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NEXUS BETWEEN TAX STRUCTURE AND INCOME INEQUALITY IN INDIA

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ABSTRACT

This study empirically examines the long-run effect of tax structure on income inequality in India. It considers annual time-series data from 1980 to 2019. The unit root and Johansen cointegration tests substantiate a long-run relationship between tax variables and income inequality. We employ Fully Modified OLS (FMOLS) and Dynamic OLS (DOLS) techniques for the baseline analysis. For a robustness check, we utilize the Canonical Cointegration Regression (CCR) technique. The results show that the top marginal tax rate (TMTR) reduces income inequality, whereas customs duty (CD) significantly increases income inequality. Personal income tax (PIT), corporate income tax (CIT), and excise duty (ED) have no significant association with income inequality. In addition, GDP per capita significantly reduces income inequality, whereas GDP per capita squared aggravates income inequality, reflecting the absence of the Kuznets hypothesis in India. Human capital measured by mean years of schooling (MYS) also significantly worsens income inequality. Our results suggest that the Indian government should increase TMTR and reduce customs duty (CD) in order to improve income distribution.

Contribution/ Originality: An analysis of the effect of tax structure on income inequality in India has not been previously explored in the literature. Thus, this examination of the long-run effect of tax structure on income inequality in India, employing sophisticated time-series techniques, contributes significantly to the literature from a policy perspective.

1. INTRODUCTION

In India, the income share of the top 1% of the population increased from 11% to 21.7% of total income between 1980 and 2021, whereas in the same period, the income share of the bottom 50% drastically plummeted from 23% to 13.1% of total income. Furthermore, in 2021, the top 10% captured 57% and the middle 40% shared only 29.7% (Chancel, Piketty, Saez, & Zucman, 2022). This fact establishes India as the second most unequal nation on earth in terms of income inequality, after South Africa (Mahendra, 2018). In addition, the impact of the Covid-19 pandemic has added fuel to the fire. The pandemic significantly reduced the share of income held by marginalized sections of society. Given the widespread negative economic outcome of the pandemic, the poor and middle classes are likely to be severely hit. A recent report by Oxfam (2021) confirms that the pandemic will deteriorate income distribution. The magnitude of deterioration could be significant in India due to India's prolonged suffering in the pandemic.

The high income inequality might limit economic performance and stand as a barrier to accomplishing many sustainable development goals (SDGs). For instance, SDGs such as no poverty, zero hunger, gender equality, decent work and economic growth, and inequality reduction may not be realized within the stipulated time. This might happen because the purchasing power of the majority low-income class has declined in comparison to the minority high-income class, and the marginal propensity to consume (MPC) is relatively higher for the low-income class than the high-income class. Hence, severe income inequality might weaken economic performance (Stiglitz, 2012). Sustainable Development Goal 10 (SDG10) affirms that income inequality affects accessibility to factors like healthcare, food and nutrition, energy, education, water, and sanitation (Sarkodie & Adams, 2020). Therefore, policies are urgently needed to reduce the income inequality in India. This study is highly significant from a policy perspective.

Rigorous policies are urgently required to ameliorate income distribution in India. Taxation is a conventional and direct policy to achieve income redistribution. In this context, this study addresses the questions: Do conventional prescriptions of taxation affect income inequality in India? Does taxation improve or worsen income distribution in India? Which tax parameter improves income distribution? Taxation, as a policy tool, has various economic objectives and develops over time. Initially, taxation was designed as an effective means of mobilizing revenue (Musgrave, 1959). Furthermore, Solow (1956) and Swan (1956) considered taxation to be an exogenous variable in their seminal works and showed that changes in tax rates could shift the intercept of the Steady-State growth path. In light of a significantly widening income inequality worldwide, tax policies are designed to improve income distribution.

Taxation can affect income distribution either positively or negatively. Progressive taxes, such as individual income tax and corporate income tax, can ameliorate income distribution. They ensure a supplementary inclusive process of economic development (Kaldor, 1963). Conversely, regressive taxes such as sales tax, VAT, customs duties, and excise duties are expected to deteriorate income distribution because of the higher burden they place on poor individuals. However, the effectiveness of taxes varies from country to country. The most debated issue is the effectiveness of tax policy in addressing income disparity in developing economies (Bird & Zolt, 2013).

The effect of taxation on income inequality in developing countries is restrained by the considerable informal sector and the dearth of appropriate administrative systems (Mahon, 2009). Similarly, Martorano (2016) revealed the limited effect of taxation on income disparity through low average tax revenue (% of GDP), a higher segment of indirect taxes in total tax revenue (TTR), a lack of ability to tax top incomes, and an insignificant contribution of property taxes to TTR in Latin America. As a developing country, India has faced vast income inequality since the beginning of liberalization policies in the 1980s. The top 1% of income earners' share of the national income is 22%, while the top 10% earn 56% (Chancel & Piketty, 2019). It is against this background that we attempt to assess the role of tax structure in affecting income inequality in India for the period 1980-2019.

In the Indian context, considering the degree of progressivity in PIT and examining the redistributive effects of income tax schedules by Atkinson's measure of inequality for 1985-86, Nayak and Paul (1989) showed that a fall in marginal tax rate at the lower as well as the upper end of the income scale is likely to broaden the base. It also improves income redistribution more than the most progressive tax schedule. Using personal income tax data from 1961-62 to 1983-84, Aggarwal (1990) claimed, using OLS regression, that given the income distribution, a rise (fall) in the tax level or tax progressivity increases (decreases) the redistributive impact of the tax. To the best of our knowledge, no single analysis has scrutinized the effect of tax structure on income inequality in India. This gap constitutes a substantial barricade to identifying the most promising tax policies for reducing inequality. With income inequality increasing, this gap motivates us to empirically investigate the effect of tax structure on income inequality in India from a policy perspective.

Considering tax structure, Atkinson and Stiglitz (1976) maintained that equitable income distribution could be achieved through income tax alone and consumption taxes were not required for income distribution. García-

Peñalosa and Turnovsky (2011) found that an increase in both income tax and consumption tax is associated with lower output but with high after-tax income equality. Conversely, observing a tax mix model of consumption and income taxes, Cremer, Pestieau, and Rochet (2001) maintained that commodity taxes are beneficial for redistribution.

Based on this theoretical background, the present paper investigates the impact of tax structure on income inequality in India. The study employs annual data from 1980 to 2019 and various time-series econometric techniques to meet its objectives. First, we employ the Augmented Dickey-Fuller (ADF) and Phillip-Perron (PP) unit root tests to confirm the stationarity of the data. Second, the application of the Johansen cointegration test reinforced the long-run association among the variables. Third, we used FMOLS and DOLS to investigate our objectives. These models are known for their power to mitigate small sample bias, endogeneity, and serial correlation problems in a regression framework. Finally, we used the Canonical Cointegration Regression (CCR) to check the consistency of the results.

