Available Online
Journal of Economic Impact
ISSN: 2664-9764 (Online), 2664-9756 (Print)
https://www.scienceimpactpub.com/jei

URBAN FORM, NOT JUST SCALE: RETHINKING GROWTH IN A FRAGMENTED GLOBAL ORDER – EVIDENCE FROM A DYNAMIC PANEL ACROSS INCOME GROUPS

Yasir Zada Khan *, Mumtaz Anwar, Bilal Mehmood

School of Economics, University of the Punjab, Lahore, Pakistan

ARTICLE INFO

Article history
Received: August 30, 2025
Revised: November 18, 2025
Accepted: November 27, 2025

Keywords
Urban agglomeration
Population density
Business density
Dynamic panel data
System GMM
Differenced GMM
Sectoral impact

ABSTRACT

In an era marked by global economic realignments and shifting urban geographies, this study examines how urban agglomeration, population distribution, and business density shape national income dynamics across the global income spectrum. Using a panel of 214 countries from 2000 to 2023, categorized by World Bank income groups, we explore the differentiated impacts of urban population structures, within and beyond metropolitan centers, and new business density on Gross National Income (GNI) per capita. Leveraging dynamic panel techniques, including Differenced and System Generalized Method of Moments (GMM), our findings underscore that concentrated urban agglomerations significantly boost income levels, particularly in upper-middle-income economies. In contrast, dispersed urban population growth, i.e., indicative of urban sprawl, negatively correlates with income, highlighting the pitfalls of unplanned spatial expansion. Business density emerges as a key enabler of agglomeration economies, contributing positively to income growth through entrepreneurial dynamism. These results offer critical insights into the spatial-economic architecture of development, emphasizing that in a transforming global order, economic gains from urbanization depend less on scale and more on form, functionality, and institutional capacity. The study also reveals strong path dependency in income growth.

* Email: *yasirzkhan09@gmail.com*
https://doi.org/10.52223/econimpact.2025.7311
© The Author(s) 2025.
This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).

INTRODUCTION

As the global economic landscape undergoes structural shifts, deepening income disparities and urban discontent have emerged as critical development challenges. While urbanization is often celebrated as a driver of economic growth, the outcomes have been uneven and raising questions about the quality, density, and spatial organization of urban expansion (Henderson, 2003; McMillan and Rodrik, 2011). This study investigates how urban agglomeration, population dynamics, and business density influence Gross National Income (GNI) per capita across countries grouped by income levels, reflecting the divergent growth trajectories in a transforming world order. Urban growth, particularly when unaccompanied by productive density or institutional readiness, frequently leads to sprawl, spatial fragmentation, congestion, and economic inefficiency, i.e., a phenomenon increasingly observed in middle- and low-income countries (Brueckner, 2000; Ewing, 1997). At the same time, entrepreneurial activity and concentrated business clusters have shown the potential to unlock agglomeration economies and boost national income (Audretsch and Keilbach, 2004). Yet, the precise interplay between urban scale, form, and productivity remains contested across development contexts.

To address this gap, we draw on panel data from 214 countries spanning 2000 to 2023, deploying dynamic panel estimation techniques to isolate the causal impact of urban and rural population structures, sectoral value addition, and new business density on national income. By disaggregating effects across income groups, this study provides empirical insights into why some nations capitalize on urban transitions while others remain trapped in low-productivity expansion. In doing so, it offers critical policy direction on spatial planning, sectoral transformation, and entrepreneurial ecosystems for inclusive growth in the evolving global economic order.

Building on existing literature, this study draws from key works on urban agglomeration and economic growth. Urban agglomeration, defined as the concentration of populations in metropolitan areas exceeding one million inhabitants, has long been recognized for its economic advantages. Literature confirms that dense urban centers boost productivity, innovation, and efficiency through agglomeration economies. Glaeser (2011) highlights how density fosters economic growth by enabling idea exchange and resource sharing, a process further dissected by Rosenthal and Strange (2004). Duranton and Puga (2004) identify three core mechanisms, i.e., sharing, matching, and learning, that explain the efficiency of concentrated urban forms. Combes and Gobillon (2015) add that such agglomerations yield productivity gains via specialization and access to larger markets. Urbanization, more broadly, the share of people living in urban areas, also supports economic development by improving access to infrastructure and opportunities. Bloom et al. (2008) argue that urbanization accelerates industrialization and modernization, especially in developing countries. However, not all urban growth yields economic dividends. Unplanned or low-density urban sprawl can generate inefficiencies, making the quality and form of urban expansion more consequential than scale alone.

In contrast, high rural population shares often indicate underdevelopment. Todaro and Smith (2015) emphasize that economies with a higher rural population struggle with lower productivity, while Christiaensen and Todo (2014) stress that rural-to-urban migration drives structural transformation by reallocating labor toward higher-productivity urban sectors.

Sectoral value addition remains central to growth theory. Johnston and Mellor (1961) argue that as economies develop, agriculture's share declines while industry and services expand. Chenery and Taylor (1968) note that industrialization boosts productivity and employment, and Bhagwati (1984) links the growing role of services to their disembodiment from manufacturing. Eichengreen and Gupta (2013) further assert that modern services are vital to sustaining growth in high-income economies. Population density, too, plays a dual role. Ciccone and Hall (1996) show that higher density enhances productivity through increased interaction, though it may strain infrastructure if unmanaged. This spatial dimension ties directly into agglomeration economics. Finally, entrepreneurial activity, captured by new business density, reflects economic vitality. Acs and Armington (2004) and Fritsch and Mueller (2004) further show that higher firm formation rates correlate with regional growth, employment, and competitiveness.

Research Objectives

1. To assess how urban agglomerations, i.e., dense metropolitan areas, affect GNI per capita across low-, middle-, and high-income countries.
2. To examine whether broader urban population growth, including smaller or dispersed urban settlements, contributes to or constrains income growth.
3. To explore the impact of rural population shares on national income, particularly in countries with lower development levels.
4. To analyze how value-added in agriculture, industry, manufacturing, and services influences income levels across different income groups.
5. To evaluate the role of new business density in boosting national income through entrepreneurship and densification.

Hypothetical Statements

H1: Urban agglomerations have a positive and significant effect on GNI per capita, with stronger impacts in higher-income countries.

H2: Aggregate urban population (including low-density or unplanned areas) is negatively associated with GNI per capita, especially in middle-income countries.

H3: Higher population density is positively linked to GNI per capita, particularly in lower-income economies where spatial compaction drives efficiency.

H4: Rural population growth negatively affects GNI per capita, most notably in low-income countries with limited structural transformation.

H5: Sectoral value addition, especially from industry and services, positively influences GNI per capita, though the impact varies by income group.

H6: New business density is positively associated with GNI per capita across all countries, reflecting the economic benefits of entrepreneurship.

