ECONOMIC RESEARCH - EKONOMSKA ISTRAŽIVANJA
2025, VOL. 38 NO. 3, (25 - 43)
https://doi.org/10.32728/er-ei.38.3.2

Faculty of Economics and Tourism "Dr. Mijo Mirković"

ARTICLE HISTORY
Received 23 April 2024
Accepted 30 October 2025

URBAN WEALTH SCALING IN KOREA

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KEYWORDS:
Urban Wealth Scaling, Panel Data, South Korea

JEL CLASSIFICATION:
R10, O18

ABSTRACT

Previous cross-sectional investigations into urban scaling concerning regional GDP show that the scaling exponents closely align with the superlinear scaling value of 1.15. Analyzing the OECD 2016 data, this research reveals a comparable outcome, except for Korea, where a value below 1.0 is identified. Through the utilization of panel data from Korea, our empirical findings show sublinear scaling values. It appears evident that the Korean scenario contradicts the superlinear scaling principle in urban systems. Various explanations are discussed.

1. INTRODUCTION

This research undertakes an empirical examination of urban scaling within OECD countries, with a specific emphasis on South Korea (hereafter referred to as Korea), given its pronounced deviation from scaling laws among OECD nations. Diverging from the approach of many prior studies, our analysis employs both panel data and cross-sectional analysis to elucidate the unique characteristics of the Korean case.

Scaling, in the context of a system, pertains to how it responds to a change in its size. The origins of scaling theory can be traced back to biology, where it was observed that when an animal doubles in body mass, its metabolic rate increases by 75%. This scaling phenomenon extends to various biological variables, encompassing metabolic rate, growth rate, heart rate, tree height, mass of cerebral grey matter, and more. Despite the diverse forms, functions, and behaviors exhibited by living organisms, the striking simplicity and universality of scaling phenomena are noteworthy. Scaling laws ``reflect underlying generic features and physical principles that are independent of detailed dynamics or specific characteristics of particular models" (West & Brown, 2004, p.36). It is essential to highlight that scaling laws are not exclusive to biological relations; they have also been applied to social organizations such as cities and firms. Researchers argue that scaling laws are observed in cities worldwide, transcending social, cultural, and national differences (West, 2017).

Urban scaling refers to the study of the relationship between city size and various socio-economic variables, including economic output, innovation, crime, road traffic, and the spread of contagious diseases (Batty, 2013b; Bettencourt et al., 2007; Bettencourt et al., 2010; Louf et al., 2014; Pumain, 2006). This concept helps to quantify how different aspects of urban life change as cities grow, offering insights into the efficiency, productivity, and challenges of larger urban areas. The laws governing urban scaling, elucidating how social quantities evolve concerning city size, can be encapsulated by a straightforward power-law model:

$$Y = \alpha N^{\beta}, \tag{1}$$

where Y refers to a socio-economic variable, N to the city population size, α to a proportionality constant, and $ß$ to the scaling exponent.

2. URBAN SCALING

The association between city size and other variables is characterized by sublinear scaling when $ß < 1$ and superlinear scaling when $ß > 1$. Sublinear scaling is linked to the sublinear growth of inputs, such as public facilities (Gastner & Newman, 2006), supply stations (Kuhnert et al., 2006), road networks (Samaniego & Moses, 2008), and electrical cables (Bettencourt et al., 2007). On the other hand, superlinear scaling is tied to the superlinear growth of outputs, such as GDP (Bettencourt et al, 2010; Strano & Sood, 2016), patents (Bettencourt et al., 2007), walking speed (Noulas et al., 2012) and crime rates (Bettencourt et al., 2010). In essence, the outcome per person increases as a city expands. Consequently, both sublinear and superlinear scaling of cities suggest the concept of economies of scale and increasing returns to scale, signifying that larger cities are more efficient (Bettencourt et al., 2015; Bettencourt & West, 2010).

The phenomenon of sublinear scaling of inputs and superlinear scaling of outputs raises a fundamental question: Why do large cities exhibit efficiency? What factors contribute to the trend where larger cities utilize fewer inputs per capita and generate more output per capita than smaller cities? Classical urban theories (Jacobs, 1969; Romer, 1986) underscore the significance of knowledge exchange and economic competition in densely populated urban environments, fostering economic growth. The agglomeration effect in cities stimulates the exchange of ideas, leading to local idea generation and subsequent positive local economic outcomes. Larger cities, benefiting from a greater concentration of numerous and higher-ability individuals (Davis & Dingel, 2019), offer enhanced opportunities for idea exchange. Moreover, large cities confer productive advantages by fostering experimentation, facilitating learning, and providing opportunities to gain valuable experience (DelaRoca & Puga, 2017; Glaeser, 1999). This dynamic suggests that the efficiency of larger cities is rooted in their ability to stimulate innovation, knowledge sharing, and economic competition, contributing to increased productivity and output per capita.