Results from time-series techniques show that the top marginal tax rate (TMTR) reduces income inequality, whereas Customs Duty (CD) increases income inequality significantly. However, Corporate Income Tax (CIT) and Excise Duty (ED) do not affect income inequality significantly in India. In addition, GDP per capita significantly reduces income inequality, whereas GDP per capita squared aggravates income inequality, reflecting the absence of the Kuznets hypothesis in India. Human capital measured by mean years of schooling (MYS) also significantly worsens income inequality.

With these findings, our study contributes significantly to the literature. First, to the best of our knowledge, we are the first to examine the effect of tax structure on income inequality in India. Second, if series are stationary at the first difference, then variables may be cointegrated in the model. The fundamental issues concern non-stationarity in data series, which produce potential spurious correlation and endogeneity problems (Engle & Granger, 1987). Using conventional methods, in this case, may provide misleading and unreliable results. Therefore, to circumvent such issues, we used sophisticated time-series techniques, including FMOLS, DOLS, and CCR. These models remove small sample bias, spurious correlation, and endogeneity problems, thus producing reliable results. Third, other variables affect income inequality; therefore, we used three important control variables to avoid model misspecification problems. Fourth, unlike other studies that considered a single tax rate, we used overall tax structure to provide a complete picture of the impact of tax on income inequality. Finally, our results are consistent with the alternative modeling.

This paper is organized as follows. Section 2 reviews the previous literature on the link between tax and income inequality. Section 3 provides the data sources and estimation methods employed for the investigation and determines the sign of coefficients based on the theoretical groundwork. Section 4 contains empirical results and their discussion. Section 5 provides the results of the robustness check. Lastly, Section 6 concludes with policy implications.

2. LITERATURE SURVEY

This section reviews both empirical and theoretical literature in various subsections.

2.1. Tax Progressivity and Income Inequality

A tax structure is progressive if the average tax rate rises with an increase in income before tax (Jackobsson, 1976). The study of income tax progression and income distribution dates back to Musgrave and Thin (1948). They provided various measures of progressivity through which income distribution can take place. However, they failed to distinguish between the effects of changes in progressivity and those of average tax rates on income distribution. Therefore, Kakwani (1977) considered this issue and showed that a reduction in income distribution depends on both tax progressivity and the average tax rate.

Recent studies have also examined the effect of tax progressivity on income disparity. For instance, Burman (2013) tried to determine the appropriate level of tax progressivity in the federal tax system to reduce income inequality in the US. He found that the numerous factors that cause inequality and the cost of taxation are the determinants of an appropriate level of tax progressivity. On the one hand, there is little foundation for progressive taxation if the differences in income are caused by variations in effort, thrift, or occupation. On the other hand, if variations in luck or rent-seeking cause differences in income, there should be a highly progressive income tax system.

Similarly, employing various progressivity measures over the period 1981-2005, Duncan and Peter (2016) maintained that personal income tax progressivity significantly reduces observed inequality and actual inequality. However, the effect is more marginal in the case of observed inequality than actual inequality. In addition, they found that the tax progressivity effect is stronger in more developed democratic institutions than in weaker legal institutions, even though the effect can be positive in weak institutions. They also suggested that it would be more effective if changes in progressivity were reflected at the top rather than at the bottom of the income scale. However, Lambert (1993) argued that progressive taxation by itself cannot reduce income inequality; rather, income taxes that contain non-income attributes can reduce overall income inequality. Therefore, this study prescribes certain conditions which should be fulfilled to reduce overall inequality. These conditions are: (1) every member of one class is more affluent than any member of the other; (2) the members of this more affluent class are all taxed at a higher average rate than the others; (3) the tax does not induce any reversal in the income parade.

2.2. Tax Structure and Income Inequality

The study of the impact of tax structure on income inequality traces back to Musgrave (1959), who discussed how welfare and distribution change when one tax is substituted for another. However, Atkinson and Stiglitz (1976) provided the first formal model involving tax structure and found that income tax can reduce income inequality. There is no need for consumption taxes. Conversely, Cremer et al. (2001) inspected the tax mix model between income tax and commodity taxes. They found that commodity taxes are positively related to income redistribution.

Some recent empirical studies have analyzed the effect of tax structure on income inequality. Iosifidi and Mylonidis (2017) examined the effect of labor, consumption, and capital tax rates on income disparity in the OECD. They found that the redistributive effect of the single tax rate is modest. Only labor tax has a significant negative effect on inequality. The study suggested that the redistributive power of relative tax rates is more significant than that of the single tax rate. Specifically, the larger the tax burden on labor than on capital and the higher the burden on consumption than on capital, the greater the income inequality. The intensification of the labor to consumption taxes ratio leads to an aggravation of income equality.

Using the PVAR model, Ciminelli, Ernst, Merola, and Giuliodori (2019) examined the composition effects of tax-based consolidations on income inequality in 16 OECD countries from 1978 to 2012. The study found that the impact of general indirect taxes is greater than that of personal income tax in reducing income inequality through the channel of labor force participation. Finally, considering 18 Latin American economies, Martorano (2018) studied the taxation-income inequality association from 1990 to 2015. He investigated the possible effects of different tax instruments and other control variables on income inequality. The study found that recent tax changes in the early 2000s reduced income inequality. Specifically, the increasing share of direct taxes to TTR compared to that of indirect taxes to TTR promoted the tax system's progressivity and contributed to the reduction of inequality. Nevertheless, the tax policy's effectiveness in reducing income inequality was not satisfactory for various reasons, such as the low tax to GDP ratio, the inability of the governments to raise effective top tax rates, and the low contribution of property taxes to TTR in Latin America.

2.3. Tax-Expenditure Policies and Income Inequality

Taxation on its own cannot sufficiently reduce income inequality. The powerful force of income inequality can be offset by the combined effort of progressive taxation and redistributive expenditure. By increasing the tax rate on top income earners, progressive taxation reduces income inequality, and by providing more transfer payments to the poor, redistributive expenditure increases the disposable income of the poor and reduces income inequality. Aaron (2015) suggested that an increase in the tax rate on wealthy Americans as well as prudent expansion of public spending would reduce income inequality in the US. Using the Brazilian Household Microsimulation Model (BRHAMS), Immervoll, Levy, Nogueira, O' Donoghue, and De Siqueira (2006) found that tax-benefit systems successfully reduce income inequality in Brazil. Ivaškaitė-Tamošiūnė, Maestri, Malzubris, Poissonnier, and Vandeplas (2018) found that tax reforms adopted in Latvia in 2017 had a limited effect on income inequality. However, the study predicted that if pursued further, the reform of the minimum income scheme could reduce inequality.