Theoretical Framework

This study builds a framework that explains how urban form, population patterns, sectoral structure, and business activity affect national income (GNI per capita). Drawing from urban and development economics, the framework captures how these forces work differently across income groups. Urban agglomerations, i.e., large, dense metro areas, are expected to raise income through better sharing of services, faster exchange of ideas, and a wider pool of jobs and customers (Glaeser, 2011; Glaeser and Gottlieb, 2009; Duranton and Puga, 2004; Combes and Gobillon, 2015). These agglomeration benefits are strongest where cities are well-connected and organized. Urbanization, the overall share of people living in urban areas, can promote growth by improving access to services and jobs. However, when urban areas grow without proper planning or density, the benefits often fade or reverse (Henderson, 2003; Bloom et al., 2008). Population density measures how tightly people live together. Higher density can boost economic productivity by making it easier for people and businesses to interact (Ciccone and Hall, 1996; Carlino and Saiz, 2019). But too much density without infrastructure can cause congestion and inefficiency. Rural population share often reflects limited access to services and lower productivity. Moving people from rural to urban areas, when supported by jobs and housing, helps shift labor toward more productive sectors (Todaro and Smith, 2015; Christiaensen and Todo, 2014).

Entrepreneurship, measured by new business density, signals how dynamic and innovative an economy is. Areas with more startups tend to grow faster and generate more jobs, especially where business support systems are strong (Audretsch and Keilbach, 2004; Acs and Armington, 2004). Sectoral value addition shows which parts of the economy are growing. Development usually means moving from agriculture to industry and services, where productivity and incomes are higher (Johnston and Mellor, 1961; Chenery and Taylor, 1968; Szirmai, 2012; Rodrik, 2011). Services, in particular, have become key to sustaining growth in higher-income countries (Eichengreen and Gupta, 2013). Overall, the framework brings together these elements to explain income differences across countries. It is expected that each factor may matter more or less depending on a country's income level, urban structure, and economic stage, justifying the examination of income groups separately in the empirical analysis. This interplay is illustrated in Figure 1, which depicts the relationships between urban form, population patterns, sectoral structure, business activity, and GNI per capita across income groups.

METHODOLOGY

Data and Variables

This study uses data from 214 countries, classified into four income groups based on the World Bank's 2024 GNI per capita Atlas Method. This approach ensures consistency and allows comparison across countries at similar stages of development. Using a globally recognized classification helps group countries in a way that reflects real economic differences. It also makes the results more relevant for policy by showing how income levels influence development outcomes. This classification helps us understand how patterns vary across high-, middle-, and low-income countries. Full details are provided in Table 1. The variables used in the analysis are detailed in Table 2, including their codes, descriptions, time periods, and sources. Table 3 provides a simple but important snapshot of how the structural characteristics of countries differ across the global income spectrum. The numbers clearly show that high-income economies are not only richer in terms of GNI per capita but are also far more urbanized, denser, and more entrepreneurial, with significantly higher business registrations per thousand people. In contrast, low-income countries remain heavily rural, with much smaller urban agglomerations and very low levels of new business formation, which limits the emergence of agglomeration economies. The upper- and lower-middle-income groups fall between these extremes but display wide variation: upper-middle-income countries have some of the largest urban clusters, while lower-middle-income economies still carry substantial rural populations. The sectoral value-added indicators also highlight clear structural differences, with services dominating in richer economies and agriculture remaining relatively larger in poorer ones. Overall, the table helps frame why urban form, population distribution, and business density behave differently across income groups in the empirical analysis that follows.

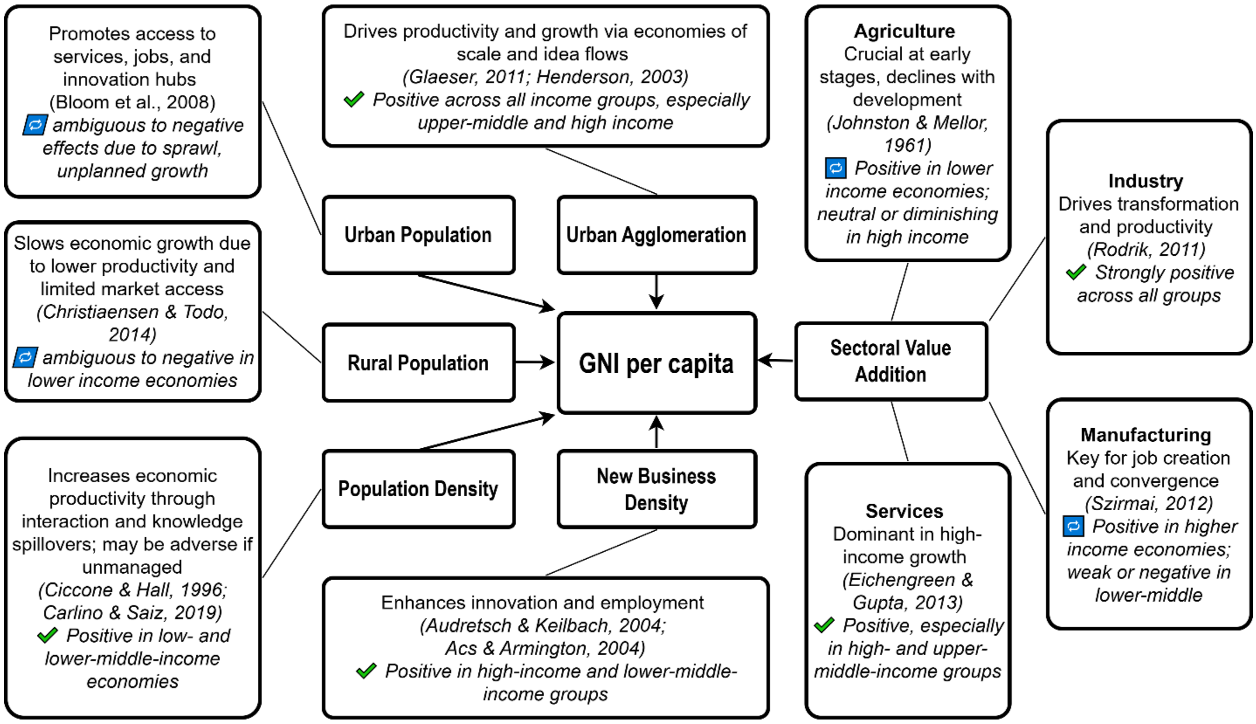

Figure 1. Theoretical Framework; Source: Author's illustration.

Table 1. Classification of groups of countries across income (GNI per capita)[1]

Income Category	GNI per Capita Range	Number of Countries
High-income	$13,846 or more	22
Upper middle-income	$4,466 - $13,845	53
Lower middle-income	$1,136 - $4,465	56
Low-income	$1,135 or less	83