The theoretical foundations of this study draw inspiration from models that highlight the role of the network of human interactions in explaining the efficiency of large cities (Arbesmen et al., 2009; Bettencourt, 2013; West, 2017; Yakubo et al., 2014). The genesis of urban scaling is intricately linked to the augmentation of social connectivity as cities expand. This heightened pace of social life, accompanying larger city sizes, can foster innovation and wealth creation, generating positive feedback loops between population growth and economic expansion (Bettencourt et al., 2008). Interactions and information transfer facilitated by social networks play a crucial role in idea generation and productivity. The efficiency of this process is closely tied to the proximity of individuals engaged in creating ideas (Pan et al., 2013).

Where does the network effect come from? The network effect in the system of cities is influenced by social and economic forces over extended periods, akin to an evolutionary mechanism (Changizi & Destefano, 2009). This evolution-like process shapes the network system of cities, mirroring the efficient energy consumption observed in biological organisms through a network, driven by natural evolution.

"From the perspective of biological scaling, the metaphor of cities as biological organisms makes specific predictions about the scaling exponents for networks of material infrastructure that carry resources (electricity, water) and the rates of resource utilization and creation, as well as characteristic associated time scales" (Bettencourt et al., 2008, p.289). Similar to living organisms, cities have undergone evolution in alignment with the scaling law. In essence, the theory of urban scaling posits allometric scaling in cities worldwide and suggests that the network effect, driven by an evolutionary process, is a fundamental cause of urban scaling. The development of cities reflects a dynamic interplay of social, economic, and infrastructural networks, contributing to their efficient functioning and growth.

In practical terms, the application of scaling laws has important implications for urban planning and development. The consistency of urban scaling laws across different countries, regardless of cultural or historical differences, offers a powerful tool for predicting changes in urban variables as cities grow. According to the scaling laws, the optimal distribution of public facilities-such as hospitals, airports, or shopping malls--requires their density to scale with population size, typically proportional to the two-thirds power, alongside the implementation of optimal networks to connect these facilities (Gastner & Newman, 2006). This insight is crucial for urban planning, as it ensures that essential services are spatially distributed in an efficient manner.

Moreover, scaling laws also apply to human mobility patterns within cities. Studies have shown that the volume of transportation is inversely proportional to a power of the city's rank (Noulas et al., 2012). This highlights how population density and spatial layout are critical in shaping human movement. As a result, these scaling laws provide valuable guidance for designing and managing transportation systems by emphasizing the need to consider the relationships between population density, spatial configuration, and efficient mobility, which are all essential for sustainable urban development.

What do empirical studies tell us about urban scaling? Is this theoretical approach able to explain empirical reality? Empirical studies on urban scaling provide substantial support for the theoretical framework. They consistently show evidence of superlinear scaling in urban systems, where various socio-economic variables follow a power law, with scaling exponents generally around ß $\approx$ 1.15. This aligns well with theoretical predictions.

For example, Bettencourt and colleagues have extensively contributed to this field, offering empirical evidence of superlinear scaling across different countries and time periods, primarily based on cross-sectional data. In their 2007 study (Bettencourt et al., 2007), they reported scaling exponents for total wages and super-creative employment around ß ≈ 1.12 and 1.15, respectively. Similarly, a 2016 study (Bettencourt & Lobo, 2016) found scaling exponents of ß ≈ 1.20 for both GDP and patents. These findings demonstrate the robustness of superlinear scaling across various urban variables in diverse contexts.

The theoretical approach suggests that larger cities benefit from network effects and the evolution-like development of urban systems, which enhance efficiency and productivity. This is substantiated by the empirical reality of consistent superlinear scaling in urban settings, reinforcing the generalizability of urban scaling laws across different socio-economic indicators and locations.