Heisz and Murphy (2016) examined the effects of taxes and transfers on income inequality in Canada from 1976 to 2011 and found that the tax and transfer system significantly reduced the increase in market income inequality. Using observational microdata across 22 OECD countries for the 1922-2013 period, Guillaud, Olckers, and Zemmour (2017) found that a combination of taxation and transfers reduced income inequality. Hanni, Martner, and Podesta (2015) examined the effect of personal income tax and transfer payments on income disparity in 17 Latin American countries. They found that the Gini coefficient was reduced by 61% due to public cash transfers, and the remaining 39% was due to personal income as well as social security contributions. Similarly, Martinez-Vazquez, Moreno-Dodson, and Vulovic (2012) explored the effect of taxes and public expenditure on income inequality for a panel of 150 economies. They maintained that both taxes and public expenditure have a significant impact on income distribution. Specifically, income tax significantly reduces income inequality, and its impact increases the greater the degree of progressivity.

2.4. Tax and Income Inequality in India

To check the degree of progressivity, Nayak and Paul (1989) investigated India's personal income tax structure for 1985-86. They also examined the redistributive impact of mathematically designed income tax schedules using Atkinson's measure of inequality. They found that India's personal income tax (PIT) structure is progressive, particularly when comparing the distribution of pre-tax and post-tax income. Nevertheless, the PIT covers less than 1% of the population, which is the main difficulty of redistribution. They suggested that a decline in marginal tax rate at the lower as well as the upper end of the income scale was likely to broaden the base. Thus, the actual tax redistribution schedules may be larger than the most progressive tax schedule. If the government wants to pursue a revenue-neutral policy, it cannot afford meager tax rates at the lower end of the income scale.

Aggarwal (1990) analyzed the effect of personal income tax on income distribution by empirically isolating income inequality from the effect of tax progressivity and tax level. He used the Gini index and Atkinson's measure of inequality to measure income redistribution. The OLS method was used to study the redistributive effect of tax instruments and income inequality. It showed that income inequality significantly affects the redistributive impact of the tax. For a given tax structure, a rise (fall) in income inequality increases (decreases) the redistributive impact of the tax. Similarly, given a level of income inequality, a rise (fall) in the tax level or tax progressivity increases (decreases) the redistributive impact of the tax.

This confirmed that tax progressivity in the form of personal income tax has more potential than other taxes to reduce income inequality across countries and time. The extant literature also suggests that a combination of taxes and transfers could reduce income inequality more effectively. However, Swagel and Boruchowicz (2017) assessed the tax policies and other measures aimed at income redistribution in the US and found that tax policies cannot effectively reduce income inequality. Redistributive transfers are likely to have a modest effect on income disparity.

Nonetheless, they believed that measures aimed at improving individual incentives for work could substantially increase both before- and after-tax incomes at the bottom of the income distribution scale.

Although a significant amount of prior literature is associated with taxation and income inequality, it nevertheless remains unclear how India's tax structure affects its income distribution. Reviewing the literature, we confirmed that no single study has investigated the effect of tax structure on income inequality in India. The empirical ambiguity involving the relationship between taxes and income distribution increases the difficulty of adopting and implementing appropriate policies. Hence, our study tries to fill this important gap in the literature from a policy perspective.

3. DATA, TIME SERIES CHARACTERISTICS, AND METHODS

3.1. Data

The present study involves data collected from various sources for empirical analysis. For the dependent variable, we consider the standardized Gini coefficient of household disposable income (post-tax, post-transfer), denoted as Gini_disp_se. For the main independent variables, we use five tax variables (denoted as tax structure): top marginal tax rate including cess and surcharge (TMTR_C&S), personal income tax (PIT) as a % of total tax revenue (TTR) (PIT/TTR), corporate income tax (CIT) as a % of TTR (CIT/TTR), excise duty (ED) as a % of TTR (ED/TTR), and customs duty (CD) as a % of TTR(CD/TTR). To circumvent model misspecification, we use additional independent variables, such as GDP per capita (GDP_PC), GDP_PC squared (GDP_PCS), and mean years of schooling (MYS). We consider GDP per capita and its square to test the Kuznets hypothesis. Table 1 provides details of the variables, their definitions, and sources.

Table 1. Variables, definitions, and sources.

Variable	Definition	Source
Dependent variable		
Gini_disp_se	Estimate of Gini index of inequality in equivalized (square root scale) household disposable (post-tax, post-transfer) income, using Luxembourg Income Study data as the standard.	SWIID version 9.0
Main independent variables		
Top Marginal Tax Rate including cess and surcharge (TMTR_C&S) Personal Income Tax (PIT)	Marginal tax rate applies to top income tax bracket including cess and surcharge. The ratio of PIT to total tax revenue (TTR).	Union Budget documents, MOF, India IPFS, MOF, India IPFS, MOF, India
Corporate Income Tax (CIT)	The ratio of CIT to TTR	IPFS, MOF, India
Excise Duty (ED)	The ratio of ED to TTR	IPFS, MOF, India
Customs Duty (CD)	The ratio of CD to TTR	IPFS, MOF, India
Additional independent variables (Control variables)		
GDP per capita (GDP_PC)	GDP per capita (constant 2010 US$)	RBI
GDP per capita squared (GDP_PCS)	GDP per capita (constant 2010 US$) squared	We converted GDP_PC to GDP_PCS
Mean Years of Schooling (MYS)	The average number of years of education received by people ages 25 and older (UNDP).	UNDP, Barro and Lee database

Note: SWIID indicates the standardized world income inequality database, IPFS indicates Indian Public Finance Statistics, MOF is the Ministry of Finance, UNDP stands for the United Nation Development Programme, and RBI indicates the Reserve Bank of India.

The Gini coefficient shows the mean income difference between all pairs over twice the mean income in the population. If the Gini coefficient (GC) is 0, then all income is distributed equally among the population. If GC is 1, then all income is concentrated in one person. Similarly, if GC takes a value from 1 to 100 (as it does in the SWIID data), it reflects the same interpretation as a GC of between 0 and 1. The GC has been widely used among researchers. The income GC data were extracted from the SWIID[1] version 9.0, created by Solt (2016). The SWIID data is very reliable and maximizes comparability for the largest possible sample of economies and years (Cevik & Correa-Caro, 2015; Jaumotte & Papageorgiou, 2008; Santiago, Fuinhas, & Marques, 2019) compared to any other database such as WID, WIID (UNU-WIDER), or World Bank. Hence, SWIID is used in this study.

