Income Inequality in India and China: The Role of Infrastructure Development, Human Capital Formation and Remittance Inflows

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Abstract:

This study explores the effects of infrastructure development, human capital formation and remittance inflows on the income inequality in India and China. Using annual data from 1980-2013, Bayer-Hanck (2013) combined cointegration and the ARDL bound testing approach to cointegration are employed. The estimated results reveal that there exists a long-run relationship among the variables; and infrastructure development increases and decreases the income inequality in China and India, respectively. On the other hand, human capital formation negatively affects income inequality in both countries both in short and long runs. However, infrastructure development increases income inequality in both countries in the short run. The effects of remittance inflow on the income inequality are negative and positive for China and India, respectively, in short and long runs.

Key words: Income Inequality; Infrastructure Development; Human Capital Formation; and Remittance Inflows; ARDL model; India and China.

JEL Codes: H54; H4; C54; C32

1. Introduction

Although poverty has decreased worldwide, income inequality is still a great concern especially in developing and emerging countries, such as India and China because (i) it reduces the well-being of the poor badly;(ii) it provides rich people with an unacceptable degree of control over others' lives; (iii) it hinders the poor people's potential and they are not fairly represented in decision and policy making;(iv) it jeopardizes the principle of " equal opportunity for all" as the poor lose the ability to provide their children (future workforce) with better food, shelter, education and health services which in turn hampers future economic growth. Several factors contribute to the income inequality of a country. For example, Perotti (1996) argues that lower levels of human capital formation is linked to the wealth inequality, which ultimately is associated with depressed economic development. Furthermore, inequalities have a negative impact on human capital formation and income disparities are a major barrier to school enrollments and attendance (Easterly, 2007).

Human capital formation is essential for reducing income inequalities. It depends on parents, quality of social surroundings, teachers and investment in education, as well as on cultural and technological innovations. Education is essential for wiping out differences in incomes and enabling progress.

It is argued that better quantity and quality of infrastructure reduces wealth disparities and could be highly effective in alleviating poverty. As pointed out by many researchers better access to infrastructural services is vital for decreasing income inequalities and these effects can be quite substantial (Estache et al., 2002; Estache, 2003; the World Bank, 2003; Lopez, 2004). Theoretically, infrastructure facilitates a connection between poorer communities and underdeveloped regions and core economic activities providing open access to new productive opportunities, *inter alia,* by cutting production and transaction costs (Gannon and Liu, 1997; Estache, 2003). For instance, enhanced access to roads and sanitation has been fundamental in narrowing the income gap in many of the poorest areas worldwide (Estache and Fay, 1995).

Remittances can also affect income inequalities although regardless of the underlying empirical approach their impact on income disparities in origin countries is not clear (Ebeke and Le Goff, 2009). There is concern among researchers that inflows of remittances could lead to income inequalities in India as international migration can be an expensive phenomenon (Oberai and Singh, 1980). While poor households will not benefit from such remittance flows, they are predisposed to creating income disparities and aggravating poverty. Remittances could decrease the poverty burden by raising recipients' wealth, which could be instrumental in smoothing consumption of the poor. Moreover, inward remittances can lessen constraints of working capital so that both physical and human capital investments of less favored households can improve. However, remittances primarily benefit the middle and upper strata instead of the poorest individuals.

Therefore, this study aims to explore the empirical effects of infrastructural development, human capital formation and remittance inflows on income inequality. The case study is focused on India and China where the size of the population is huge, and the poverty is still widespread.

Our study is different from the existing literature in the following ways. First, it makes an initial attempt to empirically explore the effects of remittance inflows, infrastructure development and human capital formation on income inequalities in two emerging economics, China and India. Second, our study uses Bayer-Hanck (2013) to test the cointegrating relationship between the series. Third, we also use Pesaran et al.'s (2001) ARDL bounds testing approach to test the long and short run relationships between the series. All these make it a unique study.

The rest of the paper is structured as follows. Section 2 provides the literature review. Section 3 explains the modeling strategy and data. Section 4 presents and discusses the results and the last section draws the conclusion.

2. Literature Review

Considerable academic research claims that **remittances** have a positive impact on economic growth (Catrinescu et al., 2009; Ziesemer, 2012; Feeny et al., 2014). Moreover, remittances stimulate financial development (Giuliano and Ruiz-Arranz (2009); Mundaca, 2009; Aggarwal et al., 2011), push up human capital formation by enhancing household expenditure on education (Yong, 2008; Adams and Cuocuecha, 2010) and raise the level of investments (Lartey, 2013). Remittances are instrumental in alleviating credit constraints that restrict firms and reduce macroeconomic volatility. A large number of scholars have investigated the impact of remittance inflows on income inequality (II) using cross-sectional and country studies documenting either their adverse impact on income disparities (Stark et al., 1986; Adams, 1989; Barhom and Boucher, 1998; Acosta et al., 2009) or their neutral impact (Yang and Martinez, 2005). Taylor and Wyatt (1996), Taylor et al., (2005), Koechlin and Leon (2007) and Zhu and Xubei (2010) point out that remittances have positive effects on income inequalities.

Further, a study of the nexus between **infrastructure development** and income inequalities leads to inconclusive findings. For instance, economic growth plays a vital role in alleviating poverty via public investments in infrastructure development such as telecommunications, power and transportation which not only narrow rural-urban income disparities but also improve wealth distribution (Calderon and Serven, 2004; Ferranti et al., 2004; Fan and Zhang, 2004). In the same vein, Calderon and Chong (2004) indicate that infrastructure development is negatively associated with II in developing countries. In contrast, Brakman et al., (2002), Artadiand Salai-i- Martin (2003) and Chatterjee and Turnovsky (2012) note that higher infrastructure development is not beneficial as it increases regional disparities. **Human capital** development also plays a vital role in the expansion of economic activities. Opponents of this thinking argue that investments in human capital accentuate income inequalities (Loury, 1981; Benabou, 1993; Galor and Zeira, 1993). The quality of education not only makes a difference in the job market, but it also benefits rich people thereby widening the income gap. Among different subsidy policies, the most effective and efficient way to reduce II is by subsidizing low-income families' early-education investments which can mitigate young parents' budgetary concerns (Galor and Tsiddon, 1997; Giannini, 2001).