Income Group	Countries (Alphabetical)
High income	American Samoa, Andorra, Antigua and Barbuda, Aruba, Australia, Austria, Bahamas, The, Bahrain, Barbados, Belgium, Bermuda, British Virgin Islands, Brunei Darussalam, Canada, Cayman Islands, Channel Islands, Chile, Croatia, Curaçao, Cyprus, Czechia, Denmark, Estonia, Faroe Islands, Finland, France, French Polynesia, Germany, Gibraltar, Greece, Greenland, Guam, Guyana, Hong Kong SAR, China, Hungary, Iceland, Ireland, Isle of Man, Israel, Italy, Japan, Korea, Rep., Kuwait, Latvia, Liechtenstein, Lithuania, Luxembourg, Macao SAR, China, Malta, Monaco, Nauru, Netherlands, New Caledonia, New Zealand, Northern Mariana Islands, Norway, Oman, Panama, Poland, Portugal, Puerto Rico, Qatar, Romania, San Marino, Saudi Arabia, Seychelles, Singapore, Sint Maarten (Dutch part), Slovak Republic, Slovenia, Spain, St. Kitts and Nevis, St. Martin (French part), Sweden, Switzerland, Taiwan, China, Trinidad and Tobago, Turks and Caicos Islands, United Arab Emirates, United Kingdom, United States, Uruguay, Virgin Islands (U.S.)
Upper middle income	Albania, Argentina, Armenia, Azerbaijan, Belarus, Belize, Bosnia and Herzegovina, Botswana, Brazil, Bulgaria, China, Colombia, Costa Rica, Cuba, Dominica, Dominican Republic, Ecuador, El Salvador, Equatorial Guinea, Fiji, Gabon, Georgia, Grenada, Guatemala, Indonesia, Iraq, Jamaica, Kazakhstan, Kosovo, Libya, Malaysia, Maldives, Marshall Islands, Mauritius, Mexico, Moldova, Montenegro, Namibia, North Macedonia, Palau, Paraguay, Peru, Russian Federation, Serbia, South Africa, St. Lucia, St. Vincent and the Grenadines, Suriname, Thailand, Tonga, Turkmenistan, Türkiye, Tuvalu, West Bank and Gaza
Lower middle income	Algeria, Angola, Bangladesh, Benin, Bhutan, Bolivia, Cabo Verde, Cambodia, Cameroon, Comoros, Congo, Rep., Côte d'Ivoire, Djibouti, Egypt, Arab Rep., Eswatini, Ghana, Guinea, Haiti, Honduras, India, Iran, Islamic Rep., Jordan, Kenya, Kiribati, Kyrgyz Republic, Lao PDR, Lebanon, Lesotho, Mauritania, Micronesia, Fed. Sts., Mongolia, Morocco, Myanmar, Nepal, Nicaragua, Nigeria, Pakistan, Papua New Guinea, Philippines, Samoa, São Tomé and Príncipe, Senegal, Solomon Islands, Sri Lanka, Tajikistan, Tanzania, Timor-Leste, Tunisia, Ukraine, Uzbekistan, Vanuatu, Vietnam, Zambia, Zimbabwe

[1] GNI per capita in current US dollar terms is estimated using the World Bank Atlas method based on World Bank national accounts data, and OECD National Accounts data files.

Low income	Afghanistan, Burkina Faso, Burundi, Central African Republic, Chad, Congo, Dem. Rep., Eritrea, Ethiopia, Gambia, The, Guinea-Bissau, Korea, Dem. People's Rep., Liberia, Madagascar, Malawi, Mali, Mozambique, Niger, Rwanda, Sierra Leone, Somalia, South Sudan, Sudan, Syrian Arab Republic, Togo, Uganda, Yemen, Rep.

Source: World Bank, Country Classification by Income groups, 2024.

Table 2. Description of variables and data source.

Variable Code	Variable Name	Brief Description	Time Period	Data Source
gnipercapitaatlas	GNI per capita, Atlas Method (current international $)	Gross national income per capita using Atlas method; sum of value added plus net primary income.	2000-2023	WB national accounts data, OECD National Accounts data.
urbanagglomeration	Population in urban agglomerations of more than 1 million	Population in metropolitan areas over 1 million (as of 2018).	2000-2023	United Nations, World Urbanization Prospects.
urbanpopulation	Aggregate urban population	Urban population as defined by national offices, based on UN prospects.	2000-2023	WB staff estimates based on the United Nations Population Division's World Urbanization Prospects: 2018 Revision.
ruralpopulation	Aggregate rural population	Rural population as difference between total and urban, based on UN prospects.	2000-2023	
agriculturevaluegdp	Agriculture, forestry, and fishing, value added (current US$)	Value added in agriculture/forestry/fishing (ISIC 1-3), no deductions for depreciation/depletion.	2000-2023	WB national accounts data, and OECD National Accounts data files.
industryvaluegdp	Industry (including construction), value added (current US$)	Value added in industry/construction (ISIC 05-43), no deductions for depreciation/depletion.	2000-2023	
manufacturingvaluegdp	Manufacturing, value added (current US$)	Value added in manufacturing (ISIC 15-37), no deductions for depreciation/depletion.	2000-2023	
servicesvaluegdp	Services, value added (current US$)	Value added in services (ISIC 50-99), no deductions for depreciation/depletion.	2000-2023	
populationdensity	Population density (people per sq. km of land area)	Midyear population divided by land area (excl. water bodies, shelves, zones).	2000-2023	Food and Agriculture Organization and World Bank population estimate.
newbusinessdensity	New business density (new registrations per 1,000 people ages 15-64)	New limited liability companies per 1,000 working-age adults (15-64) per year.	2000-2023	WB's Entrepreneurship Database

Table 3. Summary statistics across income groups (2000–2023).

Variable	All Countries (Mean)	High Income (Mean)	Upper-Middle (Mean)	Lower-Middle (Mean)	Low Income (Mean)
GNI per capita (Atlas USD)	12,986	37,532	7,822	2,556	611
Urban agglomeration population	12.8 million	12.3 million	19.7 million	13.9 million	6.6 million
Urban population	17.2 million	12.5 million	24.6 million	21.0 million	12.4 million
Rural population	15.7 million	3.6 million	12.3 million	26.2 million	27.4 million
Agriculture value added (USD)	13.6 billion	10.5 billion	21.7 billion	15.4 billion	6.15 billion
Industry value added (USD)	92.2 billion	176 billion	120 billion	39.1 billion	9.15 billion
Manufacturing value added (USD)	57.1 billion	104 billion	75.3 billion	22.4 billion	4.05 billion
Services value added (USD)	215 billion	520 billion	187 billion	55.9 billion	13.5 billion
Population density (people/km^2)	406	957	148	132	109
New business density (registrations per 1000 people)	5.49	12.48	3.29	1.36	0.38

Before conducting cointegration analysis, panel unit root tests were performed to assess the stationarity of the variables in levels and first differences, ensuring the data are integrated of order one (I(1)) and suitable for long-run modeling. Specifically, the Fisher-type Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests were employed, which combine individual unit root tests across panels while allowing for panel-specific autoregressive parameters and accommodating unbalanced panels (Maddala and Wu, 1999; Choi, 2001). These tests were applied with a time trend, panel means, and cross-sectional demeaning to account for structural heterogeneity and potential cross-country dependencies. Results indicate that most variables are non-stationary in levels but become stationary after first differencing, validating the use of differenced variables in the GMM estimators. Detailed outcomes are presented in Table 4.

The Kao, Pedroni, and Westerlund panel cointegration tests consistently reject the null hypothesis of no cointegration at the 1% significance level. This confirms the presence of a strong and stable long-run equilibrium relationship among GDP per capita, urban agglomeration, urban population, population density, and the sectoral composition of GDP (agriculture, industry, manufacturing, and services). The results indicate that these economic and urbanization indicators move together over time across countries, and short-run deviations are corrected through an adjustment process. Therefore, the panel data satisfy long-run integration requirements, justifying the use of long-run estimators. The results of the cointegration tests are summarized in Table 5, which shows consistent rejection of the null hypothesis across all income groups.

Model

Ordinary Least Squares (OLS) is unsuitable for dynamic panel data models due to its inefficiency and bias, particularly when lagged dependent variables are included, leading to inconsistent estimates (Nerlove, 1997; Dang et al., 2015).