Table 1. Previous studies of urban scaling for GDP

Literature	Country	Year	N	ß	95% CI
Bettencourt et al. (2007)	China	2002	295	1.15	[1.06, 1.23]
	EU	2002	361	1.26	[1.09, 1.46]
	Germany	2003	37	1.13	[1.03, 1.23]
Bettencourt (2013)	US	2006	363	1.12	[1.10, 1.14]
Bettencourt and Lobo (2016)	France	2012	15	1.20	[1.15, 1.26]
	UK	2012	15	1.12	[1.00, 1.25]
	Spain	2012	8	1.13	[0.97, 1.30]
	Italy	2012	11	1.08	[0.82, 1.35]
	Germany	2012	24	1.17	[1.06, 1.28]
	Europe		102	1.17	[1.11, 1.22]
Strano and Sood (2016)	West EU	2010	248	1.03	[0.98, 1.08]
	East EU			1.42	[1.22, 1.62]

Note: The table summarizes previous empirical studies of the relationship between city size and GDP. *N* refers to sample size, *ß* to the scaling exponent, and *CI* to confidence interval.
Source: Author's computation

This study emphasizes regional GDP as the key indicator of overall economic activity. Table 1 summarizes the existing evidence on the scaling of regional GDP, with past empirical studies consistently reporting scaling exponents (*ß*) around 1.15. To further explore the urban scaling of GDP in practical contexts, our research undertakes an empirical analysis. The following section provides a comprehensive examination of this analysis, using recent cross-sectional and panel data from cities to investigate the relationship between city size and economic activity.

3. EMPIRICAL ANALYSIS: CROSS-SECTION

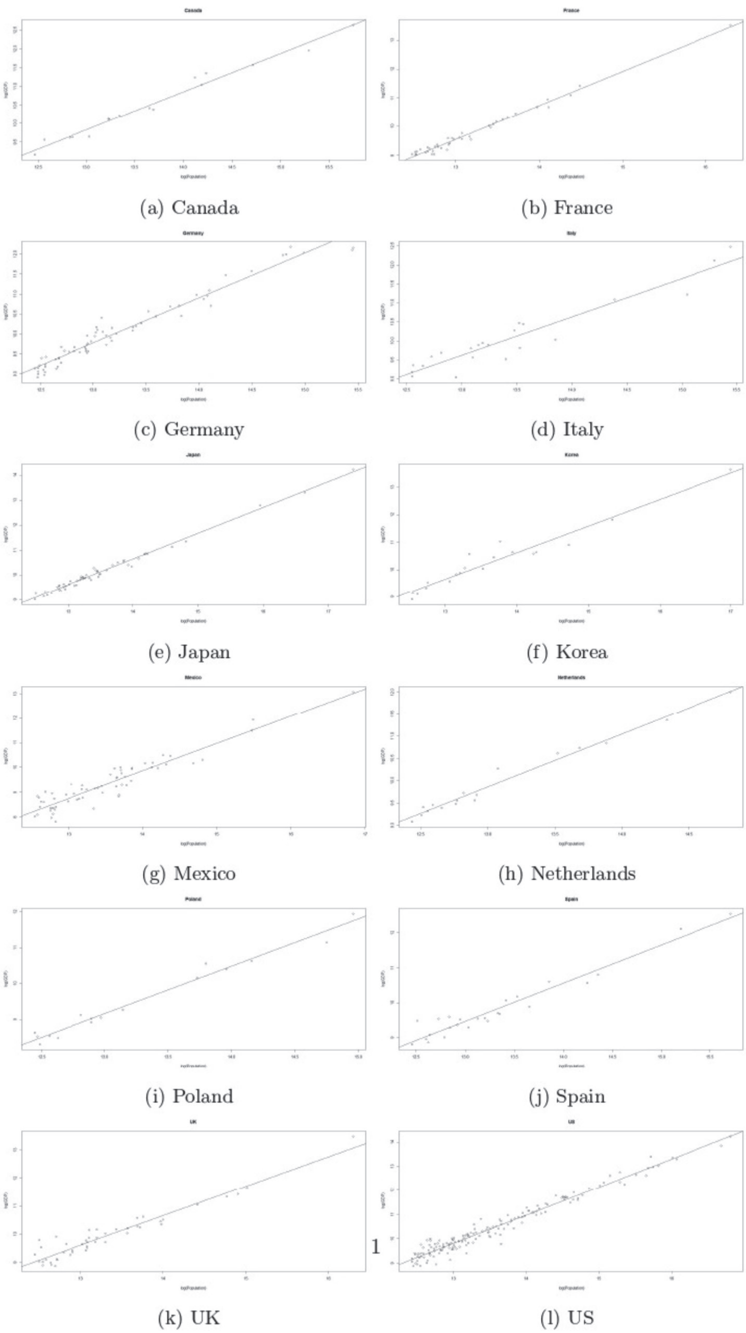
In line with the approach taken by the majority of prior studies, our current research initiates the analysis by examining cross-sectional data to unveil urban scaling patterns. Subsequently, we delve into a comprehensive investigation of scaling dynamics through an evolutionary perspective, utilizing panel data of cities. This dual analytical approach allows for a thorough exploration of the relationships between city size and relevant variables, shedding light on both the immediate cross-sectional patterns and the longitudinal evolution of urban scaling phenomena.

