMYS_t, \varepsilon_t) \dots\dots\dots (1)$$

To get complete Eq., Eq. 1 can be written as Eq.2

$$lnGin\ disp\ se_t = \beta_0 + \beta_1 lnND_t + \beta_2 lnGDPpc_t + \beta_3 lnTI_t + \beta_4 lnMYS_t + \varepsilon_t \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (2)$$

Where, f is the functional notation, β_0 is the intercept, β_1 to β_4 are the coefficient of slope parameters, and ε_t is the stochastic error term. FMOLS, DOLS and CCR models have been estimated under Eq. 2. Note that DOLS and CCR are incorporated to confirm the consistency of results.

To distinguish between short-run and long-run impact of natural disasters, economic development, technological innovation, and human capital on India's income inequality, we used ARDL [5] model. Pesaran, Shin, and Smith (1996) and Pesaran and Shin (199) advanced this ARDL approach. The ARDL method performs better if all series in a model are I (1) or I(0) or some I(1) and some I(0). This cointegration method provides robust results and consistent estimates of the long-run coefficient in the context of a small sample.

Given the advantage of ARDL model, this analysis lays down the following Eq. 3.

$$\Delta ln(Gini\ disp_t) = \alpha_0 + \sum_{i-1}^{p} \alpha_{1i}\, \Delta ln(Gini\ disp_{t-i}) + \sum_{i-1}^{p} \alpha_{2i}\, \Delta ln(ND_{t-i}) + \sum_{i-1}^{p} \alpha_{3i}\, \Delta ln(GDPpc_{t-i}) + \sum_{i-1}^{p} \alpha_{4i}\, \Delta ln(TI_{t-i}) + \sum_{i-1}^{p} \alpha_{5i}\, \Delta \ln(MYS_{t-i}) + + \alpha_6 ln(Gini\ disp_{t-1}) + \alpha_7 ln(ND_{t-1}) + \alpha_8 ln(GDPpc_{t-1}) + \alpha_9 ln(TI_{t-1}) + \alpha_{10} ln(MYS_{t-1}) + \gamma EC_{t-1} + u_t \dots\dots\dots (3)$$

Where, Δ is the first difference operator. ln is the natural logarithm form. p is the optimal lag length. α_1 to α_5 indicate short-run dynamics of model and α_6 to α_{10} are long-run elasticities. γ is the speed of adjustment coefficient. EC indicates Error Correction term derived from the long-run relationship among variables. Gin disp is the Gini coefficient of household disposable income and treated as a measure of income inequality. ND is natural disaster proxied by the total number of people affected and death. GDPpc is the

[4] FMOLS, DOLS, and CCR indicate Fully Modified OLS, Dynomic OLS, and Canonical Cointegration Regression, respectively.

[5] ARDL indicates Autoregresive distributed Lag.

GDP per capita. TI is technological innovation. MYS is the mean year of schooling representing human capital. To find the short and long-run relationship between variables of interest, we applied the bounds test in Eq.3. Akaiki information criteria (AIC) guides to select the optimal lag length of variables all other notations are mentioned in the footnote of Table 1.

The possible sign (reflecting the direction of relationship between independent variables and dependent variables in Eq.2 and 3) can be assigned to each of the coefficients in Eq.2 and Eq.3, as follow.

(i) If $\beta_1, \beta_2, \beta_3$, and β_4, in Eq.2, $\alpha_2 \ldots\ldots \alpha_5$, and $\alpha_7 \ldots\ldots \alpha_8$ in Eq.3 = 0, then, it indicates no relationship of all independent variables (ND, GDPpc, TI, and MYS) with income inequality (dependent variable).
(ii) If $\beta_1, \beta_2, \beta_3$, and β_4, in Eq. 2, $\alpha_2 \ldots\ldots \alpha_5$, and $\alpha_7 \ldots\ldots \alpha_8$ in Eq.3 > 0, then, a monotonic increasing relationship of all independent variables (ND, GDPpc, TI, and MYS) with income inequality (dependent variable).
(iii) If $\beta_1, \beta_2, \beta_3$, and β_4, in Eq. 2, $\alpha_2 \ldots\ldots \alpha_5$, and $\alpha_7 \ldots\ldots \alpha_8$ in Eq.3 > 0, then, a monotonic decreasing relationship of all independent variables (ND, GDPpc, TI, and MYS) with income inequality (dependent variable).

4. RESULTS AND DISCUSSION

The illustration of summary statistics is presented in Table 3. The mean and median value of the total affected is much higher compared to any other series under consideration. Similarly, the maximum and minimum value of total affected is substantially high than any other series. The standard deviation is very high in the total affected series, followed by TI and total death. The Jerque-Bera statistics suggest that three series such as total affected, total death, and TI series are not normally distributed, whereas series such as Gini disp, MYS, and GDPpc are normally distributed. The total observation in a series is 40.