To control for unobserved, time-invariant heterogeneity, Fixed Effects (FE) models, also known as within estimators, are often used. They eliminate these constant effects through transformations like first-differencing. However, FE models may suffer from Nickell bias in short panels with lagged dependent variables (Phillips and Sul, 2007).

While Random Effects (RE) models can offer efficiency gains under strict exogeneity and uncorrelated individual effects, they too fall short in dynamic settings, as both FE and RE are essentially static; they fail to account for the persistence in the dependent variable.

Dynamic panel models, by contrast, incorporate both current and lagged values of regressors, allowing for richer modeling of temporal dynamics and state dependence. To overcome endogeneity, autocorrelation, and measurement error, this study employs GMM estimators.

Generalized Method of Moments (GMM)

The study shall utilize double-log models, developed separately for each income classification, by applying natural logarithms 'ln' to the variables, as denoted in equation (1). This functional form allows for elasticity interpretation, stabilizes variance, and improves linearity in relationships, making cross-country comparisons more meaningful and statistically robust.

$$\begin{aligned} ln\_gnipercapitaatlas_{it} &= \alpha + \beta_1(ln\_urbanagglomeration_{it}) \\ &+ \beta_2(ln\_urbanpopulation_{it}) \\ &+ \beta_3(ln\_ruralpopulation_{it}) \\ &+ \beta_4(ln\_agriculturevaluegdp_{it}) \\ &+ \beta_5(ln\_industryvaluegdp_{it}) \\ &+ \beta_6(ln\_manufacturingvaluegdp_{it}) \\ &+ \beta_7(ln\_servicesvaluegdp_{it}) \\ &+ \beta_8(ln\_populationdensity_{it}) \\ &+ \beta_9(newbusinessdensity_{it}) + (\eta_i + \mu_{it} + \delta_{it} + \sigma_{it}) \\ &+ \varepsilon_{it} \end{aligned} \tag{1}$$

Table 4. Panel unit root test ADF and PP results (Full Sample).

Variable	ADF Level: Inv. χ^2 (p-value)	ADF Diff: Inv. χ^2 (p-value)	PP Level: Inv. χ^2 (p-value)	PP Diff: Inv. χ^2 (p-value)
ln_gnipercapitaatlas	569.28 (0.00)	973.89 (0.00)	211.40 (1.00)	1195.88 (0.00)
ln_urbanagglomeration	391.17 (0.00)	535.73 (0.00)	475.72 (0.00)	680.57 (0.00)
ln_urbanpopulation	997.16 (0.00)	1112.41 (0.00)	522.01 (0.00)	814.53 (0.00)
ln_ruralpopulation	4835.33 (0.00)	699.19 (0.00)	562.60 (0.00)	4813.39 (0.00)
ln_agriculturevaluegdp	358.89 (0.96)	1934.74 (0.00)	465.15 (0.03)	3331.33 (0.00)
ln_industryvaluegdp	428.39 (0.28)	1443.35 (0.00)	356.62 (0.98)	2131.45 (0.00)
ln_manufacturingvaluegdp	258.17 (1.00)	1484.32 (0.00)	368.77 (0.88)	2649.99 (0.00)
ln_servicesvaluegdp	479.21 (0.01)	1341.82 (0.00)	399.87 (0.60)	2143.17 (0.00)
ln_populationdensity	221.64 (1.00)	800.12 (0.00)	308.77 (1.00)	859.24 (0.00)
ln_newbusinessdensity	510.17 (0.00)	1030.26 (0.00)	616.77 (0.00)	1878.85 (0.00)

Source: Author's estimations

Table 5. Summary of Kao, Pedroni, and Westerlund cointegration tests.

Test	Statistic	Full Sample	High-Income	Upper-Middle	Lower-Middle	Low-Income
Kao	Modified Dickey–Fuller test	−14.70 (0.00)	−10.36 (0.00)	−6.57 (0.00)	−7.45 (0.00)	−6.69 (0.00)
	Dickey–Fuller test	−13.30 (0.00)	−7.53 (0.00)	−6.44 (0.00)	−6.29 (0.00)	−6.20 (0.00)
	Augmented DF test	−15.58 (0.00)	−12.00 (0.00)	−9.66 (0.00)	−7.09 (0.00)	−5.46 (0.00)
	Unadjusted Modified DF test	−17.09 (0.00)	−9.86 (0.00)	−9.00 (0.00)	−8.00 (0.00)	−7.35 (0.00)
	Unadjusted DF test	−13.99 (0.00)	−7.41 (0.00)	−7.21 (0.00)	−6.45 (0.00)	−6.35 (0.00)
Pedroni	Modified Phillips–Perron test	14.19 (0.00)	8.36 (0.00)	6.91 (0.00)	6.75 (0.00)	3.77 (0.00)
	Phillips–Perron test	−4.39 (0.00)	−0.30 (0.38)	−3.59 (0.00)	−5.95 (0.00)	−2.71 (0.00)
	Augmented DF test	−6.44 (0.00)	−0.02 (0.49)	−4.59 (0.00)	−5.14 (0.00)	−10.72 (0.00)
Westerlund	Variance Ratio	−2.68 (0.00)	−1.20 (0.12)	−1.56 (0.06)	−1.29 (0.10)	−0.82 (0.21)

Whereas, η_i denotes the country-specific effects (unobserved heterogeneity constant over time), μ_{it} denotes the year-specific effects (common shocks across all countries in a given year), δ_{it} is considered an autoregressive shock in GNI per capita (dependence on lagged GNI per capita), σ_{it} accounts for measurement error, while ε_{it} represents the error term.

The model also includes the lagged dependent variable and lags of independent variables to account for inertia and delayed effects in macroeconomic adjustment processes. This double-log functional form allows coefficients to be interpreted as elasticities, providing a more intuitive understanding of relative impacts across variables and countries. Given the within-transformation structure of GMM, the estimated coefficients reflect short- to medium-run within-country impacts over time.

The level form of the equation, denoted as (2), under the dynamic model is as follows:

$$ln\_gnipercapitaatlas_{it} = \alpha + \beta_1(\ln\_urbanagglomeration_{it}) + \beta_2(\ln\_urbanpopulation_{it}) + \beta_3(\ln\_ruralpopulation_{it}) + \beta_4(\ln\_agriculturevaluegdp_{it}) + \beta_5(\ln\_industryvaluegdp_{it}) + \beta_6(\ln\_manufacturingvaluegdp_{it}) + \beta_7(\ln\_servicesvaluegdp_{it}) + \beta_8(\ln\_populationdensity_{it}) + \beta_9(newbusinessdensity_{it}) + \emptyset_1(\ln\_gnipercapitaatlas_{it-1}) + \gamma_1(\ln\_urbanagglomeration_{it-1}) + \gamma_2(\ln\_urbanpopulation_{it-1}) + \gamma_3(\ln\_ruralpopulation_{it-1}) + \gamma_4(\ln\_agriculturevaluegdp_{it-1}) + \gamma_5(\ln\_industryvaluegdp_{it-1}) + \gamma_6(\ln\_manufacturingvaluegdp_{it-1}) + \gamma_7(\ln\_servicesvaluegdp_{it-1}) + \gamma_8(\ln\_populationdensity_{it-1}) + \gamma_9(newbusinessdensity_{it-1}) + \emptyset_2(\ln\_gnipercapitaatlas_{it-2}) + \pi_1(\ln\_urbanagglomeration_{it-2}) + \pi_2(\ln\_urbanpopulation_{it-2}) + \pi_3(\ln\_ruralpopulation_{it-2}) + \pi_4(\ln\_agriculturevaluegdp_{it-2}) + \pi_5(\ln\_industryvaluegdp_{it-2}) + \pi_6(\ln\_manufacturingvaluegdp_{it-2}) + \pi_7(\ln\_servicesvaluegdp_{it-2}) + \pi_8(\ln\_populationdensity_{it-2}) + \pi_9(newbusinessdensity_{it-2}) + (\eta_i + \mu_{it} + \delta_{it} + \sigma_{it}) + \varepsilon_{it} \quad (2)$$