Table 2. Urban scaling for GDP: OECD data

Country	Year	N	ß	t	95% CI	R2
Total	2016	621	1.11***	59.26	[1.07, 1.15]	0.85
Canada	2016	16	1.02***	25.21	[0.94, 1.10]	0.97
France	2016	41	1.18***	51.16	[1.13, 1.22]	0.98
Germany	2016	68	1.12***	38.32	[1.06, 1.18]	0.95
Italy	2016	22	1.01***	13.79	[0.86, 1.15]	0.90
Japan	2016	53	1.02***	64.76	[0.99, 1.06]	0.98
Korea	2016	19	0.96***	16.34	[0.85, 1.08]	0.94
Mexico	2016	62	1.10***	21.04	[1.00, 1.21]	0.88
Netherlands	2016	17	1.18***	26.77	[1.09, 1.27]	0.97
Poland	2016	16	1.32***	23.62	[1.21, 1.43]	0.97
Spain	2016	25	1.09***	19.74	[0.98, 1.20]	0.94
UK	2016	46	1.04***	22.23	[0.95, 1.14]	0.91
US	2016	162	1.16***	63.13	[1.12, 1.19]	0.96

Note: The table summarizes the relationship between city size and GDP for the OECD 2016 data. *N* refers to sample size, *ß* to the scaling exponent, t to the t value, *CI* to confidence interval, and R^2 to R-squared value. ***, **, and *, respectively, indicate significance levels at 0.1%, 1%, and 5% levels. The data are available at https://measuringurban.oecd.org/#story=0.
Source: Author's computation

Figure 1. Urban scaling for OECD data: log(GDP)~log(Population)



(a) Canada (b) France

(c) Germany (d) Italy

(e) Japan (f) Korea

(g) Mexico (h) Netherlands

(i) Poland (j) Spain

(k) UK (l) US

Source: Authors

In this study, we utilize the 2016 data from the OECD to calculate the scaling exponents for regional GDP across countries, as detailed in Table 2. The dataset, available at https://measuringurban.oecd.org/#story=0, employs the concept of functional urban areas (FUAs), comprising cities with at least 50,000 inhabitants along with their surrounding commuting zones (Ribeiro et al., 2021). The table presents results for countries with more than 15 cities in the data set. The calculated scaling exponent for all countries is 1.11, with Poland exhibiting the highest value at 1.32. Across all countries, the scaling exponent values are consistently above 1.00, except for Korea (ß = 0.96). Figure 1 visually depicts all the ß coefficient values, and they are found to be statistically significant at the 1 percent level. This prompts a question: Is Korea an exceptional case, or does it reflect the specific nature of the country? To address this question, we proceed to collect and analyze recent data specifically focused on cities in Korea.

Table 3. Urban scaling for regional GDP: Korea

Year	N	ß	t	95% CI	R2
Total	587	1.02***	57.30	[0.98, 1.05]	0.84
2010	83	1.04***	21.59	[0.94, 1.13]	0.85
2011	83	1.03***	21.50	[0.94, 1.13]	0.85
2012	84	1.02***	21.38	[0.93, 1.12]	0.84
2013	84	1.02***	21.69	[0.92, 1.11]	0.85
2014	84	1.01***	21.54	[0.91, 1.10]	0.84
2015	84	1.00***	21.83	[0.91, 1.10]	0.85
2016	85	1.01***	22.06	[0.91, 1.10]	0.85

Note: The table summarizes the urban scaling exponents for the Korean data 2010-2016. **N** refers to sample size, *ß* to the scaling exponent, t to the t value, *CI* to confidence interval, and R^2 to R-squared value. ***, **, and *, respectively, indicate significance levels at 0.1%, 1%, and 5% levels. The data are available at http://kosis.kr/index/index.do.
Source: Author's computation

In our analysis of Korean data from 2010 to 2016, we investigate the urban scaling exponents for GDP during this period. The results are presented in Table 3, with data sourced from the Korean Statistical Information Services website (http://kosis.kr/index/index.do). For this study, a city is defined as an urbanized area with a population of at least 50,000. The study adopts an administrative definition, wherein areas with populations exceeding 50,000 are classified as cities in Korea. This administrative criterion is beneficial for comparison with other studies due to its universal applicability and consistency, allowing for more standardized cross-study analyses. The selected period is from 2010 to 2016, as regional GDP data for Korean cities are available for these years. Our sample size exceeds 80, significantly larger than the OECD dataset for Korea, which includes only 19 cities.