Table-3: Summary statistics (1980-2019)

	Gini disp.	Total affected	Total death	MYS	TI	GDPpc
Mean	44.842	49767655	4037.200	4.200	4954.300	975.461
Median	43.850	18540864	2413.000	4.300	2226.500	818.4049
Maxi.	49.700	3.47E+08	21045.00	6.500	19454.00	2151.726
Min.	40.600	1806800.	524.00	2.000	982.0000	422.903
Std. Dev.	3.677	87980100	4475.512	1.402	5056.677	508.626
J-Bera	5.073	106.95	84.02452	2.461	10.92312	5.364
Prob.	0.079	0.000000	0.000000	0.292	0.004247	0.0684
Obs.	40	40	40	40	40	40

Source: Author' estimation

Note: Gini disp: Gini coefficient on household disposable income. Total affected and total death: Total number of people affected and death, respectively, due to various natural disasters. MYS: Mean years of schooling. TI: technological innovation measured by the number of patent applications issued by residents. GDPpc: GDP per capita (constant 2010 $US). Maxi: Maximum. Min: Minimum. Std.Dev: standard deviation. J-Bera, Prob., and Obs. represents Jerque-Bera, Probability and observation, respectively.

4.1 Results from FMOLS, DOLS, and CCR models

In this section, we are presenting the results from six estimated models. The first three models include the total number of people affected as a proxy for natural disasters, and the second three models incorporate the total number of deaths as a proxy for natural disasters. We resort to many model estimations to portray robust and consistent results. From Table 4 (a) and (b), first, many studies predict and find that natural disaster aggravates income inequality because natural disaster affects people disproportionately. Our empirical result also goes with the consensus of the hypothesis. It indicates by β_1 in Eq. 2, which greater than zero. Specifically, if a 1% increase in a natural disaster (lnND) represented by total affected and total death, then income inequality increases by 0.035% to 0.062%, whereas it is 0.065 to 0.093% significantly in India (See Table 4 a and b). The results of the CCR model provides a higher picture than FMOLS models. However, it is a fact that India is highly exposed to natural disasters, affecting millions, killing thousands of people, and destroying a significant amount of assets annually, reflecting in rising income inequality.

Second, theoretically, Kuznets (1955) hypothesized that the low level of economic development measured by GDP per capita accelerate income inequality and lessens at a higher level of economic development. Presently, India has low economic development; therefore, our result shows that economic development worsens income inequality significant at the 1% level. It reflects by β_2 in Eq.2, which is greater than zero significantly. Therefore, India's current economic development is not inclusive and hence, a significant factor that intensifies inequality. Statistically, if 1% increase in economic development (lnGDPpc), then income inequality increased by 2.082% to 2.644% (when we used total affected as one of the independent variables) and by

1.933% to 3.31 % (when we used total death instead of total affected as one of the independent variables) significantly. The results vary from model to model. However, all the models provide the same direction of interpretation, indicating the consistency of our findings.

Table-4: Results from FMOLS, DOLS, and CCR models (a)

Dependent variable: lnGini_disp_se			
Variable	FMOLS	DOLS	CCR
lnTotal affected	0.035*** (2.814)	0.051** (2.501)	0.062*** (3.288)
lnGDPpc	2.082*** (5.450)	2.644*** (8.526)	2.195*** (5.494)
lnTI	-0.448*** (-3.417)	-0.588*** (-5.946)	-0.448*** (-3.397)
lnMYS	-1.734*** (-7.159)	-1.945*** (-7.968)	-1.865*** (-7.396)
C	-3.630*** (-6.064)	-4.840*** (-8.618)	-4.072*** (-6.322)

Source: Author's estimation

(b)

Dependent variable: ln Gini_disp_se			
Variable	FMOLS	DOLS	CCR
lnTotal death	0.065*** (3.087)	0.132*** (7.497)	0.093*** (9.721)
lnGDPpc	1.933*** (4.919)	3.321*** (17.756)	1.980*** (4.559)
lnTI	-0.322** (-2.412)	-0.701 (-13.588)	-0.323 (-2.418)
lnMYS	-1.906*** (-7.352)	-2.515*** (-15.983)	-1.887*** (-6.624)
C	-3.494*** (-5.549)	-6.169*** (-17.217)	-3.735*** (-4.968)

Source: Author's estimation

Note: FMOLS, DOLS, and CCR indicate Fully Modified OLS, Dynamic OLS, and Canonical Cointegration regression, respectively. C is constant in the model. ln is the natural logarithm form of variables. Total affected and total death represents the total number of people affected and the total number of people dying, respectively, due to different natural disasters and used as proxies for natural disasters in models. T-statistic is in parenthesis. This note represents both Table 4 (A) and 4 (B) and notations in succeeding tables.