In addition to these theoretical arguments on the nexus between remittance inflows, infrastructure development, human capital formation and income inequality, we also review existing literature that focuses on Indian and Chinese economies. In the case of India, Banerjee and Somanathan (2007) observe that critical infrastructure services and public goods are positively linked with social status, indicating that higher public investments in transportation and communication improve the standard of living. Mitra et al., (2002) show that infrastructure development can constitute a powerful engine of industrial takeoff and rising II. The government is opening up new opportunities for leading sector industries at the cost of the rest (handloom, small scale industries). The social connection among households deepens inequalities and income disparities via social stratification and the caste system (Johny et al., 2017; Meena et al., 2017). A World Bank (2006) report highlights that quality and performance of state-provided infrastructural services tends to be the worst in India’s poorest states. A marginal increase in agricultural productivity and labor income reduce wealth disparities (Azam and Shariff, 2011).

In the Chinese economy, men receive higher wages as compared to women which increases II (Knight and Song, 1993; Zhong 2011; Xie and Zhou, 2014), widening the rural-urban income gap among communities (Wang et al., 2014; Campos et al., 2016). Scholars also suggest that parental investments in human capital formation (health and education) reduce income disparities (Morduch and Sicular, 2002; Fleisher et al., 2010; Li and Gibson, 2013; Tian et al., 2016), minimizing the income gap. These educationally efficient children get employed and become a source of income that decreases wealth disparities between the rich and poor. According to the Wilkinson hypothesis, increased income inequalities in a society are correlated to worse health performance. China is a particularly interesting case due to the rapid socioeconomic changes taking place in the country. The country has been a major participant in the process of globalization for the past two decades. It is virtually certain that it will become even more important in the world economy due to its huge size, dynamic economic growth, continuing policy reforms and in particular because of its recent entry into the

World Trade Organization. Perhaps like other developing countries, China's economic integration has been accompanied with growing regional inequalities -- the income gap between coastal and inland areas has risen dramatically since the mid-1980s (Kanbur and Zhang, 1999; Zhang and Kanbur, 2001). Further, the increases in regional disparities might lead to China's dissolution (Hu, 1996) driven by heavy industry and global integration for the sake of development.

3. Data and Modeling Strategy

3.1 Data

The description of data and their sources are noted in Table 1. The study coveres the period 1980-2013.We use data of net Gini as a proxy of income inequality. Infrastructure index is used as a proxy of infrastructure development. GDP per capita (constant 2010 US$) is used as a proxy of economic growth. All variables are considered in natural logarithms and the observations are annual. Our variables of interest and other additional variables used in the study are based on earlier literature [see, for example, Taylor and Wyatt (1996), Taylor et al., (2005), Koechlin and Leon (2007) and Zhu and Xubei (2010)]. The model that we consider is noted in Equation 1 where we have added some controlled variables which are relevant for explaining II to mitigate the omitted variable bias.

$$LNGINI_t = f(LNGDP_t, LNURB_t, LNEHE_t, LNINF_t, LNEG_t, LNREM_t, LNFDI_t) \quad (1)$$

Table 1. Data Description

Variables	Definition	Data Sources
LNGDP	GDP per capita (constant 2010 US$)	WDI
LNEHE	Edu plus Health Spending as a % of GDP (Human Capital Formation)	WDI
LNGINI	net GINI	SWIID
LNEG	Economic Globalization	KOF Globalization Index
LNURB	Urban population (% of total)	WDI
LNINF	Infrastructure Index	WDI
LNREM	Personal remittances, received (% of GDP)	WDI
LNFDI	Foreign direct investments, net inflows (% of GDP)	WDI