We use four tax ratios – PIT/TTR, CIT/TTR, ED/TTR, and CD/TTR – to establish the tax structure of India. The data on these four tax ratios are extracted from the Indian Public Finance Statistics (IPFS) published by MOF,[2] GOI.[3] The top marginal income tax rate (TMTR) is conventionally used as a parameter of personal income tax progressivity. Progressivity of personal income tax increases with a rise in the TMTR. The TMTR data were drawn from union budget documents of the government of India between 1980 and 2019. GDP per capita, as well as GDP per capita squared, were computed from the data on GDP at constant price and population extracted from RBI. Education has been noted as an important variable that influences income inequality. So we took mean years of schooling (MYS) as a proxy for education. MYS data was taken from both UNDP and Barro and Lee databases due to data unavailability from any one source. MYS data from 1980 to 1990 was drawn from the Barro and Lee database. The missing MYS data between 1980 and 1990 was filled by the annual average growth rate of MYS between 1980 and 1990. Furthermore, MYS data for 1990 to 2019 was extracted from the UNDP database.

3.1.1. Summary Statistics and Correlation Matrix

Table 2 shows that among all the variables, GDP per capita (GDP_PC) has the highest mean, median, maximum, minimum, and standard deviation values. Conversely, Gini_disp_se has the lowest mean, median, maximum, minimum, and standard deviation values. All the variables are normally distributed as demonstrated by the Jarque-Bera statistic and its corresponding p-values. All p-values are more than 0.05. The total observations in each series are 40.

Table 2. Summary statistics.

Variable	Gini_disp_se	TMTR_ C&S	PIT/TTR	CIT/TTR	ED/TTR	CD/TTR	GDP_PC	MYS
Mean	1.402	42.901	11.501	23.276	28.566	28.899	47779.54	4.149
Median	1.400	35.550	11.442	21.149	30.755	30.577	38575.29	4.300
Maximum	1.800	72.000	23.797	38.725	40.790	48.909	108620.0	6.500
Minimum	0.800	30.000	2.152	12.254	14.503	5.232	19776.87	1.870
Std. Dev.	0.174	12.881	7.852	8.243	7.895	14.496	26483.26	1.468
Skewness	0.200	0.829	0.080	0.316	-0.273	-0.068	0.900	0.021
Kurtosis	2.474	2.315	1.205	1.797	1.815	1.414	2.591	1.793
Jarque-Bera	0.729	5.367	5.411	3.077	2.836	4.223	5.686	2.430
P-Value	0.694	0.068	0.066	0.214	0.242	0.121	0.0582	0.296
Observations	40	40	40	40	40	40	40	40

The correlation matrix (represented in Table 3) reveals that TMTR, the tax ratios PIT/TTR, CIT/TTR, ED/TTR, and MYS are negatively associated with the Gini coefficient. CD/TTR and GDP per capita are positively associated with the Gini coefficient. The correlation coefficient suggests the absence of a high degree of correlation between the Gini coefficient and all other variables of interest. Nevertheless, a high degree of correlation exists among the explanatory variables. The high degree of correlation between the explanatory variables reflects a potential multicollinearity problem in the models. To avoid the multicollinearity problem, first, we use sophisticated models of estimation that correct for this issue. Second, we use a single tax variable in a model and estimate five

[1] Standardized World Income Inequality Database (SWIID).

[2] Ministry of Finance (MOF).

[3] The Government of India (GOI).

different models. Our method of estimation involving sophisticated econometrics tools solves the potential multicollinearity problem in the models.

3.2. Time Series Characteristics

Time series data is subject to two significant issues: stationarity of series and cointegration among variables. To address both issues, it helps to select appropriate econometrics techniques and thereby provide unbiased, consistent, and accurate results. We are proceeding with the two time series features detailed below.

Table 3. Correlation matrix.

Variable	Gini_disp_se	TMTR_C&S	PIT_TTR	CIT_TTR	ED_TTR	CD_TTR	GDP_PC	MYS
Gini_disp_se	1.000 ----- -----							
TMTR_C&S	-0.370 (2.459) [0.018]	1.000 ----- -----						
PIT/TTR	-0.088 (-0.545) [0.588]	-0.763 (-7.280) [0.000]	1.000 ----- -----					
CIT/TTR	-0.195 (-1.226) [0.227]	-0.748 (-6.950) [0.000]	0.848 (9.870) [0.000]	1.000 ----- -----				
ED/TTR	-0.110 (-0.687) [0.496]	0.569 (4.269) [0.000]	-0.626 (-4.950) [0.000]	-0.791 (-7.985) [0.000]	1.000 ----- -----			
CD/TTR	0.009 (0.005) [0.995]	0.678 (5.699) [0.000}	-0.975 (-27.482) [0.000]	-0.837 (-9.465) [0.000]	0.591 (4.520) [0.000]	1.000 ----- -----		
GDP_PC	0.255 (1.628) [0.111]	-0.651 (-5.289) [0.000]	0.873 (11.087) [0.000]	0.781 (7.712) [0.000]	-0.808 (-8.467) [0.000]	-0.880 (-11.453) [0.000]	1.000 ----- -----	
MYS	-0.0019 (-0.012) [0.990]	-0.842 (-9.645) [0.000]	0.921 (14.655) [0.000]	0.847 (9.832) [0.000]	-0.757 (-7.163) [0.000]	-0.896 (-12.477) [0.000]	0.940 (17.025) [0.000]	1.000 ----- -----

Note: For abbreviations, see the text. The values in the square brackets and parentheses represent p-values and t-statistics, respectively.

Table 4. Unit root results.

Variable	ADF TEST		PP TEST	
	C	C+T	C	C+T
lnGini_disp_se	-2.273	-0.696	-2.266	-1.975
ΔlnGini_disp_se	-3.300**	-6.747***	-8.154***	-8.269***
lnTMTR_C&S	-2.063	-2.195	-2.082	-2.195
ΔlnTMTR_C&S	-7.601***	-6.382***	-8.155***	-11.923***
lnPIT/TTR	-0.699	-2.730	-0.579	-2.715
ΔlnPIT/TTR	-7.664***	-7.579***	-7.790***	-7.691***
lnCIT/TTR	-1.240	-1.202	-1.280	-1.420
ΔlnCIT/TTR	-4.932***	-4.874***	-4.932***	-4.874***
lnED/TTR	-0.788	-2.832	-0.891	-2.303
ΔlnED/TTR	-4.933***	-4.929***	-4.809***	-4.808***
lnCD/TTR	1.491	-1.330	1.380	-1.330
ΔlnCD/TTR	-5.020***	-5.617***	-5.015***	-5.618***
lnGDP pc	2.914	-1.306	3.299	-1.277
ΔlnGDP pc	-4.619***	-5.679***	-4.593***	-5.666***
lnMYS	-2.488	-0.871	-4.990	-0.287
ΔlnMYS	-5.162***	-5.889***	-5.147***	-9.723***

Notes: ** and *** denote the level of significance at 5%, and 1%, respectively. Here, C stands for constant, and C+T indicates the constant plus trend.