Differenced GMM

Introduced by Arellano and Bond (1991), Differenced GMM addresses endogeneity in panel data by first-differencing the model to eliminate fixed effects and using lagged levels of the dependent and explanatory variables as instruments. However, this method may suffer from weak instruments, especially when the autoregressive parameter is near unity or when individual-specific effects exhibit high variance (Blundell and Bond, 1998). In such cases, estimates tend to be biased toward those from fixed effects models.

While first-differencing helps address time-invariant unobserved heterogeneity, it also introduces correlation between weakly exogenous regressors and the differenced error term. Compared to within transformation, which makes all individual-specific regressors endogenous, first-differencing offers cleaner instrument validity but may worsen data gaps in unbalanced panels. To mitigate this, Forward Orthogonal Deviations (FOD) as proposed by Arellano and Bover (1995) can be used as an alternative transformation that preserves sample size while addressing endogeneity and serial correlation more efficiently.

Thus, the differenced form of the equation, denoted as (3), under the dynamic model is as follows:

$$\Delta ln\_gnipercapitaatlas_{it} = \alpha + \beta_1\Delta(\ln\_urbanagglomeration_{it}) + \beta_2\Delta(\ln\_urbanpopulation_{it}) + \beta_3\Delta(\ln\_ruralpopulation_{it}) + \beta_4\Delta(\ln\_agriculturevaluegdp_{it}) + \beta_5\Delta(\ln\_industryvaluegdp_{it}) + \beta_6\Delta(\ln\_manufacturingvaluegdp_{it}) + \beta_7\Delta(\ln\_servicesvaluegdp_{it}) + \beta_8\Delta(\ln\_populationdensity_{it}) + \beta_9\Delta(newbusinessdensity_{it}) + \emptyset_1\Delta(\ln\_gnipercapitaatlas_{it-1}) + \gamma_1\Delta(\ln\_urbanagglomeration_{it-1}) + \gamma_2\Delta(\ln\_urbanpopulation_{it-1}) + \gamma_3\Delta(\ln\_ruralpopulation_{it-1}) + \gamma_4\Delta(\ln\_agriculturevaluegdp_{it-1}) + \gamma_5\Delta(\ln\_industryvaluegdp_{it-1}) + \gamma_6\Delta(\ln\_manufacturingvaluegdp_{it-1}) + \gamma_7\Delta(\ln\_servicesvaluegdp_{it-1}) + \gamma_8\Delta(\ln\_populationdensity_{it-1}) + \gamma_9\Delta(newbusinessdensity_{it-1}) + \emptyset_2\Delta(\ln\_gnipercapitaatlas_{it-2}) + \pi_1\Delta(\ln\_urbanagglomeration_{it-2}) + \pi_2\Delta(\ln\_urbanpopulation_{it-2}) + \pi_3\Delta(\ln\_ruralpopulation_{it-2}) + \pi_4\Delta(\ln\_agriculturevaluegdp_{it-2}) + \pi_5\Delta(\ln\_industryvaluegdp_{it-2}) + \pi_6\Delta(\ln\_manufacturingvaluegdp_{it-2}) + \pi_7\Delta(\ln\_servicesvaluegdp_{it-2}) + \pi_8\Delta(\ln\_populationdensity_{it-2}) + \pi_9\Delta(newbusinessdensity_{it-2}) + \Delta(\eta_i + \mu_{it} + \delta_{it} + \sigma_{it}) + \Delta\varepsilon_{it} \quad (3)$$

By deriving instruments from the equation, we achieve the removal of endogeneity through the use of exogenous instruments as denoted in (4):

$$E\ (\Delta gnipercapitaatlas_{it-1}\ \Delta\varepsilon it) = 0 \quad (4)$$

The instruments derived under the GMM technique are identical to the weakly exogenous regressors and are uncorrelated with the error term, thus removing both the year-specific effects and country-specific effects in the differenced form of the equation and addressing endogeneity.

System GMM

The system GMM technique uses suitably lagged first differences of the variables as instruments for the equations in levels. By combining both sets of moment conditions in a system containing both Differenced (i) and level equations (ii), we derive estimates from the advanced form of the GMM technique, known as the System GMM estimator. This approach instruments the variables in levels in the second equation with their own first differences, which usually increases efficiency. Exploiting additional moment conditions of this type can reduce finite sample bias and enhance precision, especially when the autoregressive parameter is only weakly identified from the first differenced equations.

In the dynamic panel data model with a large number of cross-sections and a finite time period, the GMM technique is used. Under the autoregressive model, weak instruments may generate large finite-sample bias. This bias can be reduced by imposing further moment conditions and restrictions, termed as the System GMM technique. Additionally, the use of lagged first differences as instruments for the equations in levels, in addition to the usual lagged levels as instruments in the equations in first differences, is noted (Arellano and Bover, 1995).

However, there are two important considerations when using system GMM. First, because system GMM uses more instruments than difference GMM, it may not be appropriate for datasets with a small number of countries. When the number of instruments exceeds the number of countries, the Sargan test may be weak. With the null hypothesis stating that the instruments are exogenous, a higher P-value of the test indicates better results. Secondly, in a panel with fixed effects, including the equation in levels requires a new assumption: the first-differenced instruments used for the variables in levels should not be correlated with the unobserved country effects. This assumption depends on the initial conditions, and some authors prefer to include in the Levels equation only those variables uncorrelated with the fixed effects (Roodman, 2009).

To account for these dynamics and heterogeneity across development levels, this study employs both Differenced and System GMM estimators. Separate models are estimated for four income groups: (I) High-Income, (II) Upper-Middle-Income, (III) Lower-Middle-Income, and (IV) Low-Income countries.

Estimations

Differenced GMM addresses endogeneity and unobserved heterogeneity by using lagged values of GNI per capita and explanatory variables as instruments in first-differenced equations. Results from the estimation for each of the models in equation (ii) are consolidated in Table 6 along with key tests and diagnostics in Table 7.

AR(1) tests indicate first-order autocorrelation in Models (I) and (IV), but not in Models (II) and (III), while AR(2) results are insignificant across all models, confirming no second-order autocorrelation and validating instrument relevance. Sargan tests further support instrument validity with no overidentification issues. System GMM, by combining level (i) and differenced equation (ii) with appropriate lagged instruments, leverages additional moment conditions to improve coefficient precision across income groups. The estimation results for each model are consolidated in Table 8 along with key tests and diagnostics in Table 9.