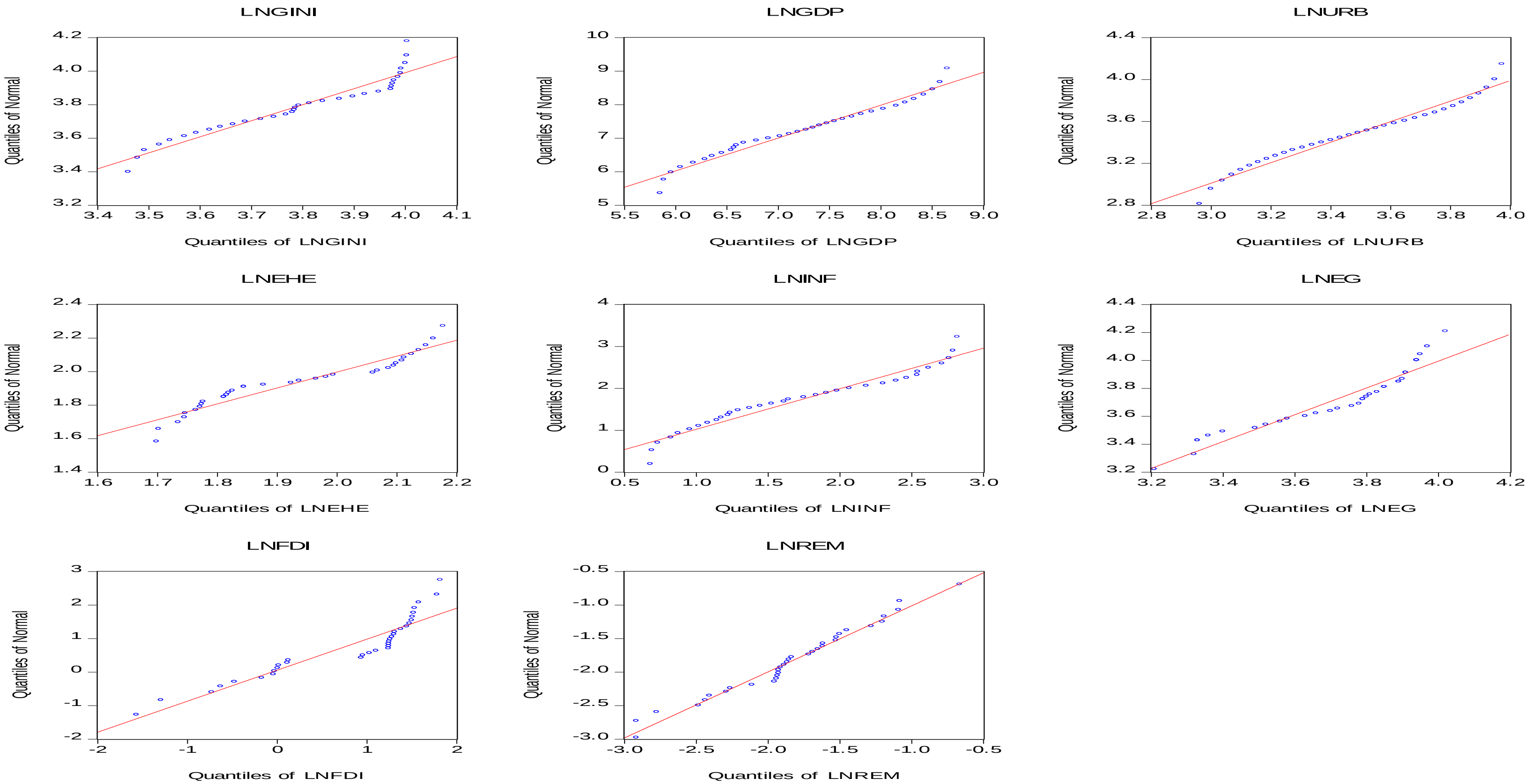
Note: WDI: World Development Indicators, the World Bank.

SWIID- Standardized World Income Inequality Database.

Infrastructure Index is a combination of electric power consumption (kWh per capita), energy use (kg of oil equivalent per capita), fixed telephone subscriptions (per 100 people), mobile cellular subscriptions (per 100 people), air transport, freight (million ton-km) and road density and rail lines (total route-km).

The graph plotted in Figure 1 shows that income inequalities in China are increasing along with increasing GDP and increasing urbanization and infrastructural development. However, though the other variables show positive trends there are variations in the pattern of movement. In contrast to Figure 1, Figure 2 for India shows that there is a fluctuating trend in income inequalities with increasing GDP, urbanization and infrastructural development; the other variables are also fluctuating. Therefore, it is empirically important to understand what explains income inequality trends in India, a country where a number of reform measures have been taken for eliminating poverty.

Figure1. China


LNGINI
Quantiles of Normal
Quantiles of LNGINI
LNGDP
Quantiles of Normal
Quantiles of LNGDP
LNURB
Quantiles of Normal
Quantiles of LNURB
LNEHE
Quantiles of Normal
Quantiles of LNEHE
LNINF
Quantiles of Normal
Quantiles of LNINF
LNEG
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Quantiles of LNEG
LNFDI
Quantiles of Normal
Quantiles of LNFDI
LNREM
Quantiles of Normal
Quantiles of LNREM