As summarized in Table 3, the overall scaling exponent for the entire sample is ß = 1.02. Exponent values for each individual year range from 1.00 to 1.04, with all ß coefficients being statistically significant at the 0.1 percent level. This indicates a strong and consistent urban scaling pattern across different years within the Korean context, reinforcing the robustness of these findings.

The result obtained from the Korean data for the period 2010-2016 presents a notable contrast to the OECD data mentioned earlier. This finding indicates superlinear scaling, as expected by the theoretical framework, even though the observed values are relatively small. However, it is crucial to note that the current analysis focuses on cross-sectional urban scaling, comparing small and large cities, and does not examine how an individual city has changed over time. The cross-sectional scaling pattern reported in Table 3 provides insights into the relative performance of cities of varying sizes during a specific period. To gain a comprehensive understanding of urban scaling, it would be valuable to extend the analysis to include time series scaling for individual cities. This would involve examining how the economic characteristics of a particular city have evolved over time, providing a more nuanced perspective on the dynamics of urban scaling within a specific urban context.

4. EMPIRICAL ANLAYSIS: PANEL DATA

Certainly, panel data analysis is a robust approach for examining the issue of change over time. It enables the identification of scaling trajectories for individual cities across different time periods, offering a nuanced understanding of how cities evolve economically over time. Additionally, the advantage of panel data analysis lies in its ability to control for time-constant unobserved features of cities, which may be correlated with explanatory variables such as city size. This helps in addressing potential sources of bias and provides more reliable insights into the dynamics of urban scaling. The econometric model used in the study is as follows:

$$log(\texttt{GDP})_{i,t} = \beta log(\texttt{population})_{i,t} + \epsilon_{i,t} \tag{2}$$

where the subscript i refers to city, t to time period, and ε to a classical error term. Year dummies are included but not reported for brevity. Taking the log makes the power-law relationship linear, allowing for standard linear regression. This model structure allows for the estimation of scaling trajectories over time, taking into account both city-specific and time-specific effects. It helps to discern how changes in city size relate to changes in the dependent variable while controlling for other relevant factors and potential time-specific influences. For the empirical analysis, we use fixed effects, feasible generalized least squares (FGLS), dynamic GMM, and split sample methods for the Korean panel data. The details of the methods and results obtained are explained below.

The choice between fixed effects and random effects models for panel data analysis is a crucial consideration. In the context of this analysis, where the data are drawn from a single country, it's reasonable to expect that the fixed effects model would be more appropriate than the random effects model. This is because the fixed effects model assumes that there are unobserved time-invariant factors (individual or city-specific effects) that are correlated with the explanatory variables, making it suitable for situations where there are unobserved characteristics specific to each city that may influence the dependent variable. The theoretical expectation aligns with practical considerations and is supported by statistical tests such as the F test, LM test, and Hausman test. These tests help in assessing the appropriateness of fixed effects versus random effects models based on the nature of the unobserved factors and the relationship between these factors and the explanatory variables. In this case, the confirmation of the fixed effects model as more suitable enhances the reliability of the panel data analysis. Moreover, the fixed effects model is particularly advantageous for causal inferences as it effectively addresses unobserved group-specific effects, providing unbiased estimates even in the presence of unobserved confounders (Bruderl & Luwig, 2015). This makes it a robust choice when exploring the scaling trajectories of individual cities over time in this analysis.

The use of Feasible Generalized Least Squares (FGLS) as a robust estimator in the analysis is a prudent choice, especially given its consistency and efficiency in the presence of heteroskedasticity and serial correlation, which are common issues in panel data sets. The employment of FGLS enhances the reliability of the estimates and helps address potential biases associated with these statistical challenges. The fact that we have conducted several statistical tests proposed by (Croissant & Millo, 2008) to assess the presence of heteroskedasticity and serial correlation in the sample data is a commendable practice. These tests are essential for diagnosing potential issues that could affect the validity of the results. While the specific details of the tests are not reported for simplicity, the acknowledgment of these tests implies a thorough evaluation of the assumptions underlying the model. By using FGLS and conducting diagnostic tests, we are employing robust techniques to ensure the integrity of the panel data analysis, contributing to the reliability of the findings and conclusions.