3.2.1. Unit Root in Data Series

First, if there is a non-stationarity issue (unit root problem) in the time series, without appropriate techniques, it may produce biased and inefficient estimators, leading to a misleading interpretation of the empirical results. So, we use Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests to find unit roots in the series. Conducting unit root tests helps researchers employ the appropriate empirical tools that provide unbiased results. Some literature has reported that for a small sample, ADF performs much better (Arltova & Fedorova, 2016). We conducted both techniques, incorporating a constant (C) as well as a constant plus trend (C+T). The results are shown in Table 4. The unit root results from both tests (ADF & PP) document that all series are stationary at the first difference. It implies the series are I(1) order of integration. It indicates the series are nonstationary at level and stationary at first difference. The first difference stationary data set also reflects the possible cointegration among variables (Engle & Granger, 1987). Hence, next, we deal with the cointegration test.

3.2.2. Johanson Cointegration Test

We employ the Johanson cointegration test to corroborate the cointegrating nature among the variables. The Johanson Cointegration test specification rests on a summary result with different assumptions involving the selection of optimum lags and deterministic terms (i.e., intercept and trend) in the models. The number of models hinges on tax variables. We consider five different tax variables based on their importance to income redistribution. So, we run five models incorporating the five tax variables. All five models have been considered in the cointegration test. Schwarz information criteria (SIC) are employed to navigate optimum lags in the cointegration test. Summary results involving SIC of the Johanson cointegration test suggest using two lags with linear intercept and trend for the 1^{st}, 4^{th}, and 5^{th} models, one lag with quadratic intercept and trend for the 2^{nd} model, and one lag with linear intercept and trend for the 3^{rd} model.

Johansen's (1988) cointegration test is popular and widely used. The cointegration results reflect that the variables under each model are cointegrated. It demonstrates the presence of a long-run association among variables of interest. Table 5 shows the results of the Johanson cointegration test. The trace and maximum eigenvalue statistics reject the null hypothesis (no cointegration) and accepted the alternative hypothesis: the presence of cointegration among variables of interest in all models. Specifically, trace and maximum eigenvalue demonstrate at least one cointegrating equation in each model. It implies the presence of a long-run association between tax variables and income distribution in India.

Finally, we conclude that the unit root and Johanson cointegration tests suggest that the cointegrating technique appears to be an appropriate method to evaluate the effect of tax structure on income inequality in India. Thus, the present analysis considers cointegrating models such as FMOLS, DOLS, and CCR to be time-series techniques appropriate for examining our research question.

4. METHODS

4.1. Brief Description of Techniques

The unit root and cointegration test results recommend the use of cointegrating models. Thus, we make use of sophisticated estimation techniques to circumvent omitted variables, unit root, and reverse causality problems by employing FMOLS, DOLS, and CCR. These techniques yield better results than the traditional OLS estimators, as they correct serial correlation and endogeneity problems. The FMOLS, DOLS, and CCR models determine the long-run relationship by employing a single cointegrating vector. All three models are fully efficient techniques. Note that the CCR model is used to confirm the consistency of our results.

Table 5. Johansen-cointegration test results.

1st model				
Trace statistics				
Hypothesized No. of CE(s).	**Eigenvalue**	**Trace Statistic**	**0.05 Critical Value**	**Prob.****
None *	0.766	122.512	88.803	0.000
At most 1 *	0.610	68.758	63.876	0.018
At most 2	0.382	33.833	42.915	0.296
At most 3	0.242	16.017	25.872	0.491
At most 4	0.143	5.727	12.517	0.495
Maximum Eigenvalue statistics				
No. of CE(s).	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.7660	53.753	38.331	0.000
At most 1 *	0.6108	34.924	32.118	0.022
At most 2	0.3821	17.816	25.823	0.391
At most 3	0.2427	10.290	19.387	0.587
At most 4	0.143	5.727	12.517	0.495
2nd model				
Trace statistics				
No. of CE(s).	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.692	100.258	79.341	0.000
At most 1 *	0.592	55.392	55.245	0.048
At most 2	0.289	21.324	35.010	0.620
At most 3	0.192	8.317	18.397	0.650
At most 4	0.004	0.188	3.841	0.664
Maximum Eigenvalue statistics				
No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.692	44.866	37.163	0.005
At most 1 *	0.592	34.067	30.815	0.019
At most 2	0.289	13.006	24.252	0.677
At most 3	0.1925	8.129	17.147	0.588
At most 4	0.0049	0.188	3.841	0.664
3rd model				
Trace statistics				
No. of CE(s).	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.696	120.327	88.803	0.000
At most 1 *	0.621	75.021	63.876	0.004
At most 2	0.376	38.104	42.915	0.139
At most 3	0.316	20.128	25.872	0.219
At most 4	0.138	5.649	12.517	0.506
Maximum Eigenvalue statistics				
No. of CE(s).	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.696	45.305	38.331	0.006
At most 1 *	0.621	36.917	32.118	0.012
At most 2	0.376	17.975	25.823	0.379
At most 3	0.316	14.478	19.387	0.223
At most 4	0.138	5.649	12.517	0.506
4th model				
Trace statistics				
No. of CE(s).	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.796	137.310	88.803	0.000
At most 1 *	0.597	78.468	63.876	0.001
At most 2 *	0.510	44.754	42.915	0.032
At most 3	0.289	18.324	25.872	0.322
At most 4	0.142	5.680	12.517	0.502
Maximum Eigenvalue statistics				
No. of CE(s).	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.796	58.842	38.331	0.000
At most 1 *	0.597	33.713	32.118	0.031
At most 2 *	0.510	26.430	25.823	0.041
At most 3	0.289	12.644	19.387	0.357
At most 4	0.142	5.680	12.517	0.502
5th model				
Trace statistics				
No. of CE(s).	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.7839	128.391	88.803	0.000
At most 1 *	0.5423	71.700	63.876	0.009
At most 2	0.3810	42.780	42.915	0.051

At most 3	0.3498	25.030	25.872	0.063
At most 4	0.2180	9.098	12.517	0.174
Maximum Eigenvalue statistics				
No. of CE(s).	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.783	56.690	38.331	0.000
At most 1	0.542	28.920	32.118	0.117
At most 2	0.381	17.749	25.823	0.396
At most 3	0.349	15.932	19.387	0.148
At most 4	0.2180	9.098	12.517	0.174

Note: * Denotes rejection of the hypothesis at the 0.05 level.
**MacKinnon-Haug-Michelis p-values.