Figure 2. India

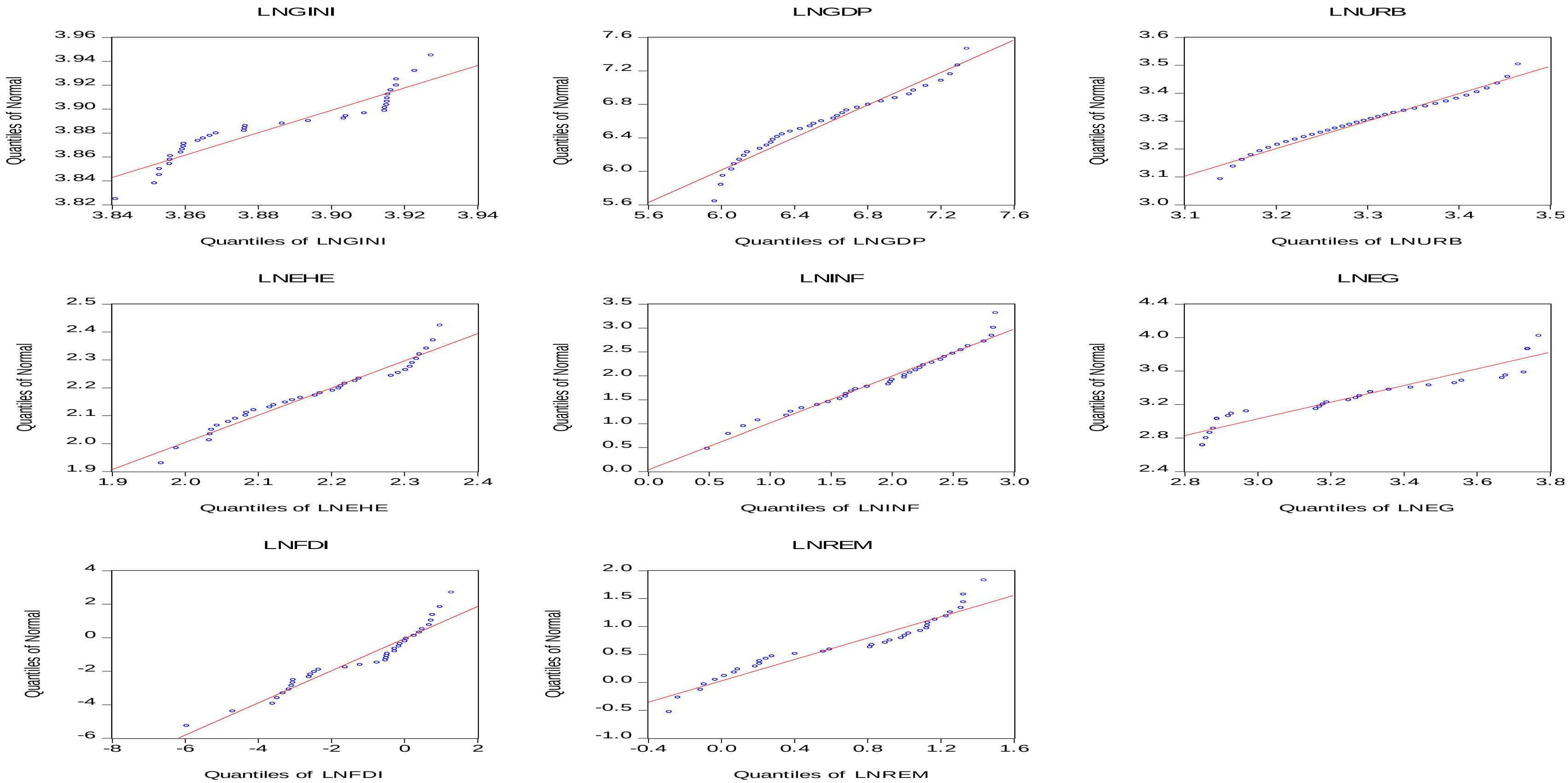


Table 2 presents the summary statistics of various factors used in explaining the income inequality variable. It is noted that the average level of income inequality, real GDP, urbanization, economic globalization and human capital formation are high in India. Also the mean value of income inequality, real GDP, urbanization and economic globalization show a high trend in China.

Table 2. Summary Statistics

Variables	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
CHINA									
LNGINI	3.798835	3.792713	4.004031	3.478329	0.172091	-0.371829	1.852116	2.572163	0.276352
LNGDP	7.262231	7.275016	8.652020	5.889500	0.832627	0.057712	1.840082	1.868257	0.392928
LNURB	3.495391	3.492956	3.973457	3.001615	0.296912	0.004246	1.767260	2.089615	0.351760
LNEHE	1.933850	1.924249	2.178281	1.699279	0.157354	0.115901	1.500834	3.164194	0.205544
LNINF	1.745151	1.645513	2.821317	0.694025	0.683597	0.138361	1.677312	2.510856	0.284954
LNEG	3.730909	3.790000	4.020000	3.320000	0.211459	-0.714378	2.272318	3.534938	0.170765
LNFDI	0.763249	1.248078	1.822432	-1.562257	0.929182	-0.995385	2.828665	5.489720	0.064257
LNREM	-1.830634	-1.851823	-0.660845	-2.913263	0.532623	200869	2.807006	0.273130	0.872350

INDIA									
LNGINI	3.885471	3.876578	3.927468	3.841042	0.027870	0.057184	1.361476	3.709532	0.156490
LNGDP	6.570909	6.508188	7.346102	6.001113	0.412055	0.386041	1.953117	2.326603	0.312453
LNURB	3.302813	3.296873	3.465548	3.153462	0.091539	0.132324	1.918291	1.705183	0.426309
LNEHE	2.183230	2.184927	2.349551	1.988765	0.108845	-0.034962	1.711632	2.289076	0.318371
LNINF	1.937828	2.003124	2.852365	0.661821	0.611284	-0.34958	2.248477	1.448740	0.484630
LNEG	3.302121	3.280000	3.770000	2.850000	0.332883	0.038008	1.573402	2.806320	0.245819
LNFDI	-1.2278	-0.48762	1.296630	-5.94496	1.824643	-0.69422	2.615689	2.853781	0.240054
LNREM	0.658681	0.824243	1.437594	-0.28410	0.548005	-0.26492	1.564215	3.220539	0.199834

3.2 The Bayer-Hanck (2013) Combined Cointegration Approach

This study uses the combined cointegration test developed by Bayer and Hanck (2013) to verify the presence of a long-run relationship between the variables. Though Engle and Granger (1987) developed the residual based cointegration test, it has limitations in providing unbiased estimates. The main problem with the Engle and Granger (1987) cointegration test is that long-run regression results may be inefficient if the residuals are not normally distributed. Under such circumstances, it becomes difficult for researchers to make any sensible decisions regarding cointegration between the variables in the long run. To overcome these issues, we estimated the Engle and Yoo (1991) cointegration test which provides more efficient empirical results due to its power and size. This test can be applied if the distribution of estimators from the cointegrating vector is non-normal. Subsequently, we also used the cointegration test proposed by Philips and Hansen (1990) to eliminate the biasness of ordinary least squares (OLS) estimates.

Moreover, we also used the Johansen and Juselius (1990) maximum likelihood cointegration approach to examine cointegration between the variables under the unique order of condition in the system of equation. Although this is a cointegration technique based on the system of an equation, its estimation becomes invalid if any of the variables is integrated of I(0) in the system or happens to belong to a mixed order of integration. The Johansen and Juselius (1990) maximum likelihood cointegration results are also sensitive to incorporating the exogenous and endogenous variables in the model. This test only indicates the presence of cointegration between the variables for the long run but provides no information about short run dynamics.