This is true that India's economic pie is not equally distributed among all section of society. Thus, economic development is one of the most important parameters that worsen income distribution in India. Many economists and international organizations also concern regarding the distributive effect of Indian's economic development.

Third, several studies document that technological innovation (lnTI) is complementary to skilled workers by its nature, and thus, unskilled workers are left behind. In turn, it paves to generate a gap between the income of skilled and unskilled workers, leading to increase income inequality. However, our finding contradicts this hypothesis. The result shows that technological innovation improves rather than worsens income distribution in India. If 1% increases in technological innovation, then income inequality reduces by 0.448 % to 0.588 in Table 4 (a) and 0.322% to 0.701% in Table 4 (b). Thus, β_3 in Eq.2 is less than zero. It demonstrates that more technological innovation will help to reduce income inequality in India.

Last, human capital is one of the most equalizing forces in society, explained both theoretically and empirically. This common consensus holds well with empirical findings in the present analysis. Our results show, if 1% increase in human capital, then there is a reduction in income inequality by 1.734% to 1.945% in Table 4 (a) and 1.887% to 2.515% in Table 4 (b). Thus, $\beta_4 < 0$ in Eq.2, which indicates human capital is monotonically decreasing income inequality. Human capital is the most powerful instrument to reduce income inequality in India.

4.2 RESULTS FROM ARDL MODEL

This part of the analysis deals with the long-run and short-run connection between variables. For investigation, we conducted the bounded ARDL model. The null hypothesis - no cointegration against alternative hypothesis – the presence of cointegration among variables. We estimated two bounds test involving two models-changing measures of natural disasters. The bound test rest on a comparison between F-statistic and critical value. To reach a final decision about long-run relationship, we consider a critical value of 10%, 5%, 2.5% and 1% level of significance. Generally, the bounds test shows three conclusions: (i) if F-statistic > upper bound of critical value, then variables are cointegrated in the long run, (ii) if F-statistic < lower bound of critical value, it means no cointegration in long run, and (iii) if F-statistic lies within lower as well as upper bounds, the results are not conclusive.

Table-5: ARDL bound test result

1st model				**2nd model**		
Significance	I0 Bound	I1 Bound	F-statistic	I0 Bound	I1 Bound	F-statistic
10%	2.45	3.52	5.054	2.45	3.52	4.452783
5%	2.86	4.01		2.86	4.01	
2.5%	3.25	4.49		3.25	4.49	
1%	3.74	5.06		3.74	5.06	

Null Hypothesis: No long-run relationships exist

The bounds test results are presented in Table 5. It displays the presence of long-run cointegrating relationship in both models. However, the first model reveals the evidence of long-run relationship among variables at 10%, 5%, and 2.5% level of significance, whereas the second model shows at 10% and 5% level of significance and inconclusive at 2.5% and 1% level of significances. Given the bound test, we concluded that income inequality and other variables under analysis move together in the long run.

Table-6: Short run results

Dependent variable: lnGini_disp_se 1st model: Selected Model: ARDL (1, 0, 0, 1, 0) 2nd model: Selected Model: ARDL (1, 0, 0, 1, 0) Method: ARDL model			
1st model		2nd model	
ΔlnTotal affected	0.004 (0.308)	ΔlnTotal death	0.020 (1.096)
ΔlnGDP pc	0.721*** (2.621)	ΔlnGDP pc	0.790*** (3.294)
ΔlnMYS	1.842** (2.032)	ΔlnMYS	1.831** (2.063)
ΔlnTP	-0.135** (-1.988)	ΔlnTP	-0.137** (-2.244)
CointEq (-1)	-0.353*** (-4.754)	CointEq (-1)	-0.363*** (-9.128)

Source: Author's estimation.
Note: For short notation, please follow the note of earlier tables.

The error correction terms are represented in the bottom row of Table 6 and denoted as CointEq (-1). The coefficients of error correction terms (0.353 in the first model and 0.363 in the second model) are significant at a 1% level in both models. The significant negative sign of error correction terms documents the presence of a long-run relationship among variables. The speed of adjustment from previous years' disequilibrium in income inequality to current years' equilibrium is 35.3% and 36.3%, respectively. Hence, the long-run speed of adjustment in income inequality is high.

Table-7: Long run results

Long run ARDL result			
1st model		2nd model	
lnTotal affected	0.011 (0.323)	lnTotal death	0.055 (1.129)
lnGDP pc	2.043*** (4.951)	lnGDP pc	2.174*** (4.544)
lnMYS	-1.568*** (-6.332)	lnMYS	-1.761*** (-4.872)
lnTP	-0.385*** (-2.850)	lnTP	-0.379*** (-2.748)
C	-3.756*** (-4.745)	C	-4.156*** (-4.090)

Source: Author's estimation

The ARDL results exhibit that in short run, ND, ED, and HC worsen income inequality, whereas, in the long run, it yields similar results as FMOLS, DOLS, and CCR models. FMOLS, DOLS, and CCR models confirm that natural disasters increase income inequality significantly, whereas ARDL corroborates it increases insignificantly in both the short and long run (See Table 6 and 7 for ARDL results). Glomm and Ravikumar (2003) ensured the income gap between rich as well as poor might broaden even when all individual receives the same quality of public education. So, human capital may not help to improves income distribution in short run. Our ARDL results are in line with the findings of Glomm and Ravikumar (2003). The result shows that human capital deteriorates income distribution in short run and improves in long run.