Table 6. Results obtained from one-step Differenced GMM.

Coefficient	MODEL (I) High Income			MODEL (II) Upper-Middle			MODEL (III) Lower-Middle			MODEL (IV) Low Income		
	value	Std. Error	P-value	value	Std. Error	P-value	value	Std. Error	P-value	value	Std. Error	P-value
β_1	0.66	0.38	0.08	2.17	0.70	0.00	0.23	0.14	0.10	0.85	2.58	0.74
β_2	0.96	1.29	0.45	-2.05	1.14	0.07	-1.57	2.30	0.50	7.16	15.84	0.65
β_3	-0.11	0.43	0.80	1.29	0.89	0.15	-0.30	1.65	0.86	-51.3	24.60	0.04
β_4	-0.01	0.02	0.37	0.13	0.02	0.00	0.06	0.03	0.05	0.03	0.12	0.82
β_5	-0.08	0.08	0.30	0.28	0.05	0.00	0.14	0.02	0.00	0.11	0.03	0.00
β_6	0.26	0.10	0.01	-0.03	0.10	0.75	-0.06	0.03	0.08	-0.05	0.06	0.44
β_7	0.26	0.05	0.00	0.04	0.09	0.66	0.25	0.05	0.00	0.18	0.16	0.28
β_8	-1.79	1.46	0.22	1.15	0.69	0.10	0.73	2.65	0.78	43.50	20.85	0.04
β_9	0.02	0.01	0.10	0.00	0.01	0.60	0.03	0.02	0.09	0.02	0.02	0.19
$\emptyset_1$	0.13	0.15	0.41	0.07	0.07	0.32	-0.20	0.16	0.21	0.19	0.10	0.05
γ_1	-0.85	1.20	0.48	2.00	1.05	0.06	3.46	3.38	0.31	0.53	2.38	0.83
γ_2	-0.81	1.77	0.65	1.27	1.67	0.45	-3.23	4.62	0.49	-7.71	15.81	0.63
γ_3	0.29	0.74	0.70	-2.31	1.61	0.15	2.76	2.27	0.22	49.77	23.50	0.03
γ_4	-0.01	0.01	0.49	0.02	0.02	0.37	0.07	0.04	0.05	0.09	0.11	0.39
γ_5	0.10	0.04	0.01	0.12	0.03	0.00	0.22	0.05	0.00	0.05	0.04	0.20
γ_6	0.00	0.03	0.89	-0.01	0.03	0.58	-0.08	0.04	0.04	-0.03	0.06	0.57
γ_7	0.14	0.05	0.01	0.16	0.03	0.00	0.18	0.05	0.00	0.33	0.15	0.02
γ_8	0.34	1.76	0.85	-0.46	0.75	0.54	1.32	4.76	0.78	-41.7	20.37	0.04
γ_9	-0.01	0.01	0.14	0.01	0.01	0.14	-0.04	0.02	0.02	0.00	0.02	0.77
$\emptyset_1$	-0.22	0.06	0.00	-0.06	0.05	0.28	0.03	0.10	0.75			
π_1	0.16	1.05	0.88	-0.18	0.61	0.77	-2.54	3.15	0.42			
π_2	-0.49	1.34	0.71	0.67	0.99	0.50	3.48	5.48	0.53			
π_3	-0.21	0.45	0.63	1.05	1.05	0.32	-2.29	2.27	0.31			
π_4	0.01	0.02	0.65	-0.03	0.05	0.49	0.03	0.05	0.55			
π_5	0.16	0.08	0.05	0.22	0.05	0.00	0.23	0.07	0.00			
π_6	-0.05	0.13	0.67	-0.11	0.03	0.00	-0.13	0.08	0.10			
π_7	0.19	0.07	0.01	0.18	0.04	0.00	0.25	0.10	0.01			
π_8	0.68	1.36	0.62	-1.45	1.01	0.15	-3.32	6.23	0.60			
π_9	0.00	0.01	0.64	0.00	0.01	0.51	-0.07	0.06	0.28			

Source: Author's estimations

Table 7. AR Tests and Sargan Diagnostics, one-step Differenced GMM.

Test	High-Income	Upper-Middle	Lower-Middle	Low-Income
AR (1)	Z = (1.63), p = 0.11	Z = (0.61), p = 0.54	Z = 1.07, p = 0.28	Z = (2.31), p = 0.02
AR (2)	Z = (0.50), p = 0.61	Z = (1.08), p = 0.28	Z = (0.43), p = 0.67	Z = (0.60), p = 0.54
Sargan (overid. test)	χ^2 (19) = 25.69, p = 0.14	χ^2 (21) = 21.81, p = 0.41	χ^2 (15) = 10.72, p = 0.77	χ^2 (16) = 16.24, p = 0.44

Source: Author's estimations.

Table 8 Results obtained from one-step System GMM

Coefficient	MODEL (I) High Income			MODEL (II) Upper-Middle			MODEL (III) Lower-Middle			MODEL (IV) Low Income		
	value	Std. Error	P-value	value	Std. Error	P-value	value	Std. Error	P-value	value	Std. Error	P-value
β_1	0.78	0.44	0.07	0.33	0.48	0.48	0.15	0.18	0.41	0.45	1.35	0.74
β_2	-1.33	0.75	0.08	-0.99	1.31	0.45	-12.8	6.12	0.04	0.68	0.56	0.23
β_3	0.25	0.71	0.73	1.49	0.84	0.08	-1.10	2.19	0.62	-20.5	11.97	0.09
β_4	0.01	0.01	0.67	0.04	0.03	0.23	-0.05	0.05	0.33	0.06	0.09	0.54
β_5	0.18	0.03	0.00	0.12	0.04	0.00	0.16	0.03	0.00	0.12	0.04	0.01
β_6	-0.05	0.04	0.20	0.08	0.05	0.15	-0.09	0.05	0.04	0.04	0.05	0.39
β_7	0.27	0.03	0.00	0.29	0.05	0.00	0.29	0.06	0.00	0.10	0.16	0.55
β_8	0.00	(omitted)		-1.12	1.87	0.55	13.81	7.14	0.05	15.98	12.62	0.21
β_9	0.02	0.01	0.03	0.02	0.01	0.09	0.05	0.02	0.01	0.03	0.02	0.12
$\emptyset_1$	0.54	0.12	0.00	0.66	0.16	0.00	-0.30	0.11	0.01	0.25	0.09	0.01
γ_1	-1.05	0.94	0.27	0.00	(omitted)		4.24	2.74	0.12	-0.33	1.31	0.80
γ_2	1.48	2.25	0.51	0.00	(omitted)		10.26	8.92	0.25	0.00	(omitted)	
γ_3	0.31	1.37	0.82	0.00	(omitted)		0.98	3.58	0.78	20.52	11.73	0.08
γ_4	-0.06	0.04	0.09	0.12	0.08	0.17	0.23	0.10	0.02	0.05	0.08	0.52