Pesavento (2004) suggested that the power of cointegration tests may be sensitive to the presence of nuisance parameters. To resolve this issue, Bayer and Hanck (2013) proposed a new dynamic cointegration technique by combining all the approaches of cointegrating tests [such as Engle-Granger's (1987) residual-based test, Johansen's (1991) system based test, Boswijk (1994) and Banerjee et al.'s (1998) lagged error correction based approaches to cointegration] to provide uniform and efficient cointegration test results. Thus, efficient cointegration results are possible by ignoring the nature of multiple testing procedures. This implies that the application of combined cointegration tests not only provides efficient results but it also helps to infer robust inferences in comparison to individual t-test or a system-based test used in the field of applied economics. An insight that emerges by applying the Bayer and Hanck (2013) combined cointegration test is that it eliminates the common problem of inconsistent findings which are associated with other traditional cointegration techniques. In doing this, it is evident that both efficient and conclusive results are guaranteed by employing the Bayer and Hanck (2013) combined cointegration technique which was not the case when using other traditional cointegration models in econometrics. The Bayer and Hanck (2013) cointegration test follows the critical tabulated values of Fisher's (1932) test to combine the statistical significance level (that is, p-values of a single cointegration test and formula) which is presented as:

$$EG - JOH = -2[\ln(P_{EG}) + \ln(P_{JOH})] \qquad (2)$$

$$EG-JOH-BO-BDM = -2[\ln(P_{EG}) + \ln(P_{JOH}) + \ln(P_{BO}) + \ln(P_{BDM})] \quad (3)$$

The probability values of different individual cointegration tests including Engle-Granger (1987); Johansen (1991); Boswijk (1994); and Banerjee et al., (1998) are reported by P_{EG}, P_{JOH}, P_{BO} and P_{BDM} respectively. We also follow Fisher's (1932) critical statistical values to confirm the presence of cointegration between the variables in our model. We can confirm the presence of cointegration by rejecting the null hypothesis of no cointegration when the critical values of Bayer and Hanck (2013) are found to be less than the calculated statistical values of Fisher (1932); otherwise the reverse would hold true.

3.3. The ARDL Bounds Testing Approach to Cointegration

Our study employs the ARDL bounds testing approach as proposed by Pesaran et al., (2001) to establish both the long and short-run relationships among the variables in the model. We used the ARDL bounds testing approach to cointegration because of its several advantages over traditional cointegration procedures. First, the ARDL bounds testing approach overcomes the problem of endogeneity among the variables in the estimated model which is normally associated with Engle-Granger cointegration (Pesaran and Shin, 1996;,Pearson et al. 2001 ; Al-Mulai et al., 2015). Second, this method does not require any pre-testing in the order of the integration of the variables used in the ARDL model (Pesaran and Pesaran, 1997; Pesaran et al., 2001) because it can be applied irrespective of the mixed order of integration of regressors (for example, I(1)/I(0)). Third, it enables us to understand a simultaneous analysis of both the short and long-run effects of the independent variables on the dependent variable. Finally, it also produces superior results even with a small sample size in the time series. Given these advantages, the ARDL bounds testing approach has gained wide popularity among researchers and economists in the field of applied economics and therefore our study also uses this method for our empirical estimation.

The ARDL bounds testing approach takes the following form (Equation 4) to examine the long-run relationship between the variables:

$$\Delta LNGINI_{2t} = \alpha_0 + \sum_{i=1}^{m} \alpha_{1i}\, \Delta LNGDP_{2t-i} + \sum_{i=0}^{m} \alpha_{2i}\, \Delta LNURB_{t-i} + \sum_{i=0}^{m} \alpha_{3i}\, \Delta LNEHE_{t-i} + \sum_{i=0}^{m} \alpha_{4i}\, \Delta LNINFR_{t-i} + \sum_{i=0}^{m} \alpha_{5i}\, \Delta LNEG_{t-i} + \sum_{i=0}^{m} \alpha_{6i}\, \Delta LNFDI_{t-i} + \sum_{i=0}^{m} \alpha_{7i}\, \Delta LNREM_{t-i} + \alpha_8 LNGDP_{2t-1} + \alpha_9 LNURB_{t-1} + \alpha_{10} LNEHE_{t-1} + \alpha_{11} LNINFR_{t-1} + \alpha_{12} LNEG_{t-1} + \alpha_{13} LNFDI_{t-1} + \alpha_{14} LNREM_{t-1}\, \mu_t \qquad (4)$$

Where m denotes the optimal lag length of the variables and Δ is the first difference of the concerned variables. α_0 is the intercept. μ_t is the error term. The first and second parts of Equation 4 denote error correction dynamics and the long-run relationship among the series respectively. To test the existence of a long-run relationship, we conducted the F-test on the joint coefficients of all lagged level variables on the ARDL structure. The null hypothesis of the bounds test involves no cointegration among variables and that can be represented as $H_0 : \alpha_8 = \alpha_9 = \alpha_{10} = \alpha_{11} = \alpha_{12} = \alpha_{13} = \alpha_{14} = 0$. Its alternative hypothesis can be written as $H_1 : \alpha_8 \neq \alpha_9 \neq \alpha_{10} \neq \alpha_{11} \neq \alpha_{12} \neq \alpha_{13} \neq \alpha_{14} \neq 0$. Finally, the computed F-statistics are compared to the critical values provided by Narayan (2005). This is because Narayan's (2005) lower and upper bounds critical values are more appropriate than those of Pesaran et al., (2001) in the case of small sample sizes. A decision can be inferred about the confirmation of a cointegration relationship if the computed F-statistic falls outside the upper and lower critical bounds values as suggested by Narayan (2005). More specifically, the null hypothesis of no cointegration can be rejected if the calculated F-statistic is higher than the upper bound critical value I(1) for a given number of explanatory variables. The null hypothesis of no cointegration cannot be rejected (Narayan and Narayan, 2004) if the computed F-statistic is lower than the lower bound critical value I(0). Finally, no exact decision relating to cointegration can be made if the calculated F-statistic lies in between the lower and upper critical values (Ertugrul and Mangir, 2015; Seker et al., 2015). The optimal lag order for this model is selected on the basis of Akaike Information Criterion (AIC). The optimal lag length of the model can be decided based on the minimum AIC values.

4. **Results and Discussion**

To investigate the long-run relationship among the variables of interest it is important to identify the stationary properties of the series used in the model estimation as a prelude. **Table 3** presents the unit root test results based on traditional tests. We applied a battery of conventional unit root tests such as the Augmented Dickey Fuller (ADF, 1979) and Phillips Perron (PP, 1988) tests. Table 3 shows that the natural logarithmic values of all variables were non-stationary at their levels but stationary at their first differences for both China and India. Table 4 shows the Zivot-Andrews structural break unit root test.