Table-8: Breusch-Godfrey Serial Correlation LM Test

1st model		**2nd model**	
F-statistic (Prob. F (1,31))	1.534 (0.224)	F-statistic (Prob. F (1,31))	1.633 (0.210
Obs*R-squared (Prob. Chi Square (1))	1.839 (0.175)	Obs*R-squared (Prob. Chi-Square (1))	1.952 (0.162)

Source: Author's estimation

Table-9: Breusch-Pagan-Godfrey heteroskedasticity test

1st model		**2nd model**	
F-statistic (Prob. F (6,32))	1.681 (0.157)	F-statistic (Prob. F(6,32))	1.324 (0.275)
Obs*R-squared (Prob. Chi-Square (6))	9.349 (0.1548)	Obs*R-squared (Prob. Chi-Square (6))	7.758 (0.256)

Source: Author's estimation

Indeed, serial correlation and heteroskedasticity problems are crucial in ARDL estimations. We used the Breusch-Godfrey LM Test and Breusch-Pagan-Godfrey tests to check serial correlation and heteroskedasticity, respectively. The serial correlation and heteroskedasticity tests indicate no serial correlation and heteroskedasticity problem in the model (See Table 8 & 9). Thus, the reported results are robust concerning serial correlation and heteroskedasticity.

This study also checked the stability of the above-estimated ARDL involving an error correction framework applying Cumulative Sum of Recursive Residuals (CUSUM) stability testing methods. CUSUM plots have been presented in Fig. 3 (a) and (b), respectively. Since both CUSUM test plots remain within critical bounds at a 5% significance level, we finally concluded that both models are structurally stable.

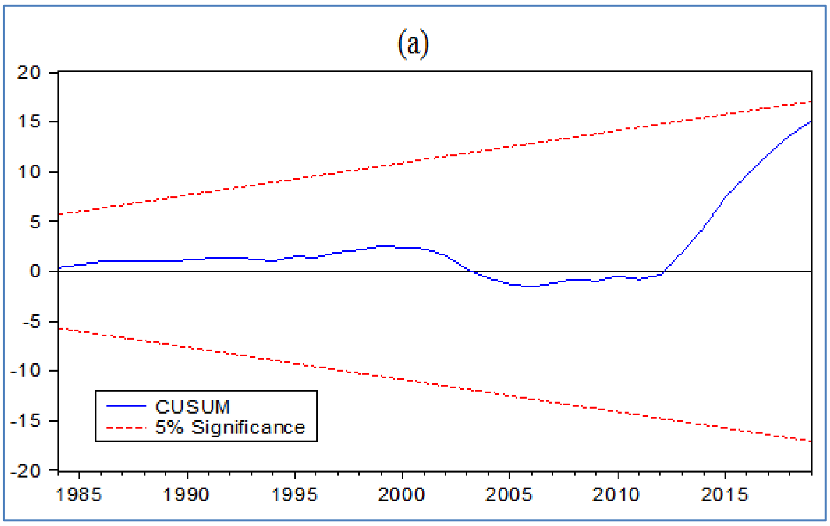

Fig-2: Trend of income inequality, economic development, human capital, and technological innovation.
Source: Author's estimation

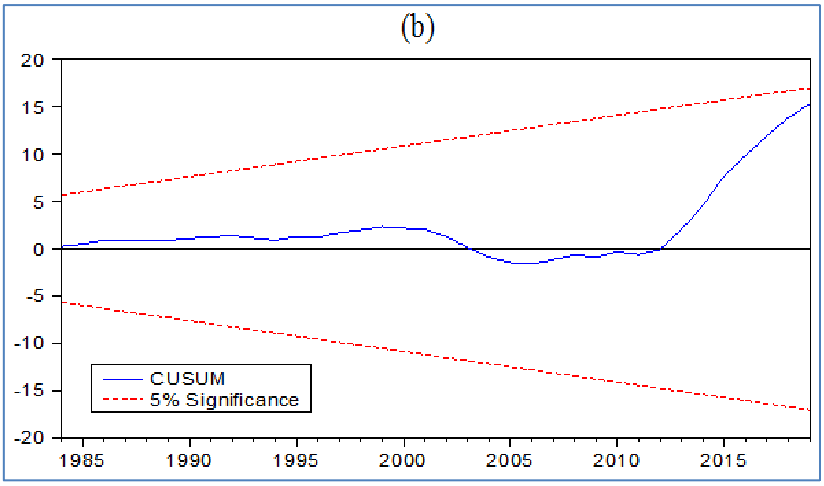

Fig-2: Trend of income inequality, economic development, human capital, and technological innovation.
Source: Author's estimation