γ_5	-0.05	0.07	0.46	0.05	0.07	0.50	0.25	0.06	0.00	0.00	0.04	0.95
γ_6	0.10	0.07	0.17	-0.34	0.14	0.01	-0.06	0.08	0.49	-0.04	0.06	0.51
γ_7	0.12	0.08	0.15	0.08	0.11	0.45	0.09	0.10	0.39	0.33	0.12	0.01
γ_8	-0.91	2.33	0.70	1.56	1.96	0.43	-13.2	10.8	0.22	-17.7	12.25	0.15
γ_9	-0.03	0.01	0.00	0.00	0.01	0.81	-0.03	0.02	0.21	0.00	0.02	0.82
$\emptyset_1$	-0.31	0.05	0.00	-0.33	0.07	0.00	-0.01	0.07	0.94			
π_1	0.36	0.60	0.55	-0.29	0.49	0.56	-3.52	2.61	0.18			
π_2	-0.17	1.98	0.93	0.79	1.30	0.55	1.52	6.12	0.80			
π_3	-0.49	0.78	0.53	-1.51	0.85	0.08	0.73	1.94	0.71			
π_4	0.02	0.04	0.51	-0.03	0.06	0.63	0.13	0.08	0.09			
π_5	0.15	0.06	0.02	0.08	0.07	0.29	0.32	0.06	0.00			
π_6	-0.12	0.07	0.08	0.14	0.10	0.17	-0.26	0.08	0.00			
π_7	0.09	0.08	0.25	0.01	0.10	0.94	0.28	0.13	0.03			
π_8	0.06	2.25	0.98	-1.00	2.14	0.64	-1.86	6.66	0.78			
π_9	0.00	0.01	0.82	0.02	0.02	0.34	-0.09	0.03	0.01			

Source: Author's estimations

Table 9. AR Tests and Sargan Diagnostics, one-step System GMM.

Test	High-Income	Upper-Middle	Lower-Middle	Low-Income
AR (1)	Z = (4.35), p = 0.00	Z = (3.48), p = 0.00	Z = (0.53), p = 0.14	Z = (2.58), p = 0.12
AR (2)	Z = (0.55), p = 0.58	Z = 0.10, p = 0.92	Z = (1.08), p = 0.67	Z = (1.31), p = 0.19
Sargan (overid. test)	χ^2 (24) = 33.50, p = 0.11	χ^2 (24) = 25.45, p = 0.38	χ^2 (24) = 21.32, p = 0.62	χ^2 (16) = 13.87, p = 0.60

Source: Author's estimations.

AR(1) tests indicate first-order autocorrelation in Models (I) and (II), but not in Models (III) and (IV), while AR(2) results are insignificant across all models, confirming no second-order autocorrelation. Sargan tests validate the instruments and show no overidentification issues.

Interpretation of Empirical Results

Below, we unpack the statistically significant relationships observed, revealing divergent relationships between urbanization patterns, sectoral structures, and national income. Across all categories, population in urban agglomerations exceeding one million inhabitants consistently shows a positive and significant association with GNI per capita. In high-income countries, a 1% increase in urban agglomeration is linked to a 0.66%–0.78% rise in GNI per capita, reaffirming established theories on productivity gains from dense cities via scale economies, labor pooling, and innovation spillovers. The elasticity intensifies notably in upper-middle-income countries, where a 1% increase in agglomeration population correlates with a remarkable 2.17% rise in income, likely reflecting accelerated agglomeration dividends from urban-industrial transitions and infrastructure investments. For lower-middle-income countries, though the effect is positive, 0.23%, its smaller size suggests constraints from infrastructure deficits or informal urban systems that prevent full realization of these benefits.

In contrast, the broader aggregate urban population, which encompasses dispersed towns and peri-urban settlements, exhibits a negative association with income in several groups. Upper-middle-income countries show a 2.05% decline in GNI per capita for every 1% increase in aggregate urban population, and the effect is more severe in lower-middle-income economies, reaching a 12.8% drop. Even in high-income countries, a modest negative elasticity of -1.33% is observed. These patterns highlight how unplanned spatial expansion, lacking economic connectivity and density, undermines productivity rather than enhancing it.

Rural population dynamics further represent structural bottlenecks, especially in low-income countries, where a 1% rise correlates with a dramatic 20.49% to 51.33% decline in GNI per capita. This confirms the structural transformation literature: persistent rural dominance tied to low-productivity subsistence agriculture severely hampers national income. Conversely, in upper-middle-income countries, rural population growth is weakly associated with a 1.49% increase in income, possibly reflecting spillovers from rural-based agro-industries or connectivity improvements.

Sectoral value-added provides additional clarity on growth engines. Agriculture remains a modest positive contributor in upper- and lower-middle-income countries with elasticities between 0.06% and 0.13%, underscoring its transitional role in economies with sizable rural populations. Industry, including construction, consistently drives income growth. In upper-middle-income countries, each 1% increase in industrial value-added correlates with a 0.12% to 0.28% rise in GNI per capita and benefits extending to lower-middle- and low-income groups. Manufacturing yields mixed results, as positively associated 0.26% in the high-income group but negatively associated -0.29% to -0.25% in lower-middle income ones. Services show robust, consistent positive associations with income, with elasticities ranging from 0.25% to 0.29% in lower-middle-income groups and up to 0.27% in high-income groups, affirming their role in later-stage development.

Complementing these findings, population density acts as a powerful spatial enabler, especially in low-income countries where a 1% increase is linked to a striking 43.5% rise in GNI per capita, suggesting that in otherwise sparse, underdeveloped geographies, density acts as a proxy for market potential and economic connectivity. Similar though smaller effects appear in lower-middle-income countries at 13.81% and upper-middle-income countries at 1.15%, further supporting the role of spatial concentration in development. Likewise, new business density reveals small but significant positive contributions having elasticities of 0.02% to 0.05%, strongest in lower-middle-income economies, highlighting entrepreneurship's role in fostering dynamism.

Discussions & Policy Implications

These results emphasize that the form of urbanization and the composition of economic activity outweigh mere scale in driving income growth, particularly when disaggregated by development stage, a key originality of this study. To harness these insights, policies must prioritize compact, productive urban forms over unchecked expansion. In upper-middle-income countries, where agglomeration and business density yield the highest returns, governments should incentivize high-density zoning, vertical development, and digital infrastructure to minimize transaction costs and optimize labor matching. Low-income nations, burdened by massive rural drags and limited urban gains, require urgent investments in planning institutions, secondary cities, and basic connectivity to avert sprawl. High-income economies should retrofit cores with resilient, green infrastructure. Sectoral strategies must be sequenced accordingly: industry stands out as the universal accelerator, demanding ecosystem-building in lower-middle-income countries (e.g., cheap energy, vocational training) and upgrading in upper-middle-income ones (e.g., mid-tech integration). Services' positive role necessitates prior industrial foundations, while agriculture in poorer contexts calls for value-chain modernization.

Managing spatial demographics is equally critical in low-income settings. Alleviating rural pressures through non-farm rural jobs, secondary town investments, and orderly migration will unlock productivity. Vibrant entrepreneurial ecosystems, embedded in dense urban hubs, amplify these effects; thus, simplifying registrations, bolstering financing, and enforcing contracts remain priorities. Above all, the strong path dependency uncovered here warns that delayed reforms entrench low-growth traps, demanding bold, long-term commitments to structural change.

