Investigating the asymmetric linkages between infrastructure development, green innovation, and consumption-based material footprint: Novel empirical estimations from highly resource-consuming economies

Razzaq, A., Ajaz, T., Li, J.C., Irfan, M. and Suksatan, W.

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Abstract

The role of a reliable resource consumption measurement is essential for devising a relevant climate policy. The consumption-based material footprint is trade-adjusted domestic resource consumption that presents an accurate picture of the domestic material footprint. Pursuing the same, this study draws asymmetric linkages between infrastructure development, green innovation, and consumption-based material footprint (MF) in the top 11 highly material-consuming countries. Our preliminary findings strictly reject the preposition of data normality and highlight that the observed relationship is quantile-dependent, which may disclose misleading results in previous studies using linear methodologies. In compliance, a novel empirical estimation technique popularized as Method of Moments Quantile Regression is employed that simultaneously deal with non-normality and structural changes in data. The results exhibit that infrastructure development (green innovation) significantly increases (decreases) MF mainly across medium to higher quantiles (medium-higher level of MF). Interestingly, the resource-depleting effect of infrastructure is highest for higher quantiles and lowest for lower quantiles of MF. Economic growth (globalization) increase MF, and their resource-depleting effect is higher (lowest) for lower quantiles and lowest (highest) for higher quantiles. Lastly, population exhibits an inverted-U shape relationship with MF across lower to higher quantiles. These results suggest pertinent policy recommendations.

Keywords: Resources consumption; consumption-based material footprints; green innovation; infrastructure development; STRIPAT; Methods of Moment Quantiles

1. Introduction:

The increase in material use impacts environmental quality in the form of climate change, natural resource depletion, increase air and water pollution, and biodiversity reduction. Besides, the increase in the use of natural resources raises the question of their eventual scarcity for the nations (Fernández-Herrero and Duro, 2019; He et al., 2021; Wang et al. 2020). Amid these rising concerns, Sustainable development Goals (SDGs) instigate resource conservation that led global economies to take sequester measures for the sustainable use of natural resources (Razzaq et al. 2021). The SDG 12 is specifically concerned with the efficient use of natural resources, including domestic material use and material footprint. Resources consumption is an important area of concern for policymakers due to economic, social, and environmental vulnerabilities (Ulucak et al. 2020; Wu et al. 2021). On the economic front, policy reasons are concerned with the sustainable use of natural resources and resource management cost. Social causes are related to the efficient distribution of the goods produced by using natural resources and materials. It leads to another challenge that is faced by most of the countries due to population growth, i.e., either country can meet the needs of its future generations or not. Lastly, the most important concern is related to the environmental impacts of natural resources and material use (Li et al. 2021). Schandl et al. (2016) highlighted this scenario and predicted that almost 180 billion tons of material would be required by 2050, which is nearly three times more than the current levels. Besides, excessive use of different metals and resources in the infrastructure sector also surges Carbon (CO_2) emissions.

Infrastructure development is considered one of the most significant detrimental factors of natural resources, particularly construction-related materials. In this study, we have utilized an accumulative infrastructure index, which integrates into four broader categories of transport, telecommunication, energy, and financial infrastructure. The widespread utilization of construction material in physical infrastructure development is exerting a positive influence on resource consumption. Also, the excessive focus on infrastructure development to boost economic growth in developing and developed countries is raising other environmental concerns such as climate change (Jafri et al.2020), excessive utilization of land (Govindu and Nigusse, 2016), CO_2 emissions (Du et al., 2019) and greenhouse gasses pollution (Zhang et al., 2020). These impacts are fully realized during and after the construction phase of the physical infrastructure (Churchill et al., 2019). Similarly, an improved and efficient road infrastructure is attributed to the higher number of vehicles on the roads, which caused a colossal sum of CO_2 emissions (Li et al. 2020; Han et al., 2017).

The prior studies explained that physical and transport infrastructure is often characterized by heavy-duty fuel-intensive equipment, and also the use of large quantities of concrete and asphalt causes environmental degradation (Rahman et al., 2017; Xie et al., 2017). However, the literature related to the impact of infrastructure development on ecological and resource degradation is inconclusive and limited (Chen et al. 2018). One strand of the literature revealed the positive effects of infrastructure development on environmental quality and resource efficiency (Zhang et al. 2015; Alshehry and Belloumi 2017; Baloch and Saud, 2018; and Khan et al., 2020; Adams et al., 2020; An et al. 2020). The second strand of literature supports the negative impacts of infrastructure development on environmental degradation (Neves et al., 2017; Batool et al., 2019; Lange et al.,2020). However, the development of well-designed, well-built, well-maintained transport infrastructure is often considered a meaningful way to reduce net CO_2 emissions (European Commission, 2016).

According to ACEA (2015) “intelligently designed, well-built and well-maintained roads are key to further reducing road transport CO_2 emissions.” Our selected countries (see Table 1) are rich in all categories of infrastructures; therefore, infrastructure is one of the main primary sources of material footprint in these economies due to the heavy usage of materials in the construction and development of infrastructures. Based on the Global Material Flows Database (GMFD), Table 1 exhibits that 66% of global consumption-based material footprint (MF) is attributed to selected sample countries. Similar sample characteristics are highlighted by Wiedmann et al. (2015) using GMFD. In today's world, global integration further fuels infrastructure construction as an imperative input to secure global growth and employment, translating into higher resource consumption and environmental consequence (Ulucak et al., 2020). It is well documented that increased interaction and integration empowers countries to boost their welfare by reducing trade barriers and dispersing technological development that is beneficial to reduce resource consumption, waste, toxic minerals, and pollution (Han et al. 2021; Shahbaz et al., 2018; Bilgili et al., 2020). Also, globalization surges the intensity of economic activities like trade and transportation, which demands more resources for their production of goods and services (Plank et al., 2018). All these economic activities put demand pressure on natural resources, as literature shows that trade improvements have a positive impact on material consumption (Giljum et al., 2014; Li et al., 2018; Schaffartzik et al., 2014; Wang et al., 2019). Thus, global economies are concerned to find out different ways to reduce resource depletion and associated CO_2 emissions.

Table 1: Consumption-based Material Footprint in Sample Countries

Sr.No.	Country	MF (Million Tons)	% of Global Share
1	China	29432	32%
2	USA	10539	11%
3	India	6162	7%
4	Brazil	3306	4%
5	Japan	1888	2%
6	Germany	1650	2%
7	Indonesia	1503	2%
8	UK	1460	2%
9	France	1457	2%
10	South Korea	1456	2%
11	Russia	1429	2%
-	Total	60281	66%
	Global MF	91975	-

Note: MF includes resources; biomass, fossil fuels, metal ores, non-metallic minerals

Source: Author's calculation from Global Material Flows Database

Technological innovation is considered one of the most prominent and efficient ways to improve resource efficiency and reduce CO_2 emissions. Technological innovation transforms economies towards environmental-friendly technologies (Lin and Zhu, 2019; Razzaq et al. 2020a). Notably, green innovation represents all those innovations related to saving resources and energy in business and economic operations (Razzaq et al. 2021b; Lingyan et al. 2021). For instance, controlling pollution (preventing the direct release of harmful substances into the air; carbon capture and storage), waste management (handling, treatment, and elimination of waste), clean technology (integrating changes in production technology), and clean-up technology (remediation technology) (Schreiber at al., 2016; Chen and Lee, 2020; Costantini et al., 2017). These innovations enhance the new and advanced technical applications and directly reduce energy consumption and increase energy efficiency (Yii and Geetha, 2017).

Technology innovations also help in economic restructuring and optimization through the conversion of traditional economic development that is relying on production factors into an innovation-driven mode. These innovations reduce resource dependency and ensure long-term environmental sustainability (Chen and Lee, 2020). The development of green technology and social responsibility stimulate green growth policies such as consuming less material, use of low-carbon goods, tracing material footprint, conceptualizing low carbon cities and green agricultures (Bununu, 2016; Bununu, 2020). Concludingly, the consumption of material inputs and their processing intrinsically affect resources and environmental quality such as resource erosion, water shortage, biodiversity loss, greenhouse gas emission, impairment to the eco-system, and global warming. Each production process needs fossil fuels, metals, ores, biomass, water, and land and depletes scarce resources. The infrastructure rudiments that we take for granted, often contain resource consumption, and resultantly greenfield land paved-over produces environmental and resource degradation (Churchill et al., 2019).

A large extent of literature has concentrated on factors that agonies global resources such as population, industrial growth, energy consumption, trade, globalization, and urbanization (Khan et al., 2020; Mi et al., 2015; Shahzad et al., 2017; Shen et al., 2018; Yao et al., 2015). In contrast, comparatively less attention has been given to factors concerning infrastructure development that are primarily considered sources of economic growth, resource consumption, and employment. A few studies scrutinized the effect of construction on the use of construction-related material (resources) or linked technical innovation with resource efficiency. However, a major strand of literature linked these factors with domestic material consumption without adjusting traded resources (see Table 2). Unlike domestic material consumption (DMC), MF, which provides a view of a nation's material consumption that, fully accounts for extraction in other countries used for local consumption and for domestic extraction ultimately used for consumption in other countries, is imperative to calculate domestic resources consumption. Also, a large extent of literature is limited to linear estimators that assumed data normality and produced mean-centered estimates. Usually, the economic and financial data follow asymmetric and non-normal behavior. The countries selected in panel studies are usually falling at different stages of socio-economic development, experiencing structural changes such as technological revolution, strong investment flows, substantial industrialization, and population that caused resource consumption contrarily at different stages

To fill the potential gap, the present study draws an asymmetric linkage between infrastructure development, green innovation, and consumption-based material footprint in the top 11 highly material-consuming countries. This study adopts a well-known IPAT theoretical framework and contributes prevailing literature manifold. First, this study analysed consumption-based (trade-adjusted) material footprint, which produces an accurate picture of domestic resource consumption. Second, we assess the impact of the cumulative infrastructure development index as a stimulating factor of resource use and green technological innovation as a potential mitigating factor towards consumption-based material footprint. Third, unlike previous studies, which are limited to mean estimators, this study employs a recently developed non-linear estimator popularised as Method of the Moments Quantile Regression (MMQR) (Machado and Silva, 2019). It applies moments restrictions of non-crossing estimates, which help to analyze the impact of infrastructure development and green innovation at different levels of MF using scale and location parameters. The overall results indicate that infrastructure development increase MF, while green innovation decrease MF. However, the resource-depleting and resource-saving impact of both variables are more pronounced at higher quantiles and negligible at lowest quantiles. Figure 1 visualizes the same.