5. Robustness check

Although results are robust with alternative modelling, we further checked whether the results are robust and consistent with alternative dependent variables under the FMOLS model. We used the Gini coefficient on household market income instead Gini coefficient on household disposable income as a proxy for income inequality. Two FMOLS models estimated concerning two measures of natural disaster. The estimated results for the robustness check are presented in Table 8. The results confirmed that natural disasters measured by total affected and total death and economic development captured by GDP per capita are the culprit, increasing the income inequality on the one hand. On the other hand, it also ensured that technological innovation and human capital are the beneficial factors, reducing income inequality at least in the long run in India.

Table-10: Empirical result from FMOLS

Dependent variable: lnGini_mkt_se		**Dependent variable: lnGini_mkt_se**	
1st model	FMOLS	2nd model	FMOLS
lnTotal Affected	**0.046** (2.414)**	**lnTotal death**	**0.062*** (2.825)**
lnGDPpc	2.511*** (4.298)	lnGDPpc	2.432*** (6.013)
lnTP	-0.593*** (-2.955)	lnMYS	-0.592*** (-4.299)
lnMYS	-2.146*** (-5.791)	lnMYS	-2.092*** (-7.840)
C	-4.129*** (-4.510)	C	-3.811*** (-5.881)

Source: Author's estimation

6. Conclusion and policy recommendations

Two crucial points motivate this analysis. First, income inequality is considerably high and still growing, which may cause a significant loss of human development and economic performance in India. Second, although there has been weak consensus on the effect of natural disasters, economic development, technological innovation, and human capital on income inequality for well over a decade, little progress has been made in determining the precise relationship between these factors and income inequality in India. Thus, to the best of our knowledge, we are the first to examine the impact of natural disasters, economic development, technological innovation, and human capital on income inequality in India under a time series framework for the period 1980 to 2019.

Using sophisticated techniques such as FM-OLS, DOLS, CCR, and Bounded ARDL models, we examine the short-run and long-run impact of natural disasters, economic development, technological innovation, and human capital on income inequality in India. From FMOLS, DOLS, CCR, and ARDL models, results show the natural disaster and economic development worsen income inequality, whereas technological innovation and human capital improve income distribution significantly, at least in the long run in India. The Bounded ARDL model shows the natural disaster, economic development, and human capital worsen income inequality, whereas only technological innovation improves India's income distribution significantly in the short run. Under ARDL framework, natural disaster shows income inequality increases due to higher natural disaster insignificantly in both short and long run. However, our results are consistent and robust with alternative modelling and alternative measurement of the dependent variable.

Natural disasters worsen income inequality significantly, irrespective of the measurement of natural disasters in India. Specifically, when total death due to natural disasters is considered affects income inequality with a higher magnitude than the measure of natural disasters by the total number of people affected. Therefore, the Government of India need to think about zero causality due to natural disasters adopting various initiatives, including disasters related advanced technology. Zero causality may reduce income inequality significantly in India. Moreover, our result shows that India's economic development is not inclusive, hence need robust macroeconomic policies for inclusive economic growth. It required sizeable structural reform for the Indian economy to boost investment and thereby, creating significant employment. This may lead to inclusive economic growth in post-pandemic period, leading to improves income distribution. Similarly, access to technology/technological innovation by larger section of society, further may help to reduce income inequality in India.

Recently, NITI Aayog acknowledged that India lacks a skilled labour force significantly compared to any other advanced and emerging economies. Therefore, the Government of India should ensure quality and inclusive education for all. Providing quality education to all sections of community is one of the essential goals of sustainable development. Hence, quality and inclusive education can improve income distribution in India and thus, policymakers should focus on formulating well-furnished inclusive and quality education strategy, which may boost economic growth and, thereby, improve income inequality in long-run. This study can be expanded, including the number of other macroeconomic parameters such as employment and unemployment rate, globalization, investment and saving, and financial development for further analysis in India.