Phillips and Hansen (1990) used semi-parametric correction to circumvent the issue produced by the long-run correlation between the cointegrating equation and stochastic regressors innovations. This Phillips and Hansen method is known as Fully Modified Ordinary Least Squares (FMOLS). It provides an asymptotically unbiased and efficient estimator letting for the standard Wald test involving asymptotic Chi-square statistical inference (Hansen, 1992). Similar to FMOLS, Park (1992) proposed a model known as Canonical Cointegration Regression (CCR). CCR employs stationary conversion of the data to attain the least square estimate to remove the long-run reliance between cointegrating equations as well as stochastic regressor shocks. The CCR conversion asymptotically removes endogeneity produced via the long-run cointegrating equation's correlation and regressor shocks (Lee & Xuan, 2019). If estimators are systematically corrected, the asymptotic property is not disturbed by endogeneity or serial correlation (Montalvo, 1995).

Finally, Stock and Watson (1993) introduced an easy method for establishing asymptotically efficient estimators that can remove the reverse causality in a cointegrating framework. This approach is known as the Dynamic Ordinary Least Squares (DOLS) model. They consider leads and lags in the framework that asymptotically eliminate any possible bias resulting from endogeneity problems or serial correlation (Montalvo, 1995). Therefore, FMOLS, CCR, and DOLS provide efficient estimators that correct small sample bias, simultaneity bias, endogeneity problems, and serial correlation in the model. However, Montalvo (1995), among others, maintained that the DOLS model performs steadily better than the FMOLS and CCR methods. Overall, we are convinced that the use of these three models will provide a consistent and robust outcome. FMOLS, CCR, and DOLS models are suitable and appropriate for this small sample analysis.

4.2. Model Specification

To investigate the relationship between tax structure and income inequality in India, we use the following equations. The specified equations are presented in Equations 1, 2, 3, 4, and 5. Where Gini_disp_se stands for the measure of income inequality; TMTR_C&S stands for top marginal tax rate including cess and surcharge; PIT is the personal income tax (%TTR); CIT is the corporate income tax (%TTR); ED is the excise duty (%TTR); CD represents custom duty (%TTR); GDP_PC is the GDP per capita, reflecting a lower economic development; GDP_PCS is the GDP per capita squared, representing a higher economic development; MYS reflects the mean years of schooling, and ln represents the natural log. All data series have been converted into log forms.

$$lnGini\_disp\_se_t = \beta_0 + \beta_1 lnTMTR\_C\&S_t + \beta_2 lnGDP\_PC_t + \beta_3 lnGDP\_PCS_t + \beta_4 lnMYS_t + \varepsilon_t \quad (1)$$

$$lnGini\_disp\_se_t = \beta_0 + \beta_1 lnPIT_t + \beta_2 lnGDP\_PC_t + \beta_3 lnGDP\_PCS_t + \beta_4 lnMYS_t + \varepsilon_t \quad (2)$$

$$lnGini\_disp\_se_t = \beta_0 + \beta_1 lnCIT_t + \beta_2 lnGDP\_PC_t + \beta_3 lnGDP\_PCS_t + \beta_4 lnMYS_t + \varepsilon_t \quad (3)$$

$$lnGini\_disp\_se_t = \beta_0 + \beta_1 lnED_t + \beta_2 lnGDP\_PC_t + \beta_3 lnGDP\_PCS_t + \beta_4 lnMYS_t + \varepsilon_t \quad (4)$$

$$lnGini\_disp\_se_t = \beta_0 + \beta_1 lnCD_t + \beta_2 lnGDP\_PC_t + \beta_3 lnGDP\_PCS_t + \beta_4 lnMYS_t + \varepsilon_t \quad (5)$$

Where β_0 is the intercept, β_1 to β_4 are the coefficients of slope parameters, and ε_t is the stochastic error term. FMOLS, DOLS, and CCR models are estimated in Equations 1, 2, 3, 4, and 5. To reduce the influence of outliers in our time series data, we transform all the variables into a natural logarithmic form, represented by ln. The same number of control variables is used in each equation.

4.3. Coefficient Sign Involving Theoretical Link

The main variable of interest: The TMTR is a measure of progressivity of personal income tax. The higher the TMTR, the greater will be the burden on the high-income class and the lower the burden will be on the low-income class. Thus, income inequality will be reduced. Hence, we predict that $\beta_1 < 0$ in Equation 1. As this study inspects the tax structure's effect on income inequality, our variables of interest are individual tax instruments. Personal income tax (PIT) is generally a progressive tax because the tax burden is greater on the high-income class than on the low-income class. So, the more revenue that is raised from personal income tax, the lower income inequality will be. Hence, it assumed that $\beta_1 < 0$ in Equation 2. Corporate income tax (CIT) is believed to be a progressive tax if the tax falls on capital income earners. However, in open economies, easy and seamless movement of capital from one country to another country shifts the corporate tax burden to labor income. Since labor income recipients naturally have lower average incomes than capital income recipients, CIT leads to higher income inequality (Harberger, 1995). Thus, we predict that $\beta_1 >/< 0$ in Eq. 3. Excise duty (ED) is expected to have a positive effect on income inequality. Hence, this study assumed that $\beta_1 > 0$ in Eq. 4. Finally, customs duty (CD) is positively related to income inequality due to its regressive nature. So, we assume that $\beta_1 > 0$ in Equation 5.

Control variables of interest: We have used some control variables in the models; hence, determining their sign is also important. However, the sign of the control variable may vary with the region. We only assign signs based on the general view provided by the extant literature. Kuznets (1955) speculated that inequality intensifies first and then declines after a certain point, owing to economic development. This pattern of income inequality relating to economic development over time is referred to as the Kuznets Inverted-U hypothesis. To capture the Kuznets hypothesis, we used GDP per capita (GDP_PC) to represent a low level of economic development and GDP per capita squared (GDP_PCS) to indicate a higher level of economic development. If $\beta_2 > 0$ and $\beta_3 < 0$, then an inverted-U-shaped or Kuznets hypothesis holds.

Human capital significantly affects income inequality. If the level of human capital increases, the study expects that it may influence income inequality, as the distribution of income depends on the level and distribution of schooling in the population (Coady & Dizioli, 2018). Thus, we used mean years of schooling (MYS) to capture human capital. It assumed that $\beta_4 < 0$, indicating that MYS reduces income inequality. However, education is poorly distributed in India, and thus the sign of β_4 may be reversed. The control variables remain the same in all equations; thus, the signs of the coefficients for the control variables take the same interpretation.