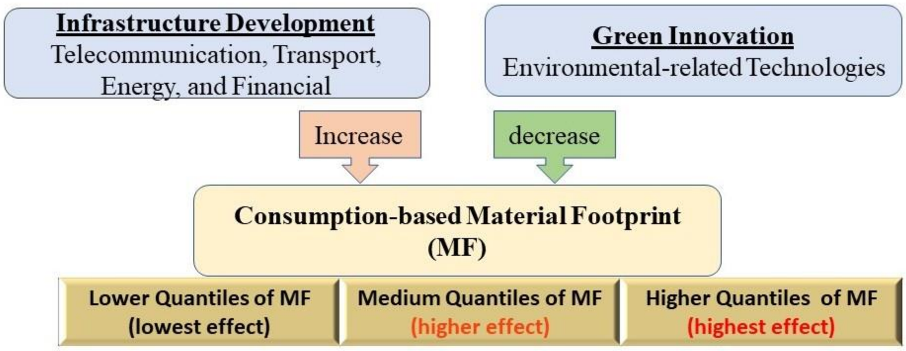


Figure 1: Graphical depiction of the proposed relationship

Usually, economic and financial data follow asymmetric and non-normal behavior (An et al., 2021; Razzaq et al., 2020). Also, the countries selected for this panel are falling at different stages of socio-economic development, experiencing structural changes such as technological revolution, strong investment flows, substantial industrialization, financial crises, and population spur caused resources consumption contrarily at different stages. Besides these arguments, our preliminary findings from the Jarque-Bera test (See Table 2) and BDS non-linearity test (See Table 7) strictly reject the preposition of data normality. Therefore, the use of appropriate methodology is imperative to integrate the non-normality of data, structural changes, and differences across countries. Therefore, MMQR is advantageous based on the distributional heterogeneity of the proposed relationship between driving factors of material footprint using moment restrictions. In addition, MMQR helps to explore the said relationship at different conditional quantiles distribution of the MF, which is not otherwise analyzed using conventional regression methods. Therefore, to our best knowledge, this paper is the first attempt to introduce the distributional heterogeneity to assess the impacts of cumulative infrastructure development index, green innovation, economic growth, globalization, and population on consumption-based MF.

This remainder of this study is organized as; section two contains literature review, section three and four present the methods, empirical results, and discussions. The last section provides conclusion and policy implications.

2. Literature Review:

The high standards of living all around the world extremely relied on the availability of natural resources. Besides, abiotic and biotic materials, water, soil, land, air, and biodiversity are also used for recreational tenacities; and for energy, we consume wind power, tidal flows, and solar power. Unfortunately, the use of these resources also generates some environmental costs in terms of resource depletion, emissions, dumping, waste, and essential production factors for forestry and farming (Adjei et al., 2018; Hu et al. 2021). The way we consume resources often provokes irrevocable ecological effects (Yu et al. 2021; Zafar et al., 2019), as natural resource depletion is a significant factor of upsurging CO_2 emissions (Hussain et al., 2020). Procession and extraction of raw material are more energy-intensive activities and need extensive use of energy, materials, and water, as a large-scale involvement of eco-system consequently creates water, soil, and air pollution.

The literature on the dynamics of natural resources and consumption of material resources paid more focus on economic growth as a primary determinant, considering Environmental Kuznets Curve (EKC) hypothesis. Economic growth and development require the production of new goods and services, and the production of unavoidably needs more material use (Seppala et al., 2001; Vehmas et al., 2007; Jaunky, 2012; Auci and Vignani, 2013; Zhang et al., 2017). The pioneering study on this relationship is explored by Grossman and Krueger (1991). They established that increase in per capita income affects the environmental quality in three different ways, namely, scale, composition, and technological effect. At the early stage of growth with no technology change, the increase in the production process requires more input (material resources and energy inputs), resultantly more waste, pollution, and deterioration in environmental quality (Torras and Boyce, 1998; Dinda, 2004), this effect is called as scale-effect. The consumption of material per capita increases in the early stage of income growth, i.e., scale-effect (Canas et al., 2003; Zhang et al., 2017).

In the second stage of growth, when income reaches a certain level, the economies need a structural transformation; due to structural transformation (industrial to service sector), economies need fewer resources as compare to the early stages (composition effect). Hence, they consume less resources and cause lower pollution. In the final stage of income growth, with technological changes (technological effect) high-income economies utilized enough resources in the R&D investment and developed those technologies which are more environment friendly (Bilgili et al., 2016). In this way, economies substitute old-fashioned technology with advanced and clean technology (Copeland & Taylor, 2004). In the latter two stages, industrial and agricultural sectors start to practice efficient and clean technologies, so the demand for efficient use of natural resource intensify (Grabarczyk et al., 2018). In the whole development, the scale-effect has a detrimental effect on environmental quality by excess use of material, whereas the composition and technological effect with the rise of per capita income mitigate the pollution effect by reducing the per capita consumption of material resources (Jaunky, 2012).

Another important driving factor that affects material consumption is globalization. The increased interaction and integration increase the economic activities, which demand more material resources to produce goods and services (Plank et al., 2018). The economic activities in terms of import, export, and transportation require sufficient resources. In the last decade, the pattern of world trade has changed, the gap between net-importing and net exporting countries of natural resources has risen. Consequently, resource extraction comes along with serious issues of environmental degradation, so raw material importers countries are switched away from consuming country. In such cases, an economy with high material imports compared to exports may be considered to run as ‘‘ecological trade deficit’’ (WWF, 2010). Therefore, an increase in economic activities associated with globalization demands more extraction of material inputs that are positively related to resource depletion (Bruckner et al., 2012; Giljum et al., 2014; Li et al., 2018; Ulucak et al., 2020).

As a remedial measure, technological innovation is an imperative tool that produces efficiency in resource consumption and translates into higher productivity and with less socio-economic cost (Yang and Li, 2017; Ahmad et al., 2019; Razzaq et al. 2021c). In a similar context, Fei et al. (2014) found a positive link between technological innovation and environmental degradation in Norway. They argued that R&D investment translates into higher innovation that allows countries to switch from traditional technologies to the most advanced and clean energies. It provides a buffering effect on environmental degradation by mitigating the pollution effect (Ahmed et al., 2016; Yang and Li, 2017). As advanced technologies enable countries to ensure efficient use of resources that demand lesser materials both on-demand side as well as the supply side (Woetzel et al., 2017). On the demand side, efficient technologies become highly integrated with business, homes, and transportation. Also, they reduced the cost of renewable energies with significant change for consumers and producers of fossil fuels. On the supply side, producers are progressively able to install a range of latest technologies in their production process, exploring mines and wells that were inaccessible, lead to improving the extraction technology of materials. So, they extracted the productivity benefit of technologies. On the other hand, literature also elaborated the inverse association between technological innovation and CO_2 emissions (Churchill et al., 2019; Lin & Zhu, 2019; Wang et al., 2020; Wen et al., 2020).

Even though physical infrastructure development is one of the essential factors to enhance the growth process, however in the recent strand of literature, we found shreds of evidence that physical infrastructure is causing an increase in overall CO2 emissions, mainly due to excessive material use in roads network expansion as well as construction. We found very limited relevant literature in defining the role of physical infrastructure development in resource depletion (MF). However, a few studies revealed a positive association between physical infrastructures such as road networks and CO_2 emissions (Muller et al.,2013; Shahbaz et al., 2015; Rahman et al., 2017; Xie et al., 2017). The infrastructure requires material inputs for transport, telecommunication, and energy. So, the metal is combined with rocks when they extract for the use of a variety of purposes that ranges from the construction of buildings, roads bridges to manufacturing of different, industrial machines (Christian 2019). During this process, the excessive use of materials such as aluminum, cement, and steel upsurge carbon footprint, which have a detrimental effect on environmental quality (Jafri et al., 2020).

We have observed that most of the existing literature focuses on the determinants of gross DMC in a single or group of countries using traditional linear methods. However, we could not find any notable study that links infrastructure development and green innovation with consumption-based MF in top material-consuming countries. Table 2 compiles a few recent studies for bird-eye view.

Table 2: Literature Review Summary

Authors	Countries	Methods	Proxy	Findings/contributors
Kassouri et al. (2021)	12 Emerging countries	STIRPAT	DMP	GDP increase the Domestic Material consumption (DMC) while Material productivity decreases DMC
Usman et al. (2020)	US	ARDL	HFP	Renewable Energy consumption and Trade policy decrease the ecological footprints, and economic growth increases the environmental degradation
Alola et al. (2021)	28 EU countries	PMG ARDL	DMC	DMC increases the environmental degradation, while Per capita income and Renewables decrease the environmental degradation
Li et al. (2020)	China	ARDL	DMC	GDP, Population, Material consumption intensity decrease DMC
Ibrahim & Alola (2020).	MENA countries	PMG ARDL	CE	Conventional Energy Efficiency and Economic Development decreases the environmental quality, whereas Renewable Energy increases the Environment sustainability
Ulucak et al. (2020)	28 EU Countries	PSTR	DMC	GDP growth, TFP, Population increases DMC, while Human capital, and Globalization decrease DMC
Ansari et al. (2020)	5 Asian sub-regions	PMG	EF MF	Energy consumption increases the material and ecological footprint. Moreover, globalization and urbanization enhance the material and ecological footprint
Langnel & Amegavi (2020)	Ghana	ARDL	EF	Globalization positively stimulates the ecological footprint, while electricity consumption deteriorates the environmental quality.

Watari et al. (2019)	Global	LCA	TMR	Global energy transition increases the Total Material Requirements (TMR) , while low Carbon Technologies decrease the Total Material Requirements
Fernández-Herrero & Duro (2019)	94 Selected Countries	RBID	TMP	Agricultural share of GDP, and global Wealth stimulate Total material productivity (TMP) Trade openness shows insignificant effect.
Grabarczyk et al. (2018)	OECD Countries	OLS, DOLS, FMOLS	MI	Material Kuznets Curve supported
Agnolucci et al. (2017)	32 EU Countries	IV Approach	DMC	GDP growth caused higher DMC
Faith G. et al. (2016)	Philippines	IPAT analysis	DMC	Population growth leads to higher DMC
Steger & Bleischwitz (2010)	25 EU Countries	OLS	DMC	Energy efficiency, new dwellings, and roads construction activities increased DMC

ARDL=Autoregressive distributed lag, PSTR=Panel smooth transition model, POLS/FEOLS =Pooled/Fixed effect Ordinary least square, PMG= Pooled mean group, CE= Carbon emissions, EF= Ecological footprint, MF= Material footprint, DOLS= Dynamic OLS, FMOLS=Fully modified OLS, RBID=Regression based inequality decomposition, MI=Material Intensity, IV=Instrumental variables, DMP= Domestic Material Productivity, DMC= Material Consumption.

3. Materials and Methods

3.1 Sample Selection and Data

This study selects the top 11 highly material-consuming countries to integrate the pronounced impact of consumption-based material footprint. The relevance of the sample can be endorsed from the fact that the top 11 countries[1] consume 66% of global resources (see Table 1) and secure the highest score in infrastructure development. These countries are also characterized as technologically advanced countries by securing the highest rank in the global innovation index 2020. Besides, the sample countries are embracing higher economic growth and globalization score. According to the well-known IPAT model, population and economic growth are two key drivers of carbon emissions/ecological deprivation. Table 3 shows that these countries account for 64.1% of global GDP and 53.9% of the global population, signifying the importance of sample. Hence, this study draws the linkages between infrastructure development, green innovation, globalization, economic growth, population, and material footprint. In doing so, we have used annual data from 1990 to 2017.

Table 3: Characteristics of Sample Countries

Country	GDP in Trillion (Constant USD 2010)	% of Global Share	Population (Million)	% of Global Share
United States	17.9	21.6%	327	4.3%
UK	2.9	3.5%	66	0.9%
China	10.9	13.1%	1393	18.3%
South Africa	0.4	0.5%	58	0.8%

1 Turkey, Italy, Canada, Mexico, Viet Nam consume 1.42%, 1.41%, 1.39%, 1.38%, 1.31% share of global resources (MF) and ranked 12, 13, 14,15, and 16, respectively. This study chooses those countries (top 11) which are responsible for more than 1.5% of MF.