Limitations

While this study offers valuable insights, several limitations should be acknowledged. First, the reliance on country-level panel data masks important within-country spatial and sectoral variations, especially in large, diverse economies. Second, the use of the World Bank's urban and sectoral indicators, though standardized, may suffer from measurement inconsistencies across countries and over time. Third, despite employing System and Differenced GMM to address endogeneity and dynamic effects, the model may still face limitations from instrument proliferation and weak instruments, particularly in low-income samples with data gaps. Fourth, key urban quality variables such as infrastructure access, governance, or informality are omitted due limited scope of research, which may bias the estimated role of urbanization. Lastly, the business density indicator captures quantity but not quality or survival of firms, which may limit its explanatory power for long-term income growth.

CONCLUSIONS

This study offers compelling empirical evidence that in today's fragmented global order, urban form, not just urban scale, defines economic destiny. The findings clearly distinguish between productive urban agglomeration and unstructured urban expansion: while high-density, well-integrated metropolitan areas drive income growth, especially in high- and upper-middle-income countries, the sprawling, informal urban growth and rising rural populations suppress GNI per capita, particularly in low-income contexts. This highlights a critical policy message: urbanization must be managed, not assumed to be beneficial. Crucially, the research advances the discourse by showing that structural transformation through industry and services, rather than sectoral reallocation alone, is key to sustained growth across all income groups. Manufacturing's growth impact is uneven, i.e., strong in advanced economies but limited elsewhere, underscoring the urgency of technological upgrading, infrastructure readiness, and skills alignment in emerging economies. Moreover, entrepreneurial dynamism and population density, when embedded in coherent urban systems, act as amplifiers of agglomeration effects. The originality of this work lies in unraveling how different spatial, demographic, and economic forces interact asymmetrically across income groups. For low-income countries, the path forward requires rural transformation, compact secondary cities, and foundational infrastructure. Middle-income countries must focus on densification, industrial deepening, and innovation ecosystems. High-income countries, meanwhile, must sustain productivity through spatial renewal, service sector innovation, and entrepreneurial scaling. In sum, this research reaffirms that the quality of urban and economic transformation, not just its quantity, determines development outcomes. Policymakers must adopt differentiated, income-sensitive strategies to harness agglomerations, foster productive sectors, and build inclusive entrepreneurial environments in a rapidly shifting global economic landscape.

REFERENCES

Acs, Z., Armington, C., 2004. Employment growth and entrepreneurial activity in cities. Reg. Stud. 38, 911–927.

Arellano, M., Bond, S., 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. Rev. Econ. Stud. 58, 277–297.

Arellano, M., Bover, O., 1995. Another look at the instrumental variable estimation of error-components models. J. Econom. 68, 29–51.

Audretsch, D.B., Keilbach, M., 2004. Entrepreneurship and regional growth: an evolutionary interpretation. J. Evol. Econ. 14, 605–616.

Bhagwati, J.N., 1984. Splintering and disembodiment of services and developing nations. World Econ. 7, 133–144.

Bloom, D.E., Canning, D., Fink, G., 2008. Urbanization and the wealth of nations. Science (80-.). 319, 772–775.

Blundell, R., Bond, S., 1998. Initial conditions and moment restrictions in dynamic panel data models. J. Econom. 87, 115–143.

Brueckner, J.K., 2000. Urban sprawl: Diagnosis and remedies. Int. Reg. Sci. Rev. 23, 160–171.

Carlino, G.A., Saiz, A., 2019. Beautiful city: Leisure amenities and urban growth. J. Reg. Sci. 59, 369–408.

Chenery, H.B., Taylor, L., 1968. Development patterns: among countries and over time. Rev. Econ. Stat. 391–416.

Choi, I., 2001. Unit root tests for panel data. J. Int. money Financ. 20, 249–272.

Christiaensen, L., Todo, Y., 2014. Poverty reduction during the rural–urban transformation–the role of the missing middle. World Dev. 63, 43–58.

Ciccone, A., Hall, R.E., 1996. Productivity and the Density of Economic Activity. Am. Econ. Rev. 86, 54–70.

Combes, P.-P., Gobillon, L., 2015. The empirics of agglomeration economies, in: Handbook of Regional and Urban Economics. Elsevier, pp. 247–348. https://doi.org/10.1016/B978-0-444-59517-1.00005-2.

Dang, V.A., Kim, M., Shin, Y., 2015. In search of robust methods for dynamic panel data models in empirical corporate finance. J. Bank. Financ. 53, 84–98.

Duranton, G., Puga, D., 2004. Micro-foundations of urban agglomeration economies, in Henderson, J.V. and Thisse, J.-F. (eds) Handbook of Regional and Urban Economics. Vol. 4. Amsterdam: Elsevier, pp. 2063–2117. https://doi.org/10.1016/S1574-0080(04)80005-1.

Eichengreen, B., Gupta, P., 2013. The two waves of service-sector growth. Oxf. Econ. Pap. 65, 96–123.

Ewing, R., 1997. Is Los Angeles-style sprawl desirable? J. Am. Plan. Assoc. 63, 107–126.

Fritsch, M., Mueller, P., 2004. Effects of new business formation on regional development over time. Reg. Stud. 38, 961–975.

Glaeser, E., 2011. Cities, productivity, and quality of life. Science (80-.). 333, 592–594.

Glaeser, E.L., Gottlieb, J.D., 2009. The wealth of cities: Agglomeration economies and spatial equilibrium in the United States. J. Econ. Lit. 47, 983–1028.

Henderson, V., 2003. The urbanization process and economic growth: The so-what question. J. Econ. Growth 8, 47–71.

Johnston, B.F., Mellor, J.W., 1961. The role of agriculture in economic development. Am. Econ. Rev. 51, 566–593.

Maddala, G.S., Wu, S., 1999. A comparative study of unit root tests with panel data and a new simple test. Oxf. Bull. Econ. Stat. 61, 631–652.

McMillan, M., Rodrik, D., Verduzco-Gallo, Í., 2014. Globalization, structural change, and productivity growth, with an update on Africa. World Dev. 63, 11–32.

Nerlove, M., 1997. Properties of Alternative Estimators of Dynamic Panel Models: An Empirical Analysis of Cross-Country Data for the Study of Economic Growth. https://ageconsearch.umn.edu/record/197852/files/agecon-maryland-98-17.pdf.

Phillips, P.C.B., Sul, D., 2007. Bias in dynamic panel estimation with fixed effects, incidental trends and cross section dependence. J. Econom. 137, 162–188.

Rodrik, D., 2011. The future of economic convergence', NBER Working Paper No. 17400. Cambridge, MA: National Bureau of Economic Research. https://www.nber.org/papers/w17400.

Roodman, D., 2009. A note on the theme of too many instruments. Oxf. Bull. Econ. Stat. 71, 135–158.

Rosenthal, S.S., Strange, W.C., 2004. Evidence on the nature and sources of agglomeration economies, in: Handbook of Regional and Urban Economics. Elsevier, pp. 2119–2171. https://www.sciencedirect.com/science/article/pii/S1574008004800063.

Szirmai, A., 2012. Industrialisation as an engine of growth in developing countries, 1950–2005. Struct. Chang. Econ. Dyn. 23, 406–420.

Todaro, M.P., Smith, S.C., 2015. Economic development. 12th edn. Harlow: Pearson Education.

Publisher's note: Science Impact Publishers remain neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license and indicate if changes were made. The images or other third-party material in this article are included in the article's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this license, visit https://creativecommons.org/licenses/by/4.0/.