Table 3. Unit root test results

Country	Variables	ADF (Augmented Dickey–Fuller test)		PP(Phillips–Perron test)		Consequence
		Level	1ST Difference	Level	1ST Difference	
CHINA						
	LNGINI	0.342	-2.042**	0.836	-3.277**	Stationary
	LNFDI	-0.850	-6.435*	-0.823	-5.178*	Stationary
	LNGDP	0.583	-3.372**	0.433	-3.435**	Stationary
	LNEG	2.094	-3.888*	2.414	-5.670*	Stationary
	LNREM	-0.758	-4.590*	-0.810	-6.271*	Stationary
	LNURB	-2.513	-3.163***	-1.657	-2.579***	Stationary
	LNINF	-0.237	-4.274*	0.466	-4.294*	Stationary
	LNEHE	1.653	-3.566*	1.864	-5.248*	Stationary
INDIA						
	LNGINI	0.459	-3.179*	0.531	-2.513**	Stationary
	LNFDI	-1.430	-4.993*	-1.491	-6.116*	Stationary
	LNGDP	-0.700	-2.280 *	-0.568	-4.251*	Stationary
	LNEG	2.979	-2.240**	3.687	-3.954*	Stationary
	LNREM	0.954	-3.562*	0.628	-7.460*	Stationary
	LNURB	-0.992	-3.885**	1.126	-3.678**	Stationary
	LNINF	4.900	-2.756*	3.088	-6.652**	Stationary
	LNEHE	1.948	-5.536*	2.087	-5.603*	Stationary

*Note: *, **, and *** denote significant levels at 1%, 5% and 10% respectively.*

Table 4. Zivot–Andrews' (Z-A, 1992) structural break unit root test

Countries	Variable	Level			1st difference		
		T-statistic	Time break	Decision	T-statistic	Time break	Decision
CHINA							
	LNGINI	-4.414 (1)	2003	Unit root	-5.728 (2)	2003	Stationary
	LNFDI	-4.173(0)	1991	Unit root	-7.348(0)	1984	Stationary
	LNGDP	-5.320 (1)	1989	Unit root	-4.616 (1)	1988	Stationary
	LNEG	-3.816(5)	2011	Unit root	-6.905(0)	1997	Stationary
	LNREM	-3.720(0)	1997	Unit root	-7.203(0)	2000	Stationary
	LNURB	-3.105 (1)	2008	Unit root	-6.261 (1)	2006	Stationary
	LNINF	-1.834(0)	1992	Unit root	-4.679(0)	2010	Stationary
	LNEHE	-2.855(8)	1999	Unit root	-6.332(0)	1990	Stationary
INDIA							
	LNGINI	-2.402(0)	2001	Unit root	-5.312(2)	2005	Stationary
	LNFDI	-3.559 (0)	1991	Unit root	-7.853 (0)	1985	Stationary
	LNGDP	-3.196 (0)	2002	Unit root	-5.171 (2)	2005	Stationary
	LNEG	-2.275(0)	1989	Unit root	-5.797(0)	2009	Stationary
	LNREM	-3.887(4)	1993	Unit root	-8.760(0)	1990	Stationary
	LNURB	-2.985 (1)	1997	Unit root	-5.755 (1)	2001	Stationary
	LNINF	-2.868(4)	2007	Unit root	-6.535(0)	1984	Stationary
	LNEHE	-2.300(2)	1993	Unit root	-7.238(1)	1992	Stationary

We verified the estimated results using Pesaran et al.’s (2001) ARDL bounds testing approach to cointegration as an alternative robust cointegration procedure. Since the ARDL bounds testing procedure is known to be sensitive to the lag length in the model, we used the AIC criterion to select the lag length which is reported in column 2 of **Table 5**. Narayan’s (2005) critical lower [I(0)] and upper [I(1)] bounds statistics are used to determine the cointegration between the series as the proposed criteria is found to be appropriate for a model based on a small number of observations. The ARDL cointegrating results of Equation 1 reported in Table 5 reveal that the calculated F-statistics were greater than the upper bound critical values of Narayan (2005) in both the Chinese and Indian contexts. These latter results confirmed the presence of a long run relationship among the variables which is consistent with the results from the Bayer-Hanck combined cointegration test reported in Table 6.

Table 5: The ARDL Bound Testing Cointegration Test

Estimated model	Optimal lag length	Structural Break	F-statistics	X^2SERIAL	X^2 ARCH	X^2RESET	X^2NORMAL
LNGINI=f(LNGDP, LNURB, LNEHE, LNINF, LNEG, LNREM, LNFDI)	4,1,2,2,1,2,2,2	2003	7.110	3.453	0.006	3.308	0.573
LNGINI=f(LNGDP, LNURB, LNEHE, LNINF, LNEG, LNREM, LNFDI)	4,2,2,2,2,0,2,2	2001	3.947*	1.727	1.152	1.569	1.006
Narayan's (2005) critical bounds values at significant levels		(t = 34, k = 8)					
		I(0)	I(1)				
	10%	1.92	2.89				
	5%	2.17	3.21				
	2.5%	2.43	3.51				
	1%	2.73	3.9				

Table 6. Results of the Bayer-Hanck (2013) Cointegration Analysis

Country	Estimated models	EG-JOH	EG-JOH-BO-BDM	Lag order	Cointegration
CHINA	LNGINI=f(LNGDP, LNURB, LNEHE, LNINF, LNEG, LNREM, LNFDI)	55.872106*	63.636352*	1	Yes
INDIA	LNGINI=f(LNGDP, LNURB, LNEHE, LNINF, LNEG, LNREM, LNFDI)	55.674615*	68.305573*	1	Yes
	Fisher's (1932) critical values at 5% level of significance	10.295	19.688		