REFERENCES

- Abdullah, A. N. M., Zander, K. K., Myers, B., Stacey, N., & Garnett, S. T. (2016). A short-term decrease in household income inequality in the Sundarbans, Bangladesh, following Cyclone Aila. *Natural Hazards*, *83*(2), 1103-1123.
- Abdullah, A., Doucouliagos, H., & E. Manning. (2015). Does education reduce income inequality? A meta-regression analysis. *Journal of Economic Surveys*, *29*(2), 301-316.
- Acemoglu, D. (1998). Why do new technologies complement skills? Directed technical change and wage inequality. *The Quarterly Journal of Economics*, *113*(4), 1055-1089.
- Acemoglu, D. (2003). Directed technical change. The Review of Economic Studies, 69(4), 781-809.
- Ahluwalia, M.S. (1976). Inequality, Poverty and Development. *Journal of Development Economics*, *3*(4), 307-342.
- Anand, I., & Thampi, A. (2016). Recent trends in wealth inequality in India. *Economic and Political Weekly*, 59-67.
- Antonelli, C., & Gehringer, A. (2017). Technological change, rent and income inequalities: A Schumpeterian approach. *Technological Forecasting and Social Change*, *115*, 85-98.
- Asteriou, D., Dimelis, S., & Moudatsou, A. (2014). Globalization and income inequality: A panel data econometric approach for the EU27 countries. *Economic modelling*, *36*, 592-599.
- Atkinson, A. B., Piketty, T., & Saez, E. (2011). Top incomes in the long run of history. *Journal of economic literature*, *49*(1), 3-71.
- Azzoni, C. R., & Servo, L. (2002). Education, cost of living and regional wage inequality in Brazil. *Papers in regional science*, *81*(2), 157-175.
- Banerjee, A., & Piketty, T. (2005). Top indian incomes, 1922–2000. *The World Bank Economic Review*, *19*(1), 1-20.
- Battistón, D., García-Domench, C., & Gasparini, L. (2014). Could an increase in education raise income inequality?: evidence for Latin America. *Latin American journal of economics*, *51*(1), 1-39.
- Becker, G. S., & Tomes, N. (1979). An equilibrium theory of the distribution of income and intergenerational mobility. *Journal of political Economy*, *87*(6), 1153-1189.
- Bui, A. T., Dungey, M., Nguyen, C. V., & T. P. Pham (2014). The impact of natural disasters on household income, expenditure, poverty and inequality: evidence from Vietnam. *Applied Economics*, *46*(15), 1751-1766.
- Castelló-Climent, A., & R. Doménech. (2014). Human capital and income inequality: Some facts and some puzzles. Retrieved from BBVA Research.
- Cevik, S., & C. Correa-Caro. (2015). Growing (un) equal: fiscal policy and income inequality in China and BRIC+. Journal of the Asia Pacific Economy, 1-20.
- Chakravorty, S., Chandrasekhar, S., & Naraparaju, K. (2016). *Income generation and inequality in India's agricultural sector: The consequences of land fragmentation* (No. 2016-028). Indira Gandhi Institute of Development Research, Mumbai, India.