The inclusion of a dynamic model in the analysis is a thoughtful extension to capture temporal dependencies and account for the impact of past behaviors on current outcomes. The specified dynamic model, represented by Equation 3, incorporates a lagged variable of regional GDP as an independent variable. This dynamic specification is instrumental in addressing the temporal dynamics and potential persistence of economic outcomes over time. The equation is structured as follows:

$$log(\texttt{GDP})_{i,t} = \beta log(\texttt{population})_{i,t} + log(\texttt{GDP})_{i,t-1} + \epsilon_{i,t}. \tag{3}$$

The lagged term $log\ (GDP)_{i,t-1}$ captures the impact of past GDP on the current GDP, introducing a dynamic element to the model. By including the lagged GDP as an independent variable, this dynamic model allows for the examination of how the current GDP is influenced not only by the current population size but also by the past economic performance of the city. This specification enhances the ability to capture the most pertinent factors that contribute to the current GDP, offering a more comprehensive understanding of the temporal dynamics in regional economic growth.

The recognition of the endogeneity problem associated with the lagged dependent variable in the dynamic model is a crucial consideration. In response to this issue, this study wisely employs the Generalized Method of Moments (GMM) method, which is known for providing consistent estimates in the presence of different sources of endogeneity (Wintoki et al, 2012). GMM is a powerful tool for addressing endogeneity concerns, and it offers two commonly used techniques: the original estimator, difference GMM (Arellano & Bond, 1991), and the expanded estimator, system GMM (Blundell & Bond, 1998). Both methods are well-suited for estimating dynamic panels with endogenous independent variables (Roodman, 2009). In this analysis, the utilization of both GMM techniques, with the inclusion of t-2 and t-3 lagged values of the GDP variable as GMM instruments, enhances the robustness of the model. These lagged values serve as instruments to address the potential endogeneity of the lagged dependent variable, offering a solution to the exogeneity assumption violation. To assess the validity of the model specification and the GMM instruments, this study wisely performs the Sargan test of overidentifying restrictions and the second-order autocorrelation test (AR(2)). These tests are crucial for evaluating the reliability of the GMM estimates and ensuring that the chosen instruments effectively address the endogeneity issue. Overall, the inclusion of GMM techniques and the subsequent diagnostic tests contribute to the rigor and validity of the econometric approach.

Table 4. Panel Analysis

Method	N	*ß*	t	95% CI	R^2	**Sargan**	**AR(2)**
Fixed Effects	587	0.75***	9.37	[0.59, 0.92]	0.59		
FGLS	587	0.73***	7.27	[0.53, 0.93]	0.99		
Difference GMM	595	0.17	0.95	[-0.19, 0.54]		0.11	0.86
System GMM	595	0.00	0.12	[-0.09, 0.10]		0.11	0.85

Note: The table summarizes the urban scaling exponents for the Korean data 2010-2016 by panel data analysis. N refers to sample size, *ß* to the scaling exponent, t to the t value, CI to confidence interval, R^2 to R-squared value, and **Sargan** and **AR(2)** to p-values for the Sargan test and AR(2) test. ***, **, and *, respectively, indicate significance levels at 0.1%, 1%, and 5% levels. The data are available at http://kosis.kr/index/index.do.
Source: Author's computation

Table 4 provides the results of the panel data analysis using the Korean data. The scaling exponents for regional GDP obtained from the panel data analysis are less than 1.0 for both the fixed effects model (ß = 0.75) and the FGLS model (ß = 0.73). Furthermore, neither the difference GMM nor the system GMM models yield statistically significant results, possibly reflecting sensitivity to the sample size, a common trait of GMM models. Overall, the findings from the panel data analysis suggest that urban superlinear scaling, as observed in cross-sectional analyses, does not appear to hold for growth over time in Korea. The results from none of the regression models provide support for the scaling pattern in the context of the temporal evolution of regional GDP in Korean cities. This nuanced insight highlights the importance of considering dynamic factors and temporal dynamics when assessing urban scaling phenomena, and it emphasizes that the relationship between city size and economic output may vary over time within a specific urban context.