India	2.8	3.4%	1353	17.8%
Indonesia	1.1	1.4%	268	3.5%
Japan	6.2	7.4%	127	1.7%
Russia	1.7	2.1%	144	1.9%
Germany	3.9	4.7%	83	1.1%
France	2.9	3.5%	67	0.9%
Brazil	2.3	2.8%	209	2.8%
Total	**53.1**	**64.1%**	**4094**	**53.9%**
Global Figure	**82.9**	**-**	**7592**	**-**

The data of MF is sourced from Global Material Flows Database (GMFD)[2]. Usually, the previous studies use DMC, which does not incorporate trade-adjusted resources. Unlike them, we used new data set developed by GMFD which provides trade adjusted resources consumption. The detailed composition of MF is given in Table 4. It provides a view of a nation's material consumption that, unlike DMC, fully accounts for extraction in other countries used for local consumption and for domestic extraction (DE) ultimately used for consumption in other countries. It is important to mention that we have used an overall consumption-based material footprint (not only construction-related materials) that included biomass, fossil fuels, metal ores, and non-metallic minerals. Also, we have taken cumulative infrastructure development index (quality and quantity) rather than specific infrastructure construction or stocks that endorse the motivation of taking overall consumption-based MF. Table 4 exhibits the summary of MF data.

Table 4: Consumption-based Material Footprint

Indicators	Description and Calculation of the Variables
DE	Domestic Extraction (Biomass, fossil fuels, metal ores, non-metallic minerals)
IM	Physical Imports (direct, territorial)
EX	Physical Exports (direct, territorial)
DMI	Direct Material Input = DE + IM
DMC	Domestic Material Consumption =DMI - EX
RME_{IM}	Raw material (equivalent of imports)
RME_{EX}	Raw material (equivalent of exports)
MF	***Material Footprint = DE+ RME_{IM} - RME_{EX}***

Source: Global Material Flows Database Revised Guidelines Published on 16/01/2018.

This study used the Global infrastructure index, which represents infrastructure development of sample countries in multiple dimensions, includes telecommunication, transport, energy, and financial infrastructure. It comprises different quality and quantity characteristics of 30 sub-indices (see Appendix Table 5a) of infrastructures constructed by Donaubauer et al. (2016). The data of green innovation is extracted from OECD Statistics measuring as environmental technologies as % of total technologies (OECD, 2018). The data of KOF globalization index represent a cumulative measure of political, social, and economic globalization, which is gathered from KOF globalization database (Dreher, 2006). Finally, gross domestic product per capita (USD Constant 2010) and population headcount are sourced from World Development Indicators (WDI, 2018). Except infrastructure index,

[2] https://www.resourcepanel.org/global-material-flows-database.

the data of all other variables are transformed into logarithm that helps to deal with outliers. Moreover, log transformation provides coefficients in the form of elasticities that make the interpretation process more convenient (An et al., 2021a; Razzaq et al., 2020; Khan et al. 2021). The complete description, acronyms, and sources of variables are explained in Table 5.

Table 5: Data Description and Sources

Variables	Description	Source
LMF	Consumption-based Material Foot Print (Tonnes Per Capita)	Global Material Flows Database (UN-IRP, 2018)[3]
INFR	New Global Infrastructure Index (Appendix 1, Table 14)	New Global Infrastructure Index (Donaubauer et al., 2016)
LGI	Environmental technologies (patents) (% of total technologies)	OECD Statistics (OECD, 2018)[4]
LGLO	KOF globalization Index (Social, Economic, and Financial	KOF Swiss Economic Institute (Dreher, 2006)
LGDP	Gross domestic product per capita (USD Constant 2010)	World Development Indicators (WDI, 2018)[5]
LPOP	Midyear Population (headcount)	World Development Indicators (WDI, 2018)

3.2 Summary Statistics

From Table 6, the results demonstrate that all variables possess a positive mean, and population shows the highest mean value (8.240) with a minimum value of 7.632, a maximum value of 9.141, and a standard deviation of 0.460. The skewed distribution comprises that most of the variables have negative skewness. It can be observed that material footprint, infrastructure index, environmental innovation, and globalization are negatively skewed while the population has positive skewness. The infrastructure development index shows the lightest tail as it has low kurtosis and most volatility due to its highest value of standard deviation. Finally, Jarque-Bera (JB) test statistics and respective probability values strictly reject the preposition of data normality for all variables at a 1% level of significance.

Table 6 : Descriptive Statistics

Variables	LMF	INFR	LGI	LGLO	LGDP	LPOP
Mean	1.125	1.034	0.912	1.823	4.087	8.240
Median	1.282	1.224	0.927	1.839	4.256	8.160
Maximum	1.600	3.116	1.311	1.954	4.727	9.141
Minimum	0.150	-0.968	0.365	1.507	2.760	7.632
Std. Dev.	0.326	1.120	0.156	0.098	0.581	0.460
Skewness	-0.761	-0.050	-0.396	-0.785	-0.713	0.737
Kurtosis	2.390	1.728	3.030	3.163	2.205	2.434
Jarque-Bera	34.55	15.584	8.068	32.025	34.27	32.060
Probability	0.000	0.004	0.017	0.000	0.000	0.000

[3] UN-IRP. (2018). Global Material Flows Database. from UN International Resources Panel http://www.resourcepanel.org/global-material-flows-database.

[4] https://data.oecd.org/envpolicy/patents-on-environmenhttps://data.oecd.org/envpolicy/patents-on-environment-technologies.htmt-technologies.htm

[5] https://databank.worldbank.org/source/world-development-indicators

Sum	346.610	237.86	281.09	561.630	1258.931	2538.063
Sum Sq. Dev.	32.741	287.389	7.528	2.950	103.765	65.0547
Observations	308	308	308	308	308	308

To follow up on JB test, we further employ BDS non-linearity test introduced by Brock, Dechert and Scheinkman1(1996), which is developed within chaos theory and considered one of the most popular tests for non-linearity. From Table 7, the test statistics reject the null of linearity, implying that a wide variety of breaks and other types of non-linearities exist in all variables across all countries. Furthermore, Figures 1a, 1b, and 1c (Appendix) visualize the data distribution histograms, quantile distributions, and trends of variables across panel, respectively. All visuals of data distribution and BDS non-linearity test confirm the relevance of asymmetric estimation procedure for reliable empirical results. Therefore, MMQR is the most appropriate technique which integrates both structural changes and non-normality of data.

Table 7: Results of BDS Nonlinearity Test

Country	MF		INF		LGI		LGLO		LGDP		LPOP	
	Z-Sat.	Prob.	Z-Sat	Prob.	Z-Sat.	Prob.	Z-Sat	Prob.	Z-Sat	Prob.	Z-Sat	Prob.
China	27.60	0.00	15.62	0.00	17.52	0.00	31.06	0.00	26.99	0.00	17.50	0.00
USA	24.31	0.00	14.58	0.00	16.38	0.00	29.54	0.00	19.27	0.00	19.71	0.00
India	26.04	0.00	17.75	0.00	18.81	0.00	35.68	0.00	15.36	0.00	17.44	0.00
Brazil	28.13	0.00	16.12	0.00	15.67	0.00	23.92	0.00	11.57	0.00	17.65	0.00
Japan	29.53	0.00	13.45	0.00	17.43	0.00	28.74	0.00	23.93	0.00	18.10	0.00
Germany	25.12	0.00	13.96	0.00	22.28	0.00	30.73	0.00	19.34	0.00	18.75	0.00
Indonesia	28.46	0.00	19.73	0.00	19.14	0.00	25.14	0.00	15.74	0.00	19.58	0.00
UK	22.96	0.00	18.41	0.00	15.99	0.00	29.85	0.00	21.07	0.00	20.61	0.00
France	24.51	0.00	21.67	0.00	23.30	0.00	24.34	0.00	19.27	0.00	21.87	0.00
South Korea	19.60	0.00	16.20	0.00	18.46	0.00	27.10	0.00	19.30	0.00	23.36	0.00
Russia	26.13	0.00	19.74	0.00	19.74	0.00	24.35	0.00	16.99	0.00	18.10	0.00

Note: z-Sat shows z-statistics of BDS test, while Prob. values are bootstrap probability values of respective z-score. z-statistics are calculated on Correlation dimension 2 at 2500 bootstrap replications. A similar result is observed for all correlation dimensions from m=3 to m6, however not reported for the sake of brevity. The test statistics reject the null of linearity, implying that a wide variety of breaks and other types of non-linearities exist in all variables across all countries.

3.3 Heterogeneous Panel estimators

Initially, this study used three heterogeneous panel techniques to produce robust and comparable estimates, namely Fixed Effect Ordinary Least Square (FE-OLS), the Dynamic Ordinary Least Squares (DOLS), and the Fully Modified Ordinary Least Square (FMOLS). The FE-OLS is applied with the help of Driscoll and Kraay standard errors, yield robust estimates in the presence of cross-sectional dependence and autocorrelation in certain lag. In this regard, Pedroni (2004) pointed out that cross-sections have heterogeneity issues both in terms of their differences in means between cross-sections and their adjusted cointegrating equilibrium as well. This problem is solved by Pedroni (2004) by proposing FE-OLS method, considering individual related intercept and includes "heterogeneous serial-correlation of the error processes" across each cross-sectional unit. This procedure is further extended by Kao and Chiang (2001), who introduced a new method known as D-OLS. Using Monte Carlo simulations for a finite sample, D-OLS estimator produces the most efficient estimates compared to FE-OLS and FM-OLS methods. DOLS is superior as it deals with endogeneity issues to overcome the endogenous response through the expansion of lead and lag differentials.

The above techniques are linear in nature; therefore, they only consider the average affect without taking the distribution of data into account. On the other hand, the panel quantile regression ascertains the association among various variables over different quantiles. This method is established by Koenker and Hallock (2001), primarily, this method is only used for quantile asymmetries or a range of quantiles where the response variable depends on the values of the exogenous variable. Additionally, the technique is also better to deal with outliers in estimation. Moreover, this method is more appropriate in the situation where relationships of conditional means of variables are weakly exist (Binder & Coad, 2011). However, the simple quantile estimator is unable to deal with non-crossing estimates while calculating various percentiles that lead to invalid distribution to the response variables.

To address the same, a novel quantile regression popularized as "Method of Moments Quantile Regression (MMQR) is introduced by Machado and Santos Silva (2019). This technique produces non-crossing estimates across the grid of diverse quantiles. A simple panel quantile regressions may vigorous to outliers, and they are incapable of accounting effectively with unknown heterogeneity that arises in panel cross-sections. In contrast, by considering the individual effects, the MMQR enables "conditional heterogeneous covariance effects" of the factors of material footprint to affect the overall distribution that is opposite to the effect established by Koenker (2004) and Canay (2011), and they only permit the fluctuating means. This method is suitable for the models which has the issue of endogenous explanatory variable, and the panel data is considered to be as individual-specific effects and also in the more extreme case when the model is non-linear.