- Chandrasekhar, C. P., & Ghosh, J. (2014). *Growth, employment patterns and inequality in Asia: A case study of India*. Bangkok, Thailand: ILO.
- Chancel, L., & Piketty, T. (2019). Indian Income Inequality, 1922-2015: From British Raj to Billionaire Raj? Review of Income and Wealth, 65, S33-S62.
- Chiu, W. H. (1998). Income inequality, human capital accumulation and economic performance. *The Economic Journal*, *108*(446), 44-59.
- Checchi, D., Ichino, A., & Rustichini, A. (1999). More equal but less mobile?: Education financing and intergenerational mobility in Italy and in the US. *Journal of public economics*, *74*(3), 351-393.
- Chu, A. C., & Cozzi, G. (2018). Effects of patents versus R&D subsidies on income inequality. Review of economic dynamics, 29, 68-84.
- Culpeper, R. (2005). Approaches to globalization and inequality within the international system. United Nations Research Institute for Social Development. Overarching Concerns Programme Paper Number 6.
- Datt, G., & H. Hoogeveen. (2003). El Niño or El Peso? Crisis, poverty and income distribution in the Philippines. *World Development, 31*(7), 1103-1124.
- Deaton, A. (2021). COVID-19 and global income inequality (No. w28392). National Bureau of Economic Research.
- Dev, S. M. (2018). Inequality, employment and public policy. The Indian Journal of Labour Economics, 61(1), 1-42.
- Ding, S., Meriluoto, L., Reed, W. R., Tao, D., & H. Wu (2011). The impact of agricultural technology adoption on income inequality in rural China: Evidence from southern Yunnan Province. *China Economic Review*, *22*(3), 344-356.
- Dion, M. L., & V. Birchfield. (2010). Economic development, income inequality, and preferences for redistribution. International Studies Quarterly, *54*(2), 315-334.
- Duman, A. (2008). Education and income inequality in Turkey: does schooling matter? Financial Theory and Practice, *32*(3), 369-385.
- Eduardo, C. S. (2010). Catastrophic Natural Disasters and Economic Growth. IDB Working paper, NO.IDB-WP-183.
- Engle, R. F., & C. W. Granger. (1987). Co-integration and error correction: representation, estimation, and testing. Econometrica: Journal of the Econometric Society, 251-276.
- Feng, S., Lu, J., Nolen, P., & L. Wang. (2016). The effect of the Wenchuan earthquake and government aid on Figini, P., & Gorg, H. (2011). Does foreign direct investment affect wage inequality? An empirical investigation. The World Economy, 34(9), 1455-1475.
- Figini, P., & Gorg, H. (2006). Does foreign direct investment affect wage inequality? An empirical investigation. University of Nottingham Research Paper, (2006/29).
- Fielding, D., & Torres, S. (2006). A simultaneous equation model of economic development and income inequality. *The Journal of Economic Inequality*, *4*(3), 279-301.
- Forbes report. (2021). https://www.forbes.com/billionaires/,
- GIRI, A. K., PANDEY, R., & MOHAPATRA, G. (2021). Does Technological Progress, Trade, or Financial Globalization Stimulate Income Inequality in India?. *The Journal of Asian Finance, Economics, and Business*, *8*(2), 111-122.
- Glomm, G., & B. Ravikumar. (2003). Public education and income inequality. European Journal of Political Economy, 19(2), 289-300.
- Gregorio, J. D., & Lee, J. W. (2002). Education and income inequality: new evidence from cross-country data. *Review of income and wealth*, *48*(3), 395-416.
- Greenwood, J. (1997). The third industrial revolution: technology, productivity, and income inequality (No. 435). American Enterprise Institute.
- Herzer, D., & Nunnenkamp, P. (2013). Inward and outward FDI and income inequality: evidence from Europe. *Review of world economics*, *149*(2), 395-422.
- Himanshu. (2007). Recent trends in poverty and inequality: Some preliminary results. *Economic and political weekly*, 497-508.
- Jaumotte, F., Lall, S., & Papageorgiou, C. (2013). Rising income inequality: technology, or trade and financial globalization?. *IMF economic review*, *61*(2), 271-309.
- Jaumotte, F., Lall, S., & Papageorgiou, C. (2013). Rising income inequality: technology, or trade and financial globalization?. *IMF economic review*, *61*(2), 271-309.
- Jayadev, A., Motiram, S., & Vakulabharanam, V. (2007). Patterns of wealth disparities in India during the liberalisation era. *Economic and Political Weekly*, 3853-3863.
- Johansen, S. (1988). Statistical analysis of cointegration vectors. Journal of economic dynamics and control, 12(2-3), 231-254.
- Karim, A., & Noy, I. (2016). Poverty and natural disasters—a qualitative survey of the empirical literature. *The Singapore Economic Review*, *61*(01), 1640001.
- Kavya, T. B., & Shijin, S. (2020). Economic development, financial development, and income inequality nexus. *Borsa Istanbul Review*, *20*(1), 80-93.
- Keerthiratne, S., & Tol, R. S. (2018). Impact of natural disasters on income inequality in Sri Lanka. *World Development*, *105*, 217-230.