The adoption of the split-sample technique in addition to the full sample regression analysis is a robust method, offering a nuanced perspective on the relationship between population size and regional GDP. By dividing the sample cities into groups based on population size and conducting separate regressions for each group, we can investigate whether the scaling pattern varies across different population size categories. Comparing the ß coefficients between the groups enables the examination of potential differences in the relationship between population size and regional GDP. If the scaling pattern differs substantially between groups, the observed differences in the ß coefficients can be interpreted as a distinct pattern, assuming there is no reason to expect such differences. The split-sample method is often employed to explore moderating roles of certain factors, shedding light on potential heterogeneity in the scaling relationships. Moreover, the split-sample technique can help address a possible endogeneity problem. While individual estimates of coefficients may be biased, the estimated differences in coefficients are expected to be unbiased. This is because any potential bias should be constant across the split samples (Hoshi et al., 1991, p.36). In essence, the split-sample approach contributes to a more comprehensive understanding of how the scaling pattern may vary across different subgroups of cities, offering valuable insights into the moderating factors influencing the relationship between population size and regional GDP.

Table 5. Split-sample Panel Analysis

Group	**Method**	*N*	*ß*	*t*	*95% CI*	R^2	**Sargan**	**AR(2)**
Small Cities	Fixed Effects	291	0.64***	4.46	[0.35, 0.92]	0.58		
	FGLS	291	0.48**	3.26	[0.19, 0.78]	0.98		
	Difference GMM	297	0.08	0.50	[-0.26, 0.44]		0.04	0.61
	System GMM	297	0.05	0.72	[-0.10, 0.21]		0.43	0.60
Large Cities	Fixed Effects	296	1.23***	12.67	[1.03, 1.42]	0.70		
	FGLS	296	0.77***	13.02	[0.65, 0.89]	0.99		
	Difference GMM	296	0.79*	2.36	[0.12, 1.47]		0.05	0.78
	System GMM	296	0.06	1.01	[-0.05, 0.17]		0.12	0.70

Note: The table summarizes the urban scaling exponents for the Korean data 2010-2016 by split-sample panel data analysis. *N* refers to sample size, *ß* to the scaling exponent, t to the t value, *CI* to confidence interval, R^2 to R-squared value, and **Sargan** and **AR(2)** to p-values for the Sargan test and AR(2) test. ***, **, and *, respectively, indicate significance levels at 0.1%, 1%, and 5% levels. The data are available at http://kosis.kr/index/index.do.
Source: Author's computation

The split-sample analysis, dividing the sample cities into small and large cities based on the median population size, yields interesting insights into the scaling patterns of regional GDP. The empirical results, as presented in Table 5, highlight distinct patterns between the two groups. For small cities, both the fixed effects model (ß = 0.64) and the FGLS model (ß = 0.48) exhibit a strong sublinear behavior of GDP. These results are statistically significant at the 0.1 percent and 1 percent levels, respectively. The dynamic GMM models do not provide meaningful results for small cities. The sublinear scaling observed in small cities is consistent with the overall results obtained for all cities. Contrastingly, for large cities, the empirical results are mixed. The fixed effects model (ß = 1.23) and the FGLS model (ß= 0.77) both indicate scaling behavior, but it is superlinear rather than sublinear. These results are statistically significant at the 0.1 percent level. The difference GMM model shows a ß of 0.7987 at the 5 percent level, while the system GMM model yields an insignificant result. In summary, the panel data analysis, both for the full sample and the split sample, suggests a sublinear scaling of regional GDP, contrary to theoretical expectations. The sublinear scaling pattern appears to be more pronounced in small cities, while large cities exhibit a mix of sublinear and superlinear behavior. This nuanced insight underscores the importance of considering city size as a moderating factor in the relationship between population size and regional GDP.

5. DISCUSSION

The exploration of urban scaling through various perspectives indeed provides a nuanced understanding of the relationship between city size and regional GDP. Previous studies, as summarized in Table 1, generally suggested superlinear scaling exponents close to the value of 1.15. The analysis of OECD 2016 data, including Korea, revealed a similar trend, but with a specific deviation for Korea (ß = 0.96), indicating a scaling exponent less than 1.0. The cross-sectional study using more sophisticated data for Korea depicted scaling exponents ranging from 1.00 to 1.04, slightly surpassing 1.0. This suggests a unique scaling pattern in Korean cities compared to the broader context captured by previous studies and the OECD data. In contrast, the panel data analysis provides a different perspective, showing sublinear scaling values (ß = 0.48, 0.64, 0.73, 0.75, 0.77 and 0.79). This divergence from the superlinear scaling trend observed in cross-sectional studies and other datasets adds complexity to the understanding of urban scaling in Korea. The Korean case indeed challenges the conventional superlinear scaling law observed in urban systems globally. This deviation highlights the importance of examining urban scaling through multiple lenses and considering diverse factors that might influence the relationship between city size and economic output. It sets the stage for further exploration and underscores the need for a more nuanced and context-specific understanding of urban scaling phenomena.