In terms of non-linearity, this method has an advantage on other methods like "Nonlinear Autoregressive Distributed Lag (NARDL)" that defined non-linearity in exogenous terms as the threshold is unchosen by data-driven method rather set to zero. This technique also allows for asymmetries that arise location-wise as the explanatory variables might be contingent on the location of the response variable, material consumption, in the conditional distribution. In this regard, the MMQR technique is the most appropriate approach which tackles both asymmetries and the non-linear association by dealing with endogeneity and heterogeneity, constructing non-crossing estimates diagonally in the structural quantiles. The conditional quantile approximation Qτ(τ| X) can be explained for the location-scale model as:

$$Y_{\mathrm{it}} = a_{i\,+}\ \ X_{it}'\beta + (\delta_i + Z_{it}{}'\gamma)U_{it} \qquad equation\ (1)$$

where the probability, $P\{\delta_i + Z_{it}'\gamma > 0\} = 1$, $(\alpha, \beta', \delta, \gamma')'$are considered as parameters to be estimated and $(a_i, \delta_i\,), i = 1, \dots, n,$ warrants the individual i fixed effects and Z is a k-vector of designated components of X which are differentiable transformations by element l specified as:

$$Z_l = Z_l(X), l = 1, \dots., k \qquad equation\ (2)$$

X_{it} has identical and independent distribution for any fixed i and also invariant across time (t). U_{it} also has identical and independent distribution across individuals (i), through time(t), and orthogonal to X_{it}, qualifies to satisfied the Machado and Silva moment conditions. The outcome-driven from equation (1) is as follows;

$$Q_\tau\,(\tau|X_{it}\,) = \big(a_i\ + \delta_i\, q(\tau)\big) + X_{it}'\beta + Z_{it}{}'\gamma q \qquad equation\ (3)$$

Where, $X_{it}{}'$ is a vector of independent variables which comprises $INFR, GI, GLO, GDP, and\ POP$. $Q_\tau\,(\tau|X_{it}\,)$ specifies the supply of the dependent variable Y_{it} (material footprint), that is conditional to the distribution of location of explanatory variables X_{it}. Whereas, $a_i\,(\tau) = a_i\ + \delta_i\, q(\tau)$ is a scalar coefficient that demonstrated quantile-τ (fixed effect) for individual (i). Though, the individual effect does not have any intercept fluctuation, unlike the OLS fixed effects. The parameters are time-invariant, and their heterogeneous effects can be differed across the quantiles of the conditional distribution of the dependent variable (material footprint). The q(τ), denotes the (τ-th) sample quantile, that is obtained from the following optimization problem:

$$min_q \sum_i \sum_t \rho_\tau \ (R_{it} - (\delta_i + Z_{it}'\gamma)\, q\ ) \qquad\qquad equation\ (4)$$

We derive a check function from the above equation is demarcated as " $\rho_\tau\,(A) = (\tau - 1)AI\{A \leq 0\} + TAI\{A > 0\}$".

3.4 Cross-Sectional Dependence (CD) and Unit Root Tests

In most of the cases, CD appeared to be an outcome of unobserved factors that can not only affect the true parameter values but also disturb the total efficiency gained from the panel data. To incorporate these effects, Pesaran (2004) CD test gained much importance as it works sound under the assumption of cross-sectional dependency heterogeneous panels. Although the current study additionally applies IPS unit root test for comparison (Im et al., 2003); however this approach produces ambiguous results and could not effectively deal with the issues of panel CD, (Khan & Ozturk, 2020). In compliance, the present study applies the Pesaran (2007) CIPS unit root test that used the assumptions of CD and efficiently deal with cointegration models as well.

2.4 Panel Cointegration Tests

The next stage of the investigation is to check the long-term relationship of the variables. We used two-panel cointegration techniques; panel cointegration test by Pedroni (2004) similar to "Engle and Granger" two-step procedure and bootstrapped panel cointegration method by Westerlund (2007). The first method proposes a comprehensive technique to test the panel cointegration. At the initial step, to control heterogeneity Pedroni (2004) classifies individual-specific effects and short-term parametric effects by performing two cointegration test based on residual. In the first stage, "within-dimension test" the study applied four test statistics applied, that includes panel ADF, panel v, panel ρ, and panel PP. In the next stage, "between-dimension test" three test statistics are used, that are group ADF, PP, and ρ. These group of statistic can efficiently estimate the panel cointegration. Whereas Westerlund (2007) offered four tests (Gt, Ga, Pt, Pa) under bootstrap panel cointegration technique with the proposition of no-cointegration as null hypothesis.

However, the above method abandons the state of "common factor restrictions" due to structural dynamics of residuals. The nonfulfillment of the condition "common factor restrictions" lead to diminish the power of cointegration tests based on residuals because structural-dynamics are compulsory to accommodate within the model (Kremers et al., 1992). So, when the constraint assumption is relaxed, then the short-run and long-run adjustment process become incompatible. In order to produce a robust test statistic, the study alleviates the discretionary effects of CD method using Westerlund (2007) bootstrap panel cointegration test. The study also used Dumitrescu and Hurlin (2012) panel causality test to check the casual association between variables. The null hypothesis of this test suggests no Granger causality between variables against the alternative hypothesis that causality prevails between variables in one of the cross-sectional units.

4. Results and Discussion

The present study applies some prerequisite tests beforehand estimating the parameters. Primarily, Tables 8 shows that all model variables are CD as P-values of all variables are less than 0.05, suggesting the rejection of null hypothesis: Cross sections are independent at a 1% level of significance. Table 9 represents that LGI, LGLO, and LPOP are stationary at level, while LMF, INFR, and LGDP are stationary at the first difference in CADF unit root test. Similar stationarity properties are endorsed by CIPS test except for LPOP, which shows stationarity at first difference.

Table 8: Cross-Sectional dependency Test

Variables	CD Test	P-Value
LMF	38.929	0.000
INFR	26.912	0.000
LGI	26.534	0.000
LGLO	35.518	0.000
LGDP	22.415	0.000
LPOP	19.421	0.000

Table 10 and 11 exhibits the results of Pedroni (2004) and Westerlund (2007) bootstrap cointegration test, respectively. The outcome shows that the test statistics of Pedroni (Panel PP/ADF, Group PP/ADF) and Westerlund (Gt, Ga, Pt, Pa) rejects the null hypothesis that entails no cointegration and accepts alternative hypotheses confirming a long-term cointegrating relationship. Both tests confirm the presence of long-run cointegration in model variables.

Table 9: Results of Stationary Analysis

Variables	lm, Pesaran and Shin (2003)				Order of Integration
	I(0)		I(I)		
	C	C&T	C	C&T	
LMF	-1.706	-2.503	-5.125***	-5.195***	I (1)
INFR	-1.711	-2.307	-4.695***	-4.822***	I (1)
LGI	-2.201	-2.748	-5.718***	-5.632***	I (1)
LGLO	-3..642***	-1.921	-4.947***	-6.111***	I (0)
LGDP	-0.772	-1.838	-3.999***	-4.145***	I (1)
LPOP	-1.991	-1.832	-4.737***	-4.566***	I (1)
Cross-Sectionally Augmented Dickey-Fuller (CADF)					
LMF	-1.933	-2.248	-4.691***	-4.701***	I (1)
INFR	-2.209	-2.235	-7.963***	-6.576***	I (1)
LGI	-2.201	-3.495***	-	-	I (0)
LGLO	-2.988***	-2.693*	-	-	I (0)
LGDP	-1.956	-2.038	-3.231***	-3.521***	I (1)
LPOP	-2.720**	-2.911**	-	-	I (0)
Cross-Sectionally Augmented IPS (CIPS)					
LMF	-1.933	-2.248	-4.691***	-4.701***	I (1)
INFR	-2.531	-2.603	-4.778***	-4.970***	I (1)
LGI	-2.744***	-3.495***	-	-	I (0)
LGLO	-2.988***	-2.921***	-	-	I (0)
LGDP	-1.956	-2.038	-3.231***	-3.521***	I (1)
LPOP	-0.482	-1.395	-2.924***	-2.988***	I (1)

*,**, and *** show significant levels at 10%, 5% and 1% respectively.

The long-run cointegration enables us to estimate long-run elasticities. In this way, it is also imperious to recapitulate that the present model has the problem of cross-sectional dependency. So, it is crucial for panel estimation to integrate such methods that are vigorous to CD effects to eliminate the probable size of distortions. Therefore, this study used several heterogeneous panel estimation techniques that effectively deal with underlined issues that include FMOLS, DOLS, FE-OLS (linear estimator), and MMQR (non-linear estimator). The estimating outcomes derived from FMOLS, DOLS, and FE-OLS procedures can be seen in Table 12.

Table 10: Panel Cointegration (Pedroni 2004)

Estimates	Stats.	Prob.
LMF = f (INF+LGI+LGLO+LGDP+LPOP)		
Panel v Statistics	-1.464	0.9285
Panel rho Statistics	0.684	0.7530
Panel PP Statistics	-2.732	0.0032
Panel ADF Statistics	-2.361	0.0091
Alternative hypothesis: individual AR coefficient		
Group rho Statistic	1.870	0.9693
Group PP Statistic	-2.962	0.0015
Group ADF Statistic	-1.962	0.0249

Source: Author Estimation

From Table 12, the coefficient of infrastructure index significantly increases the consumption of material footprint by approximately 0.2188% in the FMOLS estimator, ~ 0.365% in D-OLS procedure, and ~0.44% in the FE-OLS estimator. Infrastructure has a transformational effect on the development mode and living standard of people. It delivers various interlinked services, including construction, transportation, water, energy, and waste management. The construction process also requires increased demand for material production (cement, steel, wood, and aluminum), which boosts energy demand and translates into a higher incidence of CO_2 emissions (Wang et al., 2020). Additionally, infrastructure development is also linked with some environmental issues, for instance, natural resource depletion, climatic changes, and CO2 emission (Zhao et al., 2018; Yang et al., 2019). These impacts may occur during material production, construction, and manufacturing and when infrastructures (post-construction phase) need to be replaced or repaired. According to the Global Commission on the Energy and Climate (2014), worldwide 488.6 trillion dollars investment will be needed to invest in infrastructure by 2030. To support the infrastructure need, it will also require material inputs and energy that will lead to raising environmental degradation.

Table 11: Panel cointegration (Westerlund 2007)

Statistics	Values	Z-values	P-values	Robust P-values
Gt	-9.241	-8.314	0.000	0.000
Ga	-18.678	-19.223	0.000	0.000
Pt	-22.835	-23.639	0.000	0.000
Pa	-26.847	-25.512	0.000	0.000

On the other side, green innovation (environmental technologies) produces emissions mitigating effect. Technological advancements in the environment reduced the prices of several material products (aluminum, polyester, silicon) and increased their efficiency to consume material more efficiently. In this way, the consumption of material goes down and has a beneficial impact on the overall quality of the environment. Besides, the climate challenge and reducing the human's ecological footprint shift the lifestyle and consumption pattern differently. It led to the development of green technologies and environmentally friendly policies to boost smart growth (with efficient resources and less material consumption), low carbon emission, low carbon city, and green agricultures (Bununu, 2016; Bununu, 2020).

The globalization index displays a significant positive association with material consumption, expressing increased globalization leads to increased consumption of material inputs by approximately 0.59% in the FMOLS estimator, ~ 0.621% in the D-OLS estimator, and ~ 0.58% in the FE-OLS estimator. Numerous studies elucidate that globalization plays an important role in shaping efficient material usage and developing environmental sustainability (Copeland & Taylor, 2013). It is also observed that globalization enables economies to expand their welfare and economic activities, for instance, trade, industrial, production, and transportation, which leads to more resource usage that produces more contamination, waste, and pollution (Bilgili et al., 2020).

Table 12: Heterogeneous Panel Estimations

Variables	**FM-OLS**		**D-OLS**		**FE-OLS**	
	Coeff.	**t-stat.**	**Coeff.**	**t-stat.**	**Coeff.**	**t-stat.**
INFR	0.218**	2.502	0.365**	2.389	0.442***	5.102
LGI	-0.382***	-4.587	-0.298***	-4.119	-0.136**	-3.204
LGLO	0.592**	2.622	0.621**	2.472	0.583**	3.243
LGDP	0.443***	3.918	0.693**	2.570	0.245**	3.917
LPOP	0.307***	3.559	0.521**	2.651	0.438***	6.394

*,**, and *** show significant levels at 10%, 5% and 1% respectively.