- Kim, N. (2012). How much more exposed are the poor to natural disasters? Global and regional measurement. Disasters, 36(2), 195-211.
- Krusell, P., Ohanian, L. E., Ríos-Rull, J. V., & Violante, G. L. (2000). Capital-skill complementarity and inequality: A macroeconomic analysis. *Econometrica*, *68*(5), 1029-1053.
- Kudasheva, T., Kunitsa, S., & Mukhamediyev, B. (2015). Effects of access to education and information-communication technology on income inequality in Kazakhstan. *Procedia-Social and Behavioral Sciences*, *191*, 940-947.
- Kuznets, S. (1955). Economic growth and income inequality. The American economic review, *45*(1), 1-28.
- Law, S. H., & Tan, H. B. (2009). The role of financial development on income inequality in Malaysia. *Journal of Economic Development*, *34*(2), 153.
- Lee, J. W., & Lee, H. (2018). Human capital and income inequality. *Journal of the Asia Pacific Economy*, *23*(4), 554-583.
- Lee, K. K., & Vu, T. V. (2020). Economic complexity, human capital and income inequality: a cross-country analysis. *The Japanese Economic Review*, *71*(4), 695-718.
- Masozera, M., Bailey, M., & Kerchner, C. (2007). Distribution of impacts of natural disasters across income groups: A case study of New Orleans. *Ecological economics*, *63*(2-3), 299-306.
- Meschi, E., & Vivarelli, M. (2009). Trade and income inequality in developing countries. *World development*, *37*(2), 287-302.
- Mnif, S. (2016). Bilateral relationship between technological changes and income inequality in developing countries. *Atlantic Review of Economics: Revista Atlántica de Economía*, *1*(1), 4.
- Mohd Daud, S. N., Ahmad, A. H., & Ngah, W. A. S. W. (2021). Financialization, digital technology and income inequality. *Applied Economics Letters*, *28*(16), 1339-1343.
- Oxfam report. (2021). The Inequality Virus - Global Report.
- Park, Joon Y. (1992). “Canonical Cointegrating Regressions,” Econometrica, 60, 119-143.
- Pesaran, M. H., & Shin, Y. (1995). An autoregressive distributed lag modelling approach to cointegration analysis.
- Pesaran, M. H., Shin, Y., & Smith, R. J. (1996). *Testing for the'Existence of a Long-run Relationship'* (No. 9622). Faculty of Economics, University of Cambridge.
- Phillips, P. C., & Hansen, B. E. (1990). Statistical inference in instrumental variables regression with I (1) processes. *The Review of Economic Studies*, *57*(1), 99-125.
- Prasetyo, A.B. (2013). The Impact of Infrastructure Development to the Economic Growth and Inequality in Indonesia Land Border Area. The Bogor Institute of Agriculture (Unpublished).
- Ram, R. (1997). Level of economic development and income inequality: Evidence from the postwar developed world. *Southern Economic Journal*, 576-583.
- Restuccia, D., & Urrutia, C. (2004). Intergenerational persistence of earnings: The role of early and college education. *American Economic Review*, *94*(5), 1354-1378.
- Rodríguez-Oreggia, E. (2010). Hurricanes and labor outcomes: a differencein-difference approach for Mexico.
- Santiago, R., Fuinhas, J. A., & Marques, A. C. (2019). Income inequality, globalization, and economic growth: a panel vector autoregressive approach for Latin American Countries. In *The Extended Energy-Growth Nexus* (pp. 57-96). Academic Press.
- Santos, M., Sequeira, T. N., & Ferreira-Lopes, A. (2017). Income inequality and technological adoption. *Journal of Economic Issues*, *51*(4), 979-1000.
- Sarkar, S., & Mehta, B. S. (2010). Income inequality in India: pre-and post-reform periods. *Economic and Political Weekly*, 45-55.
- Sehrawat, M., & Singh, S. K. (2019). Human capital and income inequality in India: is there a non-linear and asymmetric relationship?. *Applied Economics*, *51*(39), 4325-4336.
- Servén, L. (2004). The effects of infrastructure development on growth and income distribution. The World Bank.
- Shari, I. (2000). Economic growth and income inequality in Malaysia, 1971–95. *Journal of the Asia Pacific Economy*, *5*(1-2), 112-124.
- Shahpari, G., & Davoudi, P. (2014). Studying effects of human capital on income inequality in Iran. *Procedia-Social and Behavioral Sciences*, *109*, 1386-1389.
- Solt, F. (2016). The standardized world income inequality database. Social science quarterly, 97(5), 1267-1281.
- Wahiba, N. F., & El Weriemmi, M. (2014). The relationship between economic growth and income inequality. *International Journal of Economics and Financial Issues*, *4*(1), 135-143.
- Stock, J. H., & Watson, M. W. (1993). A simple estimator of cointegrating vectors in higher order integrated systems. *Econometrica: journal of the Econometric Society*, 783-820.
- Subhani Keerthiratne, R. S. (2018). Impact of Natural Disaster on Income Inequality in Sri Lanka. ELSEVIER, 105, 217-230.
- Subramanian, S., & Jayaraj, D. (2006). *The distribution of household wealth in India* (No. 2006/116). WIDER Research Paper.

- Sylwester, K. (2000). Income inequality, education expenditures, and growth. *Journal of development economics*, *63*(2), 379-398.
- Toya, H., & M. Skidmore (2007). Economic development and the impacts of natural disasters. *Economics Letters, 94*(1), 20–25.
- Tripathy, S. (2019). Impact of Natural Disasters and Climate Change on Poverty and Inequality in India. *Arthika Charche, 4*(1).
- Untari, R., Priyarsono, D. S., & T. Novianti. (2019). Impact of Information and Communication Technology (ICT) Infrastructure on Economic Growth and Income Inequality in Indonesia. *Int. J. Sci. Res. Sci. Eng. Technol, 6*, 109-116.
- Wahiba, N. F., & M. El Weriemmi (2014). The relationship between economic growth and income inequality. International Journal of Economics and Financial Issues, 4(1), 135.
- WIL. (2020). World Inequality Lab - Issue Brief 2020-08
- W.J.Wouter Botzen, O. D. (2019). The Economic Impacts of Natural Disasters: A Review of Model and Empirical Studies. *Review of Environmental Economics and Policy,13*(2),167-188.
- Yamamura, E. (2015). The impact of natural disasters on income inequality: analysis using panel data during the period 1970 to 2004. *International Economic Journal, 29*(3), 359-374.
- Zacharias, A., & V. Vakulabharanam (2011). Caste stratification and wealth inequality in India. *World Development, 39*(10), 1820-1833.
- Zhang, J. (2005). Income ranking and convergence with physical and human capital and income inequality. *Journal of Economic Dynamics and Control, 29*(3), 547-566.