4.4. Estimation Process

All variables are I(1), which is another point that suggests the use of cointegrating models such as FMOLS, CCR, and DOLS. We estimate the equations mentioned above using EViews 9. For optimum lag selection, we used Akaike Information Criteria (AIC) for estimations. Notably, the long-run covariance is vital, involving time-series conclusions on heteroskedasticity and autocorrelation consistent (HAC) standard error. Long-run covariance is often used for non-stationary time-series analysis under FMOLS, CCR, and DOLS frameworks. To estimate long-run covariance under FMOLS and CCR frameworks, we consider prewhitening with optimum lag selected by AIC and a Bartlett Kernel, Newey-West fixed bandwidth of 4.0000. We estimate the DOLS model with a fixed lead and lag specification instead of letting AIC select lead and lag. This limitation is due to the low number of observations in each data series, which prevent us from considering AIC for lead and lag selection. We used one lead and one lag for the estimation of the DOLS model. We also incorporate HAC standard error and covariance estimated by prewhitening with optimum lag one and a Bartlet Kernel, Newey-West fixed bandwidth of 4.0000 under the DOLS framework. The empirical results are presented in the following section.

5. RESULTS AND DISCUSSION

Table 6 displays the outcomes of the FMOLS method in five different equations associated with the top marginal tax rate and four tax ratios as explanatory variables. As per the hypothesis, all the main explanatory variables of interest show the expected signs in relation to income inequality as measured by the Gini coefficient. The results indicate that TMTR_C&S, PIT/TTR, and CIT/TTR have a negative association with the Gini coefficient.

Table 6. The results of the FMOLS model.

Dependent Variable: lnGini_disp_se **Model:** Fully Modified Least Squares (FMOLS)					
Variable	**Coefficient (t-statistic) [P-value]**	**Coefficient (t-statistic) [P-value]**	**Coefficient (t-statistic) [P-value]**	**Coefficient (t-statistic) [P-value]**	**Coefficient (t-statistic) [P-value]**
(1st)	**(2nd)**	**(3rd)**	**(4th)**	**(5th)**	**(6th)**
lnTax structure	-0.100*** (-3.477) [0.001] *TMTR_C&S*	-0.004 (-0.496) [0.622] *PIT/TTR*	-0.014 (-0.500) [0.620] *CIT/TTR*	0.002 (0.124) [0.901] *ED/TTR*	0.036*** (3.474) [0.001] *CD/TTR*
lnGDP_PC	-14.781*** (-21.900) [0.000]	-7.132*** (-10.790) [0.000]	-7.639*** (-6.676) [0.000]	-6.865*** (-9.369) [0.000]	-7.988*** (-15.863) [0.000]
lnGDP_PCS	0.674*** (22.480) [0.000]	0.326*** (11.241) [0.000]	0.347*** (6.926) [0.000]	0.311*** (9.687) [0.000]	0.367*** (16.435) [0.000]
lnMYS	0.431*** (8.192) [0.000]	0.208*** (3.872) [0.000]	0.295*** (3.311) [0.0022]	0.269*** (4.049) [0.000]	0.226*** (5.227) [0.000]
C	80.711*** (21.33) [0.000]	38.752*** (10.558) [0.000]	41.653*** (6.593) [0.000]	37.469*** (9.177) [0.000]	43.049*** (15.550) [0.000]
R-square	0.385	0.665	0.667	0.697	0.694

Note: *** represents significance at the 1% level.

ED/TTR and CD/TTR show a positive association with the Gini coefficient. For example, the 2nd column in Table 6 shows that the coefficient of TMTR_C&S is -0.100, reflecting that a 1% increase in TMTR reduces income inequality by 0.100%. When TMTR increases, the after-tax income of the top income groups declines comparatively more than that of low-income groups (Sammartino, 2017). Our results are consistent with Aaron (2015) and Gale, Kearney, and Orszag (2015).

The impact of customs duty on income inequality is presented in the first row of the 6th column in Table 6. The coefficient of CD is 0.036, suggesting that a 1% increase in the share of CD in total tax revenue (TTR) increases income inequality by 0.036%. CD is regressive by nature. Hence, a higher CD raises income inequality because more impoverished individuals spend more of their income on consumption than the more affluent section of society and bear a relatively higher CD burden.

Though PIT, CIT, and ED all show the expected signs as per the hypothesis, they do not affect income inequality significantly. It can be concluded that although PIT and CIT can reduce income inequality, they did not affect income inequality significantly during the study period. Similarly, though excise duty increases income inequality due to its regressive nature, it did not affect income inequality during the study period.

Apart from our variable of interest, we consider certain control variables in the model; hence, determining their relationship to income inequality is also essential. The result shows that Kuznets's hypothesis does not prevail for the Indian economy. It demonstrates that the nexus of Indian economic development and inequality is characterized by decreased inequality at a lower level of economic development and significantly increasing inequality at a higher level of economic development, as shown by GDP_PC and GDP_PCS in Table 6. All models produce similar results. The signs of GDP per capita and GDP per capita squared are negative and positive, respectively. Both signs are statistically significant. This implies that income inequality declines at a low level of development and increases at a higher level of economic development. Furthermore, human capital as measured by mean years of schooling (MYS) implies that higher levels of education lead to increased income inequality in India. This is because 80% of the population receives a poor quality of education in India. Only the top income classes are able to provide a high-quality education to their sons and daughters. Considering the number of factors involved, such as rural-urban, gender, geographical region, cast group, and finally economic status, it is clear that some receive a poor quality of education compared to their counterparts. Therefore, education attainment inequality can be considered one of the causes of rising income inequality in India. Nevertheless, the FMOLS model suggests that the explanatory variables poorly explain the dependent variables, as indicated by R^2. Therefore, we proceed to test more efficient models, such as DOLS. According to Montalvo (1995), FMOLS is less efficient than DOLS.

Table 7 demonstrates the results obtained from the estimated DOLS model. Except for excise duty, the DOLS model provides results similar to those obtained from the FMOLS model. However, there are two fundamental differences in the results of the two models. First, the DOLS model provides a higher magnitude relationship between the independent variables used and income inequality (dependent variable). Second, the values in each equation are high in the DOLS model compared to the FMOLS model, indicating that the model is well specified. This is apparent because the DOLS model considers one lag and one lead. Aside from the coefficient of excise duty, the sign of each coefficient is the same in both models (see Tables 6 and 7). This demonstrates that our results are not biased due to the small explanatory power of independent variables under the FMOLS model. We used one lead and one lag to estimate the DOLS model, which specifies well for our data set. There is no significant difference in the results of the FMOLS and DOLS models.

Table 7. Results of DOLS.