The coefficient of economic growth is statistically significant and increases the consumption of material footprint. It exhibits that GDP surges material consumption by 0.443% in the FMOLS estimator, ~ 0.693% in the D-OLS estimator, and ~ 0.24% in the FE-OLS estimation procedure. Likewise, the coefficient of population illustrates that increased population is positively associated with material footprint by approximately 0.307% in the FMOLS estimation procedure, ~ 0.521% in the D-OLS estimator, and ~ 0.438% in the FE-OLS estimation procedure. The more populated and dense economies need more resources to satisfy the population's needs, which require natural and material resources for their food, housing, transportation, water, and sanitation. Consequently, the population pressure contributes to waste, soil erosion, air pollution, land degradation, and other environmental contaminations (Ray & Ray, 2011).

4.1 MMQR Estimations

From Table 13, we can infer that increase in infrastructure significantly increases the consumption of material footprint primarily in the first quantile and also more significant results in the grids of median to high (5-9) quantiles while insignificant between middle (2-4) quantiles. As infrastructure development is a resource-intensive industry, and in 2015 half of the world's material consumption was accredited to the construction industry only. Similarly, sand is also accounted as a major part of concrete used and the main component of material footprint that use as a second major natural resource after water. The exponential economic growth based on infrastructure industry is highly associated with material footprint and consequently linked with emissions, waste, and environmental degradation. Statistics show that one-third of the infrastructure is related to material consumption (Wiedmann et al., 2015), and most of them are construction-based.

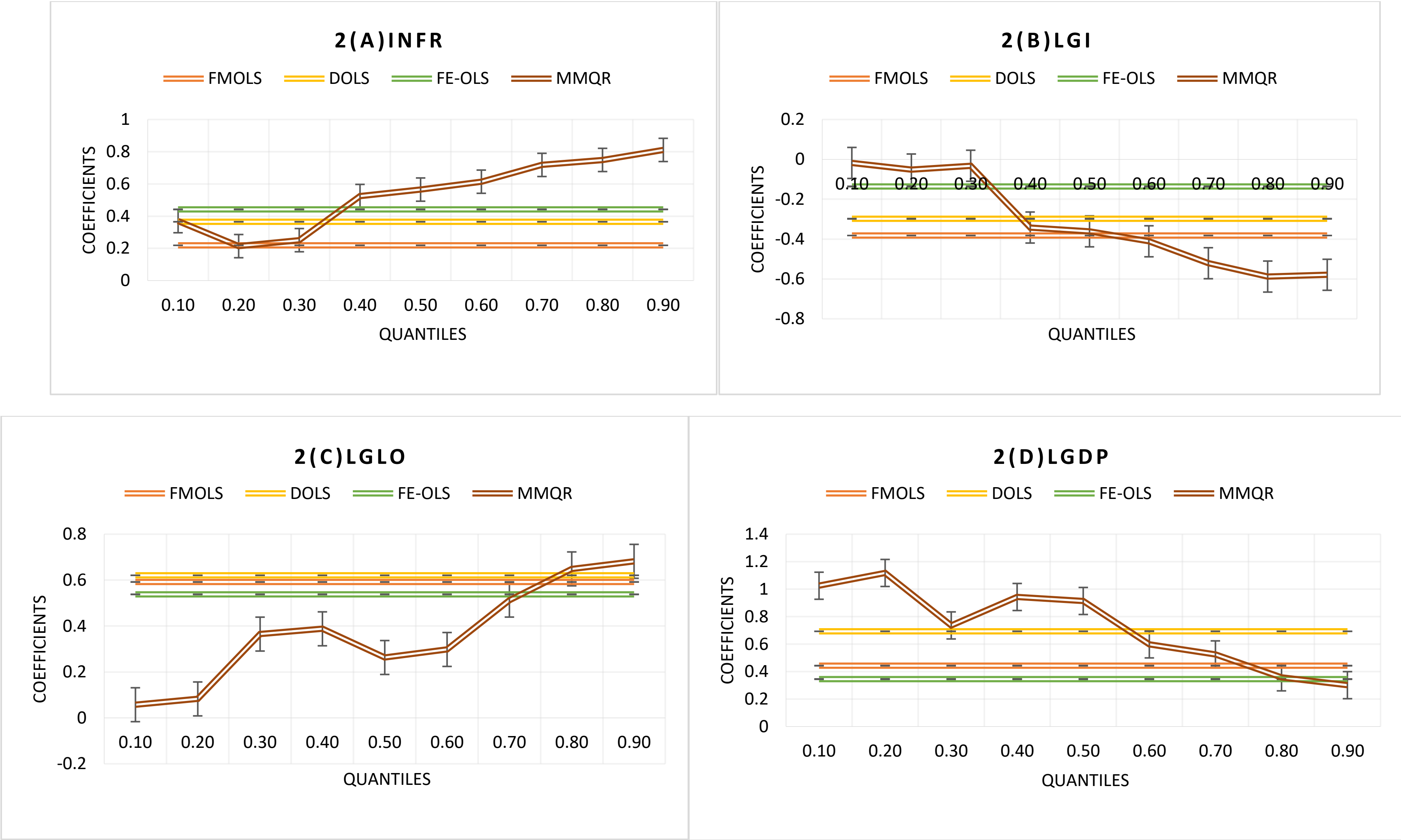
The results of green innovation have a mixed and significant effect on material consumption in the higher grid (5-9) of quantiles and an insignificant association in lower quantiles. Several studies explored the positive spillover of green technology through energy and resources conservation and promoting progressive industrial structure. It advocates the efficient use of material consumption like iron, steel, copper, and cement, and energy (Liu et al., 2017). Consequently, in countries like China, India, and European Union, the benefits of efficient use of energy, particularly reduction of sulfur dioxide and efficiency in the steel production process is achieved (Xu et al., 2014; Deif, 2011; Gandhi et al.,2018). Productivity-enhancing technology is already being deployed in mining operations and more recently, the developments in the copper industry (for instance, tapping reserves used an average ore grade of less than 1% copper). This elucidates how improved technology getting more with fewer resources. Similarly, Rio Tinto's mines Australia adopting automation technology, which is estimated to rise by 40% utilization of haul trucks and 15% of automated drills utilization.

The results also indicate that the KOF index of globalization is positively and significantly affects material consumption in the middle of the grid (3-7) quantiles. The results justify the globalization-material consumption nexus, material consumption increases when countries are at the initial stage of globalization; in this phase, countries need more material resources to invest in their project, but once projects become mature, they need not as much amount of material inputs as they need at initial levels (Bilgili et al., 2020). These results contradict Ulucak et al. (2020), who argued that a

Table 13: Results of Panel Quantile Estimations

Variables	Location	Scale	Method of Moments Quantile regression Grid of Quantiles								
			0.10	**0.20**	**0.30**	**0.40**	**0.50**	**0.60**	**0.70**	**0.80**	**0.90**
INFR	0.292**	0.427**	0.369*	0.214	0.251	0.525	0.565**	0.614**	0.718**	0.749*	0.811*
	(0.119)	(0.187)	(0.201)	(0.197)	(0.195)	(0.328)	(0.214)	(0.237)	(0.269)	(0.385)	(0.423)
	[2.453]	[2.283]	[1.836]	[1.086]	[1.287]	[1.601]	[2.640]	[2.591]	[2.669]	[1.945]	[1.917]
LGI	-0.137**	-0.245**	-0.018	-0.051	-0.032	-0.342	-0.361**	-0.411***	-0.521***	-0.588**	-0.579**
	(0.0561)	(0.0976)	(0.013)	(0.048)	(0.027)	(0.209)	(0.149)	(0.108)	(0.119)	(0.193)	(0.205)
	[-2.442]	[-2.510]	[-1.384]	[-1.063]	[-1.185]	[-1.636]	[-2.423]	[-3.806]	[-4.378]	[-3.046]	[-2.824]
LGLO	0.287*	0.156	0.057	0.082	0.365*	0.388*	0.263***	0.298**	0.513***	0.649	0.682
	(0.167)	(0.149)	(0.086)	(0.073)	(0.197)	(0.195)	(0.059)	(0.123)	(0.141)	(0.418)	(0.473)
	[1.719]	[1.047]	[0.667]	[1.129]	[1.853]	[1.989]	[4.457]	[2.423]	[3.638]	[1.552]	[1.442]
LGDP	1.579**	0.925*	1.025**	1.118**	0.736*	0.943*	0.914*	0.598**	0.525*	0.358**	0.301**
	(0.672)	(0.477)	(0.408)	(0.413)	(0.401)	(0.522)	(0.468)	(0.240)	(0.272)	(0.124)	(0.107)
	[2.349]	[1.939]	[2.512]	[2.701]	[1.835]	[1.806]	[1.953]	[2.492]	[1.930]	[2.887]	[2.813]
LPOP	0.302	0.238*	0.038	0.086	0.561	0.573**	0.419*	0.512**	0.433*	0.211***	0.201***
	(0.190)	(0.127)	(0.093)	(0.079)	(0.359)	(0.211)	(0.226)	(0.230)	(0.226)	(0.064)	(0.059)
	[1.589]	[1.874]	[0.409]	[1.088]	[1.563]	[2.716]	[1.854]	[2.226]	[1.916]	[3.297]	[3.406]

Note: ***, ** and * represent significant level at 1%, 5% and 10%, respectively. Robust standard errors and z-score is presented in round brackets and box brackets, respectively. Due to possible endogeneity arises from infrastructure to economic growth, and globalization, we have taken lag of all regressors as an instrument. Also, we run the same model without instruments using "moment restrictions" as an intrinsic instrument of MMQR estimations and found consistent results. Unlike traditional quantile estimates, MMQR possesses additional restrictions that quantiles don't cross during estimations. It helps to deal with endogeneity issues (Machado and Silva, 2019). The location and scale parameters represent that most of the model variables are asymmetrically distributed from both location dimension and dimension of dispersion (An et al. 2021a; Lingyan et al. 2021).


2(A)INFR
FMOLS
DOLS
FE-OLS
MMQR
COEFFICIENTS
QUANTILES
0.10 0.20 0.30 0.40 0.50 0.60 0.70 0.80 0.90
2(B)LGI
FMOLS
DOLS
FE-OLS
MMQR
COEFFICIENTS
QUANTILES
2(C)LGLO
FMOLS
DOLS
FE-OLS
MMQR
COEFFICIENTS
QUANTILES
2(D)LGDP
FMOLS
DOLS
FE-OLS
MMQR
COEFFICIENTS
QUANTILES

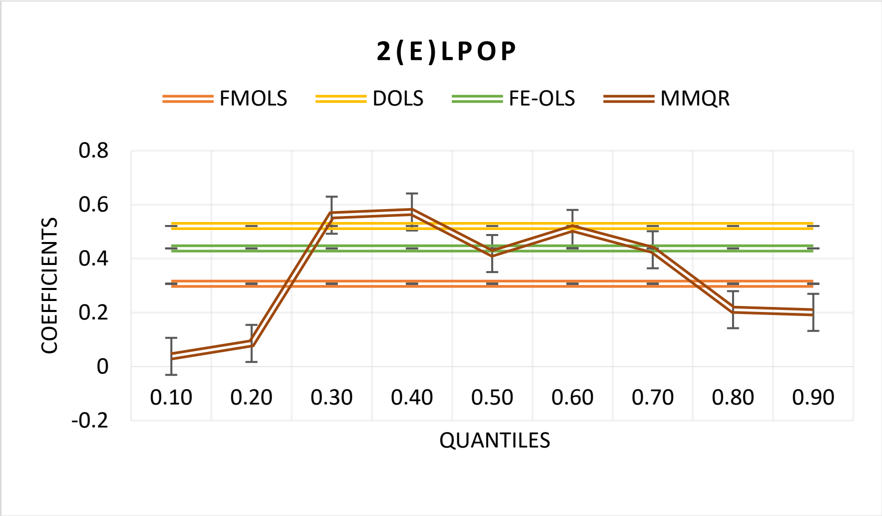


Figure 2: Graphical depiction of all estimators across quantiles

higher integration and interaction with other nations enables economies to lower their material usage and contribute to efficient use of resources at its increasing level.