* denotes significance at 5%

Given the unit root test results reported in Tables 3 4, we find that all the variables are integrated of order one, that is, I(1) process; therefore, in order to match with the order of other variables and in keeping with the usual spirit in the application of the cointegration procedures we used these variables in the differenced form so as to match with the level of the other variables. This was done after confirming the order of integration of variables with alternative unit root tests. Given our context, Bayer and Hanck's (2013) combined cointegration approach appeared to be more suitable for investigating the cointegration relationships among the variables in our income inequality function. The reason for employing Bayer and Hanck's (2013) combined cointegration is that it provides robust and efficient estimates as compared to the other traditional cointegration tests. The results reported in **Table 6** indicate that the computed values of Fisher-statistics for EG-JOH and EG-JOH-BO-BDM tests exceed the critical values of EG-JOH and EG-JOH-BO-BDM for Equation 1 for both countries at a 5 percent level of significance. This confirms the presence of cointegration among the variables in the income inequality model implying that there is a long-run relationship among the variables in the models for both China and India.

The country specific long-run and short-run estimates based on ARDL model are presented in **Table 7** and Table 8 respectively. The long-run results reported in Table 7 reveal that income inequality is negatively associated with the real GDP, urbanization, expenditure on health and education, economic globalization, remittances inflows and foreign direct investment except infrastructure development in China. In contrast, the income inequality is positively associated with infrastructure development in China. When we estimate similar models for the Indian economy, the long-run results reveal negative and significant effect of real GDP, urbanization, expenditure on health and education, and infrastructure development on the income inequality. In addition, the income inequality is found to be positively and significantly affected due to economic globalization, remittance inflows and foreign direct investment. The short-run effects of GDP, urbanization, education and health expenditures are the same on the income inequality, which is negative. However, the remittance, FDI and economic globalization have negative effect on the income inequality of China, while these variables positively affect the income inequality in India (see Table 8).

Table 7: Long-run results of the ARDL model

Long-run Analysis (Dependent variable= LNGINI)									
	Constant	LNGDP	LNURB	LNEHE	LNINF	LNEG	LNREM	LNFDI	Dt
CHINA	0.191*** [1.720]	-0.282*** [-2.539]	-0.831** [-2.721]	-0.089** [-3.356]	0.068*** [2.111]	-0.180** [-3.927]	-0.011*** [-2.000]	-0.003*** [-2.006]	0.047* [4.687]
INDIA	10.571** [2.940]	-0.467** [-2.636]	-3.679** [-2.723]	-0.203** [-2.879]	0.007** [-2.879]	0.168** [3.099]	0.049*** [2.194]	0.027* [2.842]	0.066* [4.039]

Note:*, **, and *** denote significant levels at 1%, 5% and 10% respectively. T -statistics are in parenthesis [].

Table 8: Short-run results of the ARDL model

Short-run Analysis (Dependent variable= LNGINI)												
	LNGDP	LNURB	LNEHE	LNINF	LNEG	LNREM	LNFDI	Dt.	ECM_{t-1}	R^2	F-statistics	D.W
CHINA	-0.049*** [-2.009]	-3.553* [-8.288]	-0.088* [-8.697]	0.069* [6.487]	-0.079* [-8.572]	-0.008* [-11.746]	-0.005* [-4.615]	0.047* [11.834]	-0.057* [-12.899]	0.99	7.110*	2.865
INDIA	-0.468* [-7.333]	-18.708* [-8.167]	-0.205* [-9.462]	0.026*** [2.273]	-----	0.017* [4.787]	0.017* [9.472]	0.067* [9.242]	-0.094* [-9.610]	0.98	3.947*	3.075

Note:*, **, and *** denote significant levels at 1%, 5% and 10% respectively. T -statistics are in parenthesis [].

The Diagnostic Test results are shown in Table 9 below.

Table 9: Short-run Diagnostic test results

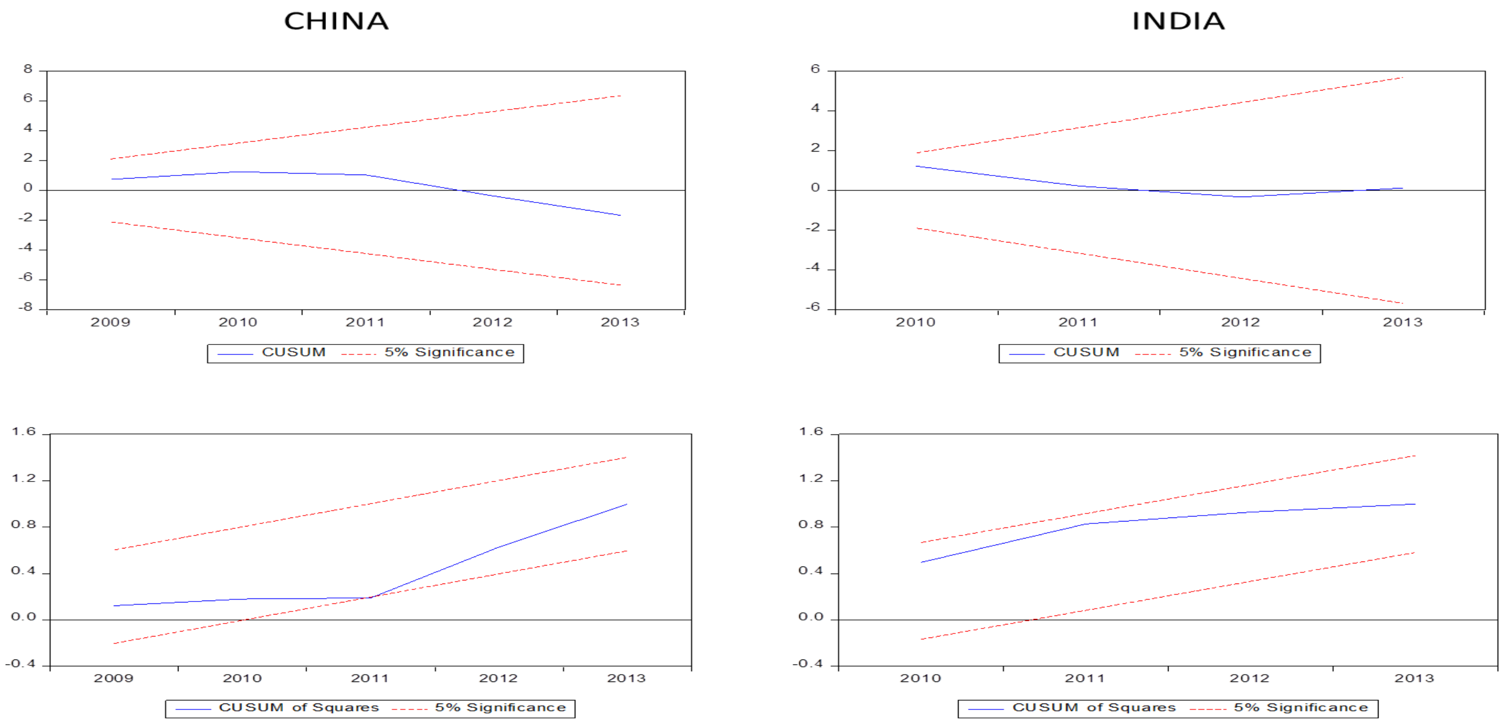
Short-run Diagnostic tests		
	CHINA	INDIA
	F-statistics	F-statistics
X^2SERIAL	3.453 [0.136]	1.727 [0.510]
X^2 ARCH	0.006 [0.935]	1.152 [0.395]
X^2NORMAL	0.573	1.006