Dependent variable: ln Gini disp_se **Model:** Dynamic Least Squares (DOLS)					
Variable	**Coefficient (t-statistic) [P-value]**	**Coefficient (t-statistic) [P-value]**	**Coefficient (t-statistic) [P-value]**	**Coefficient (t-statistic) [P-value]**	**Coefficient (t-statistic) [P-value]**
(1st)	**(2nd)**	**(3rd)**	**(4th)**	**(5th)**	**(6th)**
lnTax structure	-0.207*** (-2.795) [0.011] *TMTR_C&S*	-0.011 (-0.756) [0.458] *PIT/TTR*	-0.014 (-0.410) [0.685] *CIT/TTR*	-0.016 (-0.580) 0.568 *ED/TTR*	0.083*** (2.913) [0.008] *CD/TTR*
lnGDP_PC	-9.515*** (-5.769) [0.000]	-6.797*** (-2.775) [0.011]	-6.454*** (-4.679) [0.000]	-7.647*** (-11.735) [0.000]	-7.368** (2.543) [0.0193]
lnGDP_PCS	0.428*** (5.818) [0.000]	0.308*** (2.775) [0.011]	0.291*** (4.710) [0.000]	0.346*** (12.157) [0.000]	0.335*** (2.573) [0.018]
ln MYS	0.275** (2.350) [0.029]	0.276 (1.821) [0.083]	0.317*** (3.557) [0.002]	0.321*** (5.207) [0.000]	0.283 (1.479) 0.1547
C	53.058*** (5.764) [0.000]	37.051*** (2.790) [0.011]	35.318*** (4.702) (0.000)	41.701*** (11.190) 0.000	39.735** (2.513) [0.020]
R-square	0.830	0.7997	0.837	0.888	0.842647

Note: *** and ** represent significance at the 1% and 5% level, respectively.

6. ROBUSTNESS CHECK

The main results and discussion section presented the empirical results obtained from two models: FMOLS and DOLS. Except for the coefficient sign of excise duty, the two models provide consistent results in terms of their coefficient signs. However, the DOLS model demonstrates a higher magnitude relationship between income inequality and tax variables than the FMOLS model. This discrepancy between the two models compels us to further check the consistency and robustness of the results using the CCR model. The results obtained from CCR are presented in Table 8. The CCR estimation results are very similar to those of DOLS. However, the CCR model shows a lower magnitude relationship between income inequality and all explanatory variables. All other results remain unchanged. All three models demonstrate that the top marginal tax rate (TMTR) reduces income inequality significantly, whereas CD increases income inequality significantly. The impacts of PIT, CIT, and ED on income distribution remain insignificant in India. The results also confirmed that Kuznets' hypothesis does not hold in India. Furthermore, increased human capital aggravates income inequality in India. Finally, our results are robust with alternative modeling.

Table 8. Results of the CCR model.

Dependent Variable: lnGini_disp_se **Model:** Canonical Cointegrating Regression (CCR).					
Variable	**Coefficient (t-statistic) [P-value]**	**Coefficient (t-statistic) [P-value]**	**Coefficient (t-statistic) [P-value]**	**Coefficient (t-statistic) [P-value]**	**Coefficient (t-statistic) [P-value]**
(1st)	**(2nd)**	**(3rd)**	**(4th)**	**(5th)**	**(6th)**
lnTax structure	-0.090*** (-2.609) [0.013] *TMTR_C&S*	-0.004 (-0.541) [0.591] *PIT/TTR*	-0.001 (-0.044) [0.964] *CIT/TTR*	-0.005 (-0.264) [0.793] *ED/TTR*	0.024*** (2.762) [0.009] *CD/TTR*
lnGDP_PC	-7.931*** (-11.948) [0.000]	-5.640*** (-8.499) [0.000]	-6.919*** (-4.575) [0.000]	-6.820*** (-10.290) [0.000]	-6.599*** (-17.045) [0.000]
lnGDP_PCS	0.359*** (12.341) [0.000]	0.258*** (8.999) [0.000]	0.313*** (4.752) 0.000	0.309*** (10.954) [0.000]	0.302*** (18.056) [0.000]
lnMYS	0.257*** (4.526) [0.000]	0.162*** (2.745) [0.009]	0.271** (2.321) [0.026]	0.266*** (3.873) [0.000]	0.216478 5.655596 0.0000
C	43.693*** (11.627) [0.000]	30.593*** (8.249) [0.000]	37.788*** (4.515) [0.000]	37.282*** (9.814) [0.000]	35.659*** (16.471) [0.000]
R-square	0.663	0.628	0.675	0.697	0.711

Note: *** and ** represents significance at the 1% and 5% level, respectively.

7. CONCLUSION

Even before the Covid-19 pandemic, income inequality was high in India. The pernicious impact of Covid-19 added fuel to the fire by causing a reduction in the share of income held by marginalized sections of society. The high level of income inequality may lead to a substantial loss of human development and economic performance in India. Hence, rigorous macroeconomic policies are urgently required to ameliorate income distribution in India. Taxation is one of the conventional and direct policies to bring about income redistribution. In this context, we sought to answer the following questions. Do conventional prescriptions of taxation affect income inequality in India? Does taxation improve or worsen income distribution in India? Which tax parameter improves income distribution? This analysis has addressed these questions. To the best of our knowledge, no single analysis involving India has previously examined the effects of tax structure on income inequality. Against this background, the present study has scrutinized the effects of tax structure on income inequality in the Indian context.

Using a time-series dataset from 1980 to 2019 and employing the robust time-series techniques of FMOLS, DOLS, and CCR, we have estimated the relationship between individual tax instruments and income inequality as measured by the standardized Gini coefficient of household disposable income. The empirical exercises have shown that the TMTR reduces income inequality, whereas CD significantly aggravates income inequality in India. The results confirm that PIT, CIT, and ED do not significantly affect income inequality. Thus, the conventional prescription of using taxation to redistribute income in India only works if TMTR increases and no other taxes significantly increase income inequality. Moreover, Kuznets' hypothesis was shown not to hold in the case of India. Finally, the results also corroborate that human capital increases income inequality in India. Given these findings, the present study suggests that increasing the top marginal tax rate (TMTR) can reduce income inequality in India. To promote the redistributive effect of potential taxation, the Indian government needs to switch from a regressive tax structure to a progressive tax structure by increasing TMTR and reducing CD. The government should balance tax revenue receipts by imposing higher taxes on the rich through progressive personal income tax and lower taxes on the poor by cutting consumption taxes such as excise duty and customs duty.

Moreover, the results show that a rise in current economic development, as measured in GDP per capita, improves income distribution. Thus, the Government of India should adopt comprehensive macroeconomic policies that encourage inclusive growth and improve income distribution. Human capital captured by mean years of schooling shows that an increase in income inequality can be attributed to the unequal distribution of quality education. Therefore, quality education for all is the need of the hour, not only to reduce income inequality but also to benefit sustainable economic growth in India. The present analysis has only considered the long-run relationship between tax variables and income inequality and has ignored the short-run relationship between the two. Future research could consider the short-run relationship between tax variables and income inequality in India.

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