Economic growth possesses a positive and significant association with material footprint across the grids of all quantiles, confirming that economic growth leads to excess use of material consumption that has detrimental effects on the environment. The nexus of material consumption and economic growth is established based on the Modigliani's life-cycle hypothesis, which develops the relationship between consumption and income. After this hypothesis, various studies explored the short-run and long-run relationships of changing income on consumption (Deaton, 1986; Campbell and Mankiw, 1989; Jappelli and Pistaferri, 2010). As it is well-documented through empirical observations, the importance of material inputs makes it more demanding when countries grow over time, so for economic growth eventually surge the use of economic goods, which leads to more demand of material consumption (Agnolucci et al., 2017; Weinzettel and Kovanda, 2011). Lastly, the results illustrate that population is significantly and positively associated with MF across the middle and upper quantiles but insignificant at lower quantiles.

Figure 2 visualizes the elasticity coefficients of all four estimators, suggesting a horizontal or mean effect across all quantiles in FM-OLS, D-OLS, and FE-OLS estimators. In contrast, MMQR coefficients show significant variations across different quantiles, which is also endorsed from significant location and scale parameters in Table 11, indicating the effect of INFR, LGI, LGLO, LGDP, and LPOP on MF is significantly varied across lower, medium, and higher level of MF. The estimates of infrastructure and green innovation follow different dynamics. The MMQR estimates of infrastructure index show its highest coefficient at the highest quantile of material footprint, and green innovation has its highest coefficient at the lowest quantile. It indicates that the resource depleting (conservation) effect of infrastructure development (green innovation) is lowest (highest) for lower quantiles and highest for higher quantiles of MF. It also suggests that MF is at its highest level when countries are improving their infrastructure embodied with higher resource consumption and lower when green innovations are improving in response to ensure resource efficiency. Interestingly, the positive coefficient of infrastructure progressively increases from the lowest quantile to the highest quantile, while the negative coefficient of green innovation rises from the lowest to the highest quantile.

Similar to the infrastructure development index, globalization insignificantly contributes to resource depletion at lower quantiles of MF. In comparison, a higher and significant effect is observed when moving from lower to higher quantiles of MF. Economic growth caused more resource depletion at the lower levels of MF, and for higher-level of MF, the resource depleting effect of economic growth reduce. It also suggests the proposition of the EKC, where higher national income after a certain threshold emits technological spillovers that leads to higher resource efficiency and subsequent reduction in resource consumption. The MMQR coefficient of population shows an inverted U shape relationship with MF. The results exhibit that the positive effect of population on MF is increased from initial to medium quantiles, and after a certain threshold, it turns less pronounced.

The asymmetric effects of Infrastructure development can be attributed to host country's distinct characteristics. Countries falling at upper quantiles are relatively larger in the area (size), such as China, USA, Brazil, and India occupy 6.3%, 6.1%, 5.6%, 2.0% of global landmass, respectively. These countries are fall in the top ten countries in terms of area occupancy (Worldometer, 2021)[6]. Therefore, they have a relatively higher demand for infrastructure and natural resources. Also, it needs further resources to maintain and repair existing infrastructure stocks. In addition, infrastructure produces multiplier effects such as financial infrastructure, transport infrastructure, ICT infrastructure,

[6] https://www.worldometers.info/geography/largest-countries-in-the-world/

and energy infrastructure not only require one-time construction material but also stimulate the subsequent demands of fossil fuels, energy, and other resources due to higher economic activity. As a result, the magnitude of infrastructure coefficients is significantly higher at the highest quantiles compared to lower quantiles. Similarly, these countries are highly populated; for example, China, USA, Brazil, and India account for 18.47 %, 4.25%, 2.73%, 17.70% global population, respectively. Extent literature echoed that population and economic growth are two main deriving factors of resource consumption (Ulucak et al. 2020; Razzaq et al. 2020). Therefore, countries falling at higher quantiles exhibit a relatively higher and significant impact than lower quantiles. Although lower quantiles show an insignificant impact, however, it remains positive. Countries falling at lower quantiles such as France, UK, South Korea are comparatively smaller in size and population. Therefore, the requirement as well as maintenance of new and existing infrastructure facilities are lower and may have a negligible impact on MF.

Similarly, the effect of green innovation on MF is significantly higher at higher quantiles. Notably, higher quantile countries are technology leading countries such as USA, China, and Japan. These countries are investing hefty amounts in R&D to transforming their economies through innovation-driven models. Due to prevailing ecological challenges, they are striving to minimize resource consumption. Also, these countries have higher MF, and hence a higher margin to replace existing technologies with green innovation. Amongst others, these factors lead to a higher impact on MF at higher quantiles. A similar argument can be expanded to other variables. Apart from these justifications, there are certain factors that create non-linearity, such as different technical capacities, institutional governance, industrial transformation, structural changes, financial crises, and much more. Due to these factors, the impact of infrastructure development, green innovation, economic growth, globalization, and population on resource consumption varies at different quantiles (lower, medium, and higher) of MF.

Lastly, Dumitrescu and Hurlin, (2012) Granger causality test is employed to confirm causality between variables. The results demonstrate a one-way causality is running from independent variables (INF, LGI, LGLO, LPOP, LGDP) to the dependent variable (MF) that endorse prior findings from long-run estimators. The detailed results are not reported for the sake of brevity.

4.2 Robustness Regression

Initially, this study applies heterogeneous panel estimators (FMOLS, DOLS, FEOLS) to deal with possible heterogeneity and endogeneity in a linear framework. However, the robustness of the non-linear estimator (MMQR) is imperative to confirm due to possible cross-sectional dependency and endogeneity. Therefore, for robustness, this study applies a recently developed dynamic panel quantile regression based on common correlated effects popularized as “Dynamic Quantile Mean Group regression (DQMGR)”. This method is proposed by Harding et al. (2020), which is based on principles of well-known common correlated effects mean group (CCEMG) introduced by Chudik and Pesaran (2015). DQMGR is superior to prevailing static and dynamic panel quantile estimators because it allows for the possibility that unobserved factors and included regressors are correlated and integrate the conditions under which the slope coefficients are estimated. Moreover, it allows lagged dependent variables as additional regressors to deal with dynamic trends and endogeneity arises from unobserved factors.

DQMGR is an extension of Chudik and Pesaran (2015) with heterogeneous slopes for a situation where the time-series dimension (T) and cross-sectional dimension (N) are relatively large. It offers the possibility of estimating heterogeneous distributional effects in a dynamic quantile framework, which has great policy relevance. For example, the impact of a policy can be heterogeneous throughout the conditional distribution of the response variable, and therefore, it might not be well summarized by the average effects. The detailed assumptions and derivation of DQMGR are given in the seminal paper of Harding et al. (2020).

Table 14: Dynamic Quantile Mean Group Regression

Variables	**DQMGR Quantiles Grid**					
	0.10	**0.30**	**0.50**	**0.70**	**0.80**	**0.90**
MF_{t-1}	0.401***	0.376***	0.358***	0.349***	0.438***	0.354***
	(0.040)	(0.091)	(0.071)	(0.080)	(0.087)	(0.090)
	[10.025]	[4.132]	[5.042]	[4.362]	[5.034]	[3.933]
INFR	0.261	0.301*	0.297**	0.315**	0.322**	0.375***
	(0.183)	(0.159)	(0.123)	(0.140)	(0.128)	(0.116)
	[1.426]	[1.893]	[2.415]	[2.250]	[2.516]	[3.232]
LGI	-0.217	-0.250**	-0.216***	-0.343***	-0.326**	-0.354**
	(0.146)	(0.090)	(0.069)	(0.100)	(0.144)	(0.160)
	[-1.486]	[-2.778]	[-3.130]	[-3.430]	[-2.264]	[-2.213]
LGLO	0.134	0.196	0.217**	0.336***	0.352*	0.348*
	(0.126)	(0.117)	(0.099)	(0.109)	(0.169)	(0.151)
	[1.063]	[1.675]	[2.192]	[3.0825]	[2.083]	[2.304]
LGDP	0.670***	0.659***	0.572***	0.536**	0.510***	0.523**
	(0.198)	(0.207)	(0.169)	(0.173)	(0.217)	(0.195)
	[3.383]	[3.184]	[3.384]	[3.098]	[2.350]	[2.682]
LPOP	0.234	0.280*	0.315**	0.308***	0.317***	0.272**
	(0.167)	(0.141)	(0.116)	(0.102)	(0.090)	(0.110)
	[1.401]	[1.986]	[2.715]	[3.019]	[3.522]	[2.473]
N.	11	11	11	11	11	11
Obs.	308	308	308	308	308	308

Note: ***, ** and * represent significant level at 1%, 5% and 10%, respectively. Robust standard errors and z-score is presented in round brackets and box brackets, respectively. MF_{t-1} exhibits lag of dependent variable.

Table 14 shows the outcome of DQMGR. The results illustrate that the lag term of MF is positive and significant across all quantiles, suggesting the validity of dynamic model in an asymmetric framework. It confirms that the current year's MF is significantly affected by its own lag values at each level (lower, middle, and higher quantiles). The results of other variables are approximately or substantially the same in terms of direction of relationship; however, the magnitude and statistical significance of parameters vary across quantiles. The coefficient values of INF (LGI) are relatively lower than the former estimation through MMQR. However, it echoes a similar direction portrayed in Figure 2a (2b), where higher quantiles reflect a higher impact of INF (LGI) on MF. Overall, the coefficient magnitude of MMQR model is almost double than the DQMGR. Similarly, globalization (economic growth) shows an increasing (decreasing) trend from lower to higher quantiles, consistent with former estimations. Lastly, population shows a lower impact on MF at lower and highest quantiles.

5. Conclusions and Policy Implications

This study assessed the asymmetric association between infrastructure development, green innovation, and consumption-based material footprint in the top 11 highly material-consuming countries. Initially, this study applies three-panel estimators, namely, FMOLS, DOLS, and FEOLS to handle possible heterogeneity among cross-sections. To explore the distributional heterogeneity of the above-mentioned relationship between driving factors of material footprint, we have employed the MMQR technique. MMQR helps to analyze this relationship on a diverse range of quantiles of the conditional distribution of material footprint. For robustness, we also employ a recently developed panel technique popularised as Dynamic Quantile Mean Group regression. The empirical estimates of this study offer a few important insights that help policymakers to devise sustainable resource policies. According to the empirical results obtained from FMOLS, DOLS, and FEOLS estimators, infrastructure development, gross domestic product, globalization, and population are driving factors of material footprint, while green innovation is found a tool to mitigate material footprint across sample countries.