	[0.837]	[0.557]
X^2REMSAY	3.308 [0.297]	1.569 [0.278]

Note: P values are in [] and t-statistics are in ().

As suggested by Brown et al., (1975) the stability of the parameters of the income inequality model based on the ARDL model's estimation is investigated by employing the cumulative sum (CUSUM) of recursive residuals and the CUSUM square (CUSUMsq) of recursive residuals. This is because the model's misspecification can lead to biased coefficient estimates that might influence the explanatory power of the results. In checking the parameter's constancy, both CUSUM and the CUSUMsq tests suggested non-rejection of the null hypothesis of parameter consistency. This confirmed that the model's parameters are stable. The plots of both CUSUM and CUSUMsq tests are shown in Figures 3 at a 5 percent level of significance and the results indicate that plots for both tests fell within the critical bounds of a 5 percent level of significance. This suggests that all our estimated income inequality models are stable.

Figure 3: CUSUM test and CUSUMsq tests for China and India



5. Conclusion and Policy Recommendations

Despite significant successful efforts to alleviate poverty worldwide, income inequalities are still a major concern for policymakers. These are a severe phenomenon, particularly in developing and emerging nations such as India and China. This research examined the impact of infrastructure development, human capital formation and remittance inflows on wealth disparities in India and China. Based on annual data for 1980-2013, the study used the Bayer-Hanck (2013) combined cointegration and the Pesaran et al., (2001) ARDL bounds testing approaches to explore the effects of selected variables on the income inequality proxied by the net Gini index.

Our findings confirm the existence of a long-run relationship among the variables in the inequality equation for both India and China. The short and long-run results returned by the ARDL model surprisingly revealed that while infrastructural development is deepening the income gap, human capital formation is reducing income inequalities in both the countries. Contrastingly, our findings show that remittance inflows accelerated wealth disparities in India but diminished income inequalities in China.

Our analysis also highlights that in China income inequality is negatively associated with the real GDP, urbanization, expenditure on health and education, economic globalization, remittance inflows and foreign direct investments. In contrast, the income gap is positively correlated with the infrastructure development variable.The estimation of similar models for the Indian economy showed negative and significant effects of the real GDP, urbanization, expenditure on health and education and infrastructure development variables on the level of income inequality in the long-run. In addition, wealth disparities were positively and significantly influenced by economic globalization, remittance inflows and foreign direct investments. We also documented a negative short-run impact of GDP, urbanization, education and health expenditure on theincome inequality. However, while remittance inflows, FDI and economic globalization are narrowing the income gap in China they are deepening wealth inequalities in India.

An understanding of the interplay between the selected variables is important as it sheds light on the underlying dynamics and mechanisms of influence on disposable incomes. The negative correlations point out that infrastructure investments can increase urban development. The positively correlated indicators need careful approaches in assuring equitable access and distribution.

Comparative analyses of China and India are important. After the 1980s, income disparities have widened in both the countries but not at the same pace. In India, income inequalities followed a sharp upward trend while in China they grew moderately as the country invested more in education, health and infrastructure for its bottom 50 percent of the population. China enjoyed more successful structural changes compared to India where agrarian issues are still unsolved. Further, persistent neglect of public education and health spending in India, coupled with increasing privatization make perspectives for future wealth disparities highly desolated. In addition, the government's reluctance to adopt fiscal data transparency leads to an unclear picture of inequalities.

A significant variance in trends of income disparities among countries that share similar patterns of development emphasizes the role of national policies in shaping the income gap. In India, the gap increased dramatically following the massive transformation of the economy which was focused on deregulation and opening-up reform measures.

The deterioration in income distribution and rising wealth disparities have become one of the most pressing concerns for the two nations. In the context of China, they hamper the emergence of a harmonious society; in the case of India, this matter is a political threat to structural changes and openness and is diminishing public confidence in the government. China must reshape its income distribution policy and rethink its urban-focused growth strategy, work to improve transparency and decrease illegal incomes. In India, the policymaking arena should design equitable land reform measures and modify its economic structure and implement labor-intensive industrial schemes. In parallel, the country should place greater emphasis on public education, particularly in rural regions and promote the values of democracy and its proper practice more intensely.

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