Unlike linear estimators, the empirical findings from MMQR highlighted significant variations across the grid of quantiles and offered interesting insights. The MMQR estimates of the infrastructure index indicate that the resources depleting (conservation) effect of infrastructure development (green innovation) is lowest (highest) for lower quantiles and highest for higher quantiles of MF. Interestingly, the positive coefficient of infrastructure progressively increases from the lowest quantile to the highest quantiles, while the negative coefficient of green innovation rises from the lowest to the highest quantile. Similar to the infrastructure development index, globalization insignificantly contributes to resource depletion at lower quantiles of MF, while a higher and significant effect is observed when moving from lower to higher quantiles of MF. In contrast, economic growth caused more resource depletion at the lower level of MF, and for higher-level of MF, the resource depleting effect of economic growth reduce. It also suggests the proposition of the EKC, where higher national income after a certain threshold emits technological spillovers that leads to higher resource efficiency and subsequent reduction in resource consumption. The MMQR coefficient of population shows an inverted U shape relationship with MF. The results exhibit that the positive effect of population on MF is increased from initial to medium quantiles, and after a certain threshold, it turns less pronounced.

The primary outcomes of this study suggest that the resource depletion (conservation) effect of infrastructure development (green innovation) is not the same for all MF levels. Therefore, the non-normality should be taken into account while devising policies. For instance, infrastructure development and globalization are not significantly contributing to resource depletion at the lower level of material footprint; therefore, countries falling at the range of lower MF can increase sustainable infrastructure construction using global integration and transfer for foreign environmental technologies in the construction and production process. Similarly, the resource conservation effect of green technologies is more prominent at a higher level of MF, recommending the implementation of these technologies in highly resource-consuming countries. An integrated policy of sustainable infrastructure construction embodied with green technologies can help to reduce consumption-based material footprint.

The accomplishment of SDG 12 is imperative to secure scarce resources, which needs sequester legislation for sustainable management of infrastructure construction. *Recycling and Reusing* of Construction and Demolition (C&D) materials consist of the debris generated during the construction, renovation, and demolition of buildings, roads, and bridges can help to preserve natural resources and create employment opportunities. Green technologies in *C&D Recycling* can transform these resources from waste to reusable inputs with minimum energy cost to construct new infrastructure with minimal resource extraction. Moreover, optimal utilization of existing infrastructure is highly recommended to minimize resource consumption.

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Appendix

Table 5a: Variables and Data Sources of Infrastructure development Index

S. No	Variables	Normalization of the Variables	Data Set/Source
1	*Transport Infrastructure:* (A) Land Transport: (i) Length of Total Road Network (ii) Paved Road (iii) Proportion of Motorways (iv) Registered Passenger-Cars (v) No: Registered Commercial-Vehicles (vi) Length of Total Railway-Route (vii) Goods-Transported (viii)Railway Passengers (B) C Transport Overall Carrying - Capacity of Economy Ships. (i) Relative to its Geo-Graphic-Area (ii) % of aggregate world - carrying Capacity (C) Air Transport (i) Carrier Departure Registered (ii) Volume of Air-Fright	Population Density Area/ Population size Relative to population/country size	International Road Federation (IRF) World Road Statistic & World Development Indicators (WDI) Facts and figures of (VDA) German Association (GAAI) of the Automotive Industry United Nations Conference of Trade and Development Data Base(UNCTAD) World Development Indicators
2	*Telecommunication infrastructure* (i) No. of fixed-telephone lines (ii) Mobile-cellular-telephone subscribers (iii) No. of ISDN subscribers For quality measures (a) Faults per 100 fixed-telephones lines in1 year (expressed in per capita terms)	Relative to population/country size	World Development Indicators
3	*Energy infrastructure* (i) Consumption of electric power (ii) Production of electric power Note: both undermentioned indicators are	Relative to Country	World Development Indicators

	measure in per capita terms for quality measures: (a) Electric-power transmission and distribution losses (% of output)		
4	*Financial infrastructure* (i) Stock market turn-over ratio [efciency] (ii) No. of “Bank Account” per capita (iii) Values of overall “traded share” outside the major “10 traded companies” as a share of the aggregate value of overall traded share (iv) No. of public recorded “companies per capita” (v) “Private credit” by deposit money, banks “Relative-GDP” (vi) Values of aggregate shares traded on the “Stock Market” exchange (relative to gross domestic product) (vii) Money (M2) and quasi-money percentage of GDP	Relative to Country	World Bank Global Financial Development Data Base

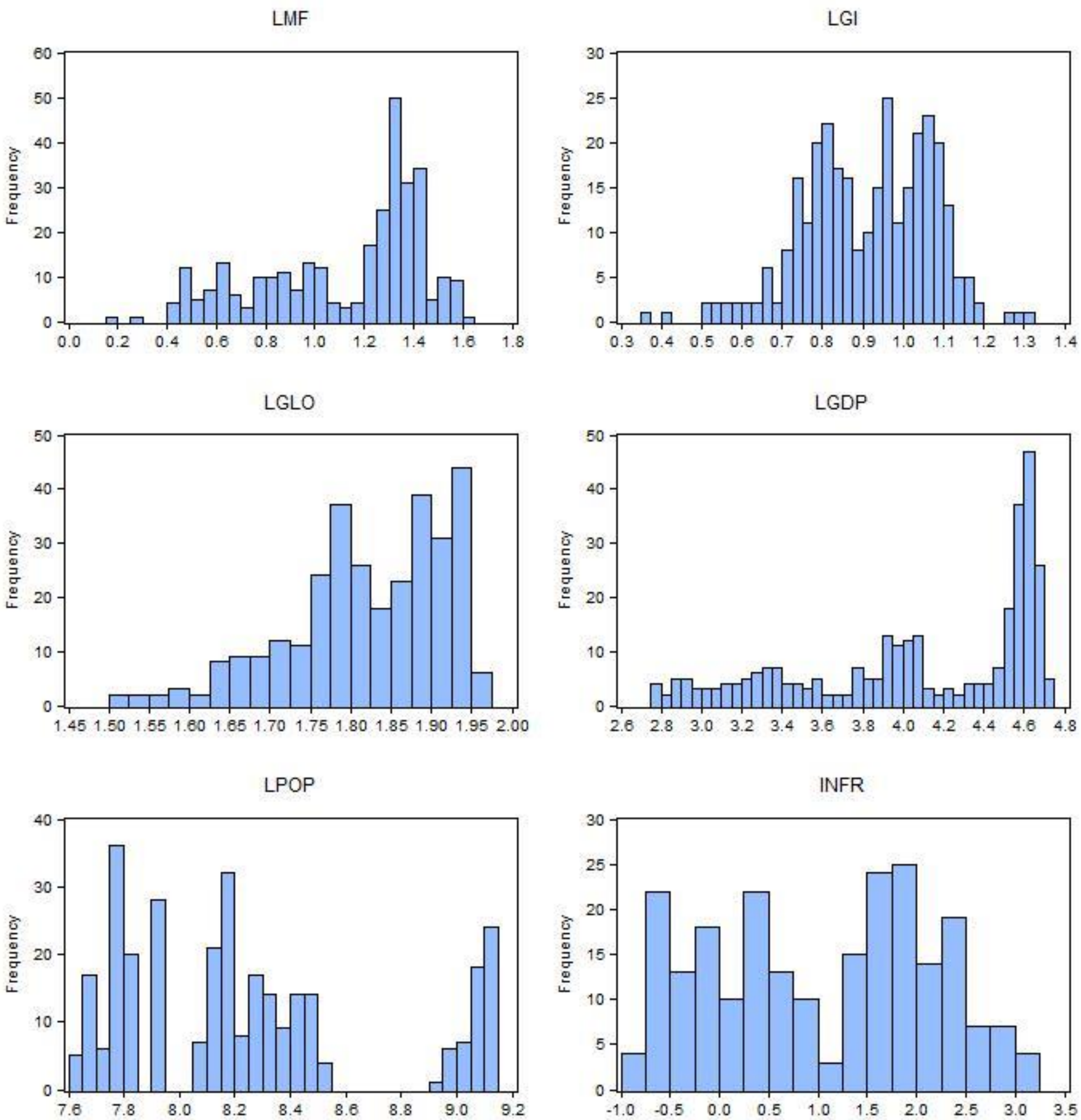


Figure 1a: Distribution of Data

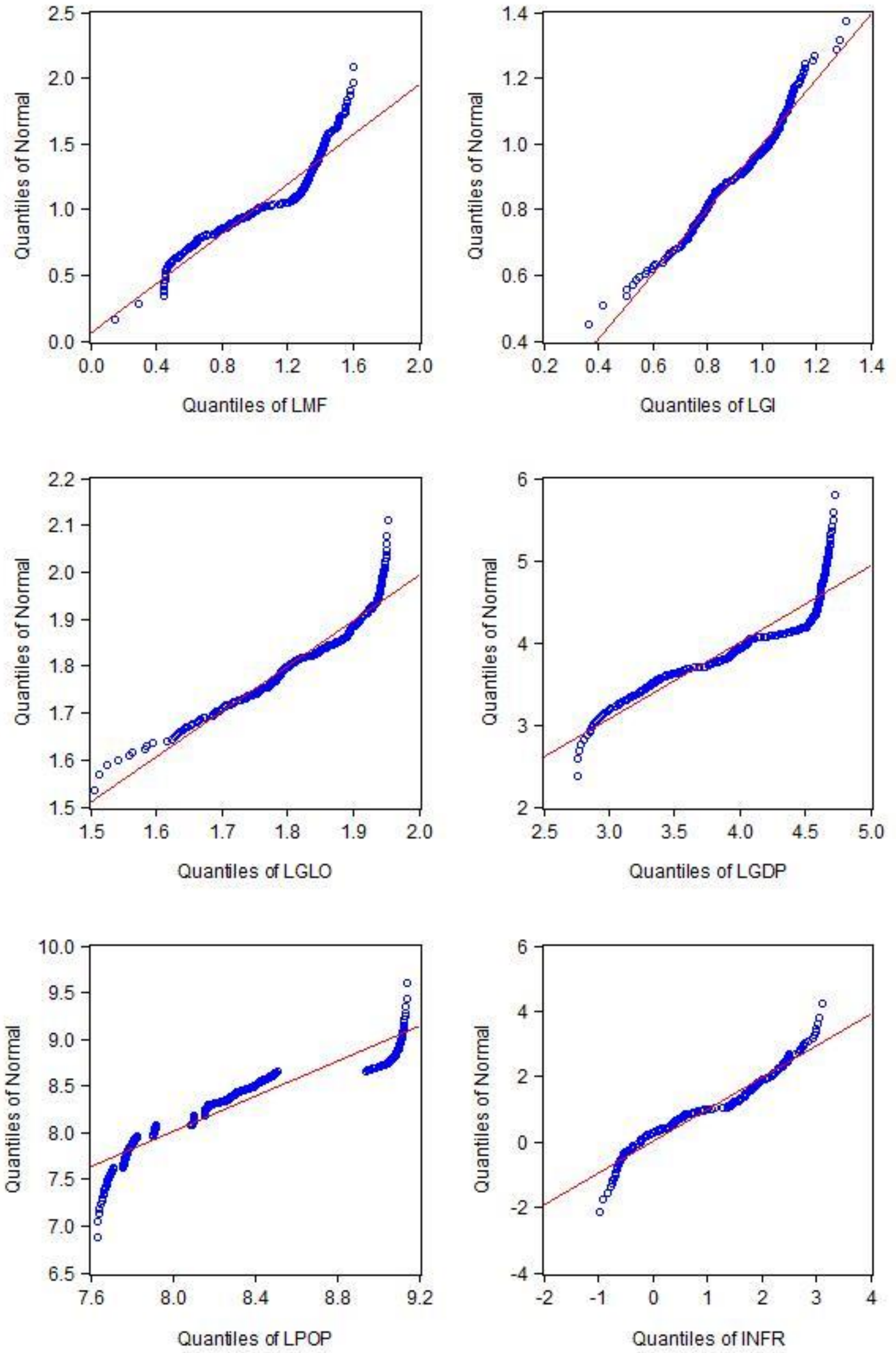
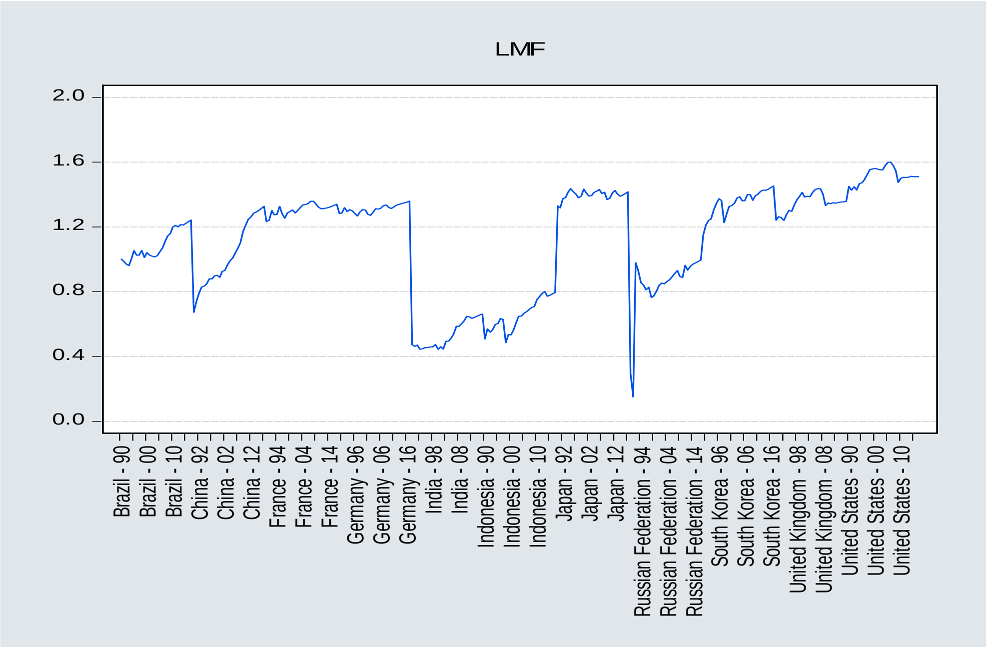
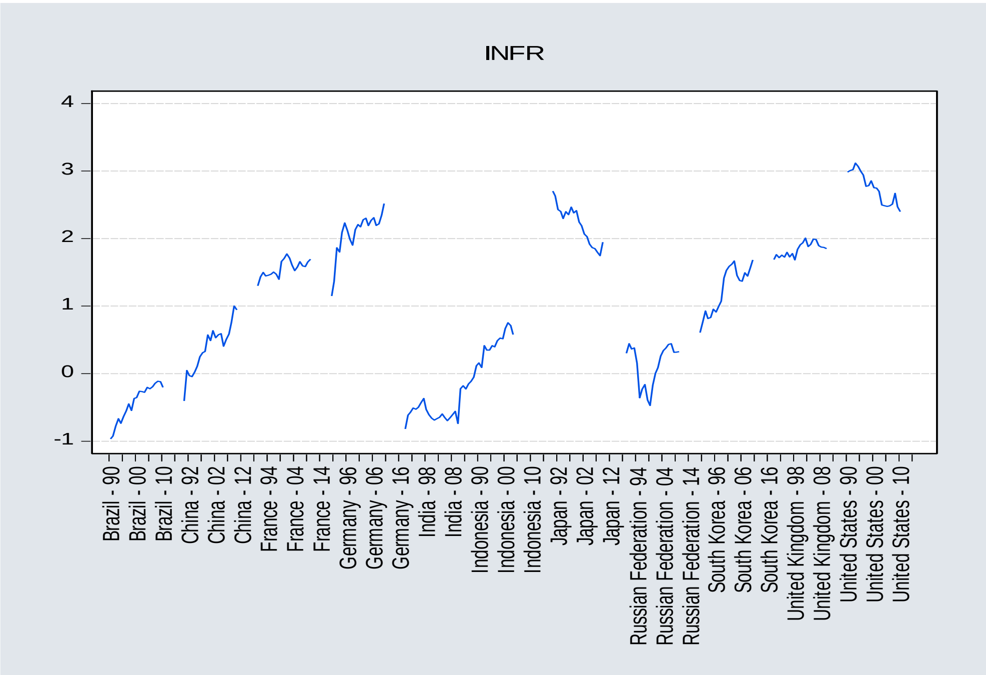
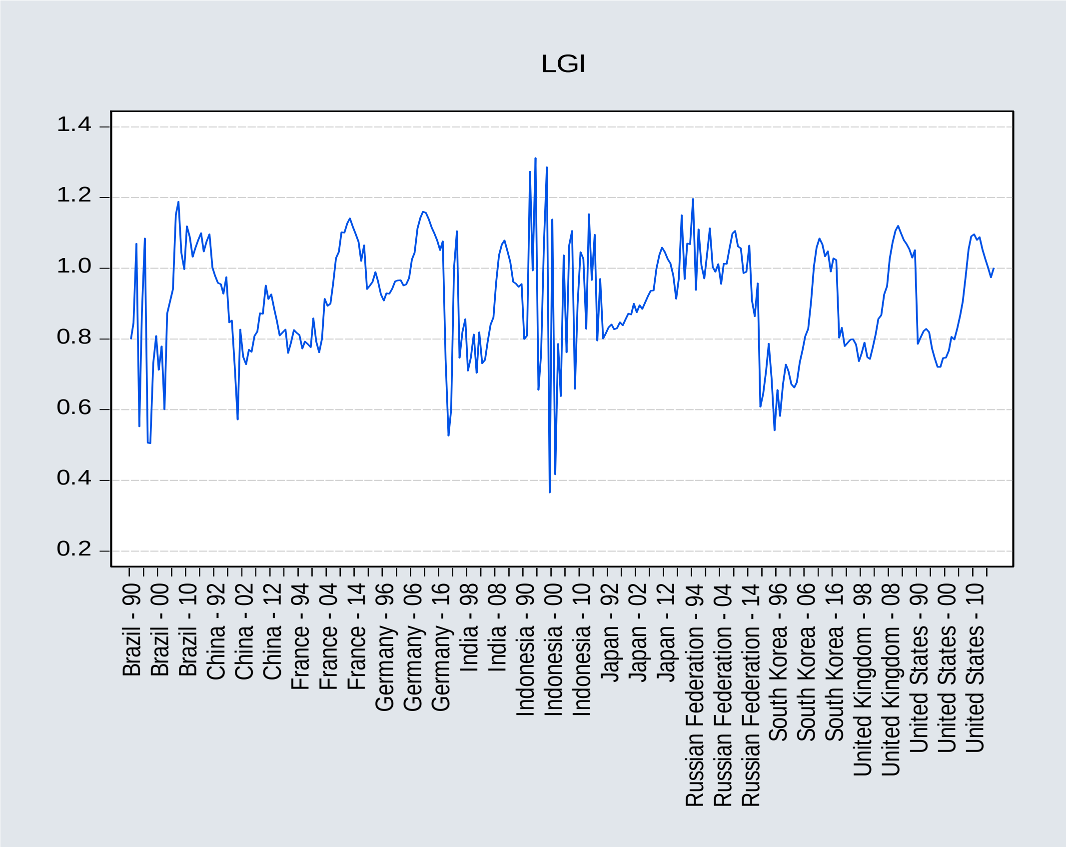


Figure 1b: Quantile distribution of Data


LMF
2.0
1.6
1.2
0.8
0.4
0.0
Brazil - 90
Brazil - 00
Brazil - 10
China - 92
China - 02
China - 12
France - 94
France - 04
France - 14
Germany - 96
Germany - 06
Germany - 16
India - 98
India - 08
Indonesia - 90
Indonesia - 00
Indonesia - 10
Japan - 92
Japan - 02
Japan - 12
Russian Federation - 94
Russian Federation - 04
Russian Federation - 14
South Korea - 96
South Korea - 06
South Korea - 16
United Kingdom - 98
United Kingdom - 08
United States - 90
United States - 00
United States - 10


INFR
4
3
2
1
0
-1
Brazil - 90
Brazil - 00
Brazil - 10
China - 92
China - 02
China - 12
France - 94
France - 04
France - 14
Germany - 96
Germany - 06
Germany - 16
India - 98
India - 08
Indonesia - 90
Indonesia - 00
Indonesia - 10
Japan - 92
Japan - 02
Japan - 12
Russian Federation - 94
Russian Federation - 04
Russian Federation - 14
South Korea - 96
South Korea - 06
South Korea - 16
United Kingdom - 98
United Kingdom - 08
United States - 90
United States - 00
United States - 10



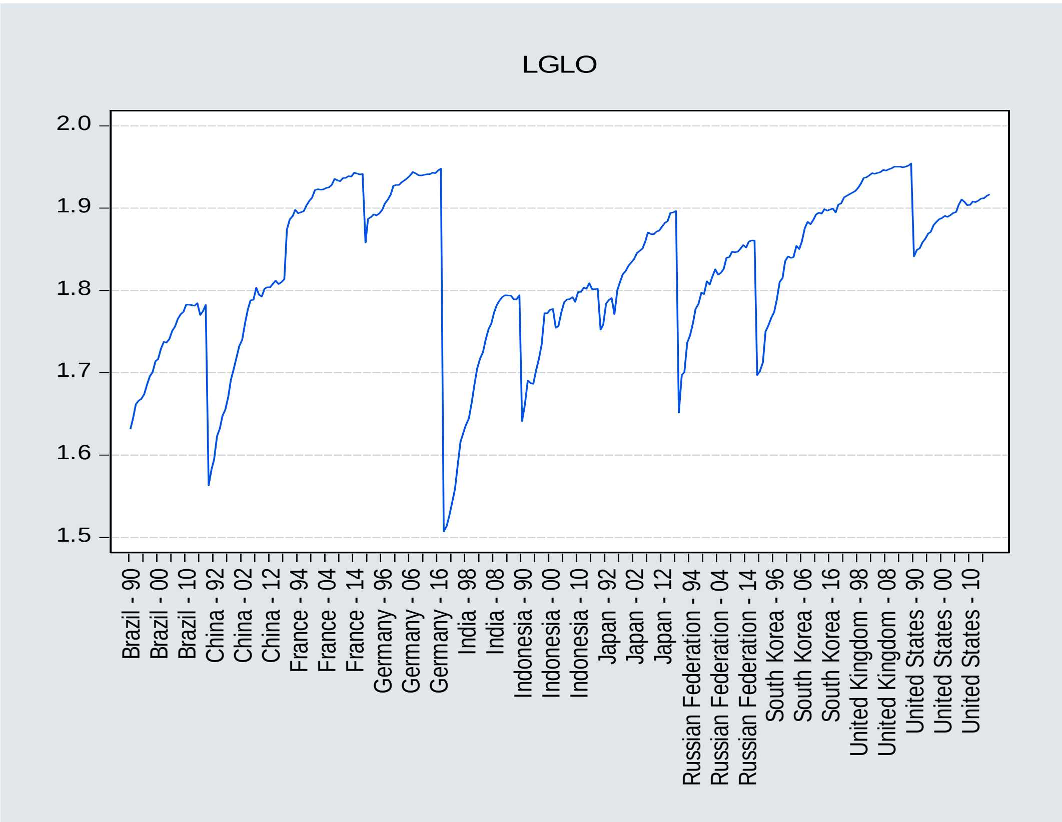


Figure 1c: Trends of core variables in panel

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