Several hypotheses may account for the unexpected results observed in Korea. One possibility is that it could be a statistical artifact. However, given that this study employs various econometric methods and consistently finds low scaling values for Korea, it is reasonable to conclude that these empirical results offer meaningful insights. This study seeks to interpret these findings through an evolutionary framework, taking into consideration the historical and cultural context of Korea.

The scaling law is tied to an evolutionary theory of urban systems, as noted earlier. Large cities tend to expand further due to their success in adopting innovations. Over time, older technologies and systems are replaced by newer ones in larger cities, while smaller cities often retain older systems. This evolutionary process is shaped by the interconnectedness of cities. Innovations diffuse and urban systems adapt through information exchange, and competition among cities also fuels innovation (Pumain et al., 2006).

Moreover, the evolution of urban systems relates to the notion that cities function as complex organizational systems (Allen, 1997; Batty, 2013; Bettencourt, 2014; Krugman, 1996; Manson & O'Sullivan, 2006; Pumain, 2020;West, 2017; White et al., 2015). This perspective suggests that the overall characteristics of cities arise from interactions among their components rather than being mere aggregates of those parts (Ortman et al., 2020). As a result, scaling patterns can be understood in the context of temporal changes, reflecting the dynamic nature of urban development and the ongoing evolution of city systems.

The empirical results for Korea do not align closely with the urban scaling law of superlinear growth. This divergence may stem from Korea's unique cultural, institutional, and historical contexts, particularly its rapid economic development and urbanization from the 1960s to the 1990s. Given that urban scaling evolves over time, it is reasonable to suggest that Korean cities might currently be in a transitional phase toward superlinear growth. This implies that these cities may not have sufficiently evolved to display superlinear scaling at this point.

A study by Strano & Sood (2016) reveals that European cities exhibit diverse and non-uniform patterns regarding GDP scaling. These variations in scaling patterns reflect economic transitions and the convergence of Eastern European economies with their Western counterparts, indicating that the scaling law for GDP captures distinct phases of economic growth.

From a historical perspective, Ortman et al. (2020) explore evidence supporting urban scaling theory by examining the relationship between population and area in both ancient settlement systems and modern cities. They emphasize that human agglomerations are formed through social networks, further illustrating how the evolution of urban systems is deeply influenced by historical and socio-cultural factors.

Urban scaling evolves through a historical process, leading to the emergence of various scaling behaviors that may eventually converge toward a common pattern over time. The unique results observed for Korea in this study may suggest that specific characteristics of the country temporarily impede superlinear scaling in its cities. However, identifying the precise factors and trajectories contributing to this phenomenon is beyond the scope of the current research. To explore this issue further, a panel data analysis involving other countries would be necessary. This remains an important avenue for future research.

Other perspectives are also important to consider, as the theory of scaling has been challenged and reevaluated by recent studies. Cities can be understood and represented through various urban metrics, and consistency among these metrics is essential for advancing towards a comprehensive science of urbanism. While the theory of scaling suggests that many of these metrics can be predicted using universal scaling principles, recent research has cast doubt on the universality of this theory by employing new databases and alternative definitions of city boundaries.

For instance, Arcaute et al. (2015) propose a framework for consistently defining cities based on thresholds related to commuting patterns and population density. They conduct numerous simulations of city systems with varying boundaries across England and Wales. Their analysis demonstrates that relying solely on population size is inadequate for accurately describing or predicting a city's condition, contradicting earlier assertions regarding scaling laws. Furthermore, the study finds that most urban indicators exhibit linear scaling with city size, irrespective of how urban boundaries are defined. In instances where nonlinear relationships are observed, the scaling exponent varies significantly, highlighting the complexity of urban dynamics and the need for a nuanced understanding of scaling behaviors.

The empirical results depend on various factors. Leitao et al. (2016) examine the presence of nonlinear scaling using a probabilistic framework that explicitly incorporates fluctuations. This framework can (i) estimate ß and confidence intervals, (ii) assess the evidence supporting $ß \neq 1$, and (iii) test the hypothesis that the observations are consistent with nonlinear scaling. Comparing five different models across fifteen datasets, the study finds that the outcomes of points (i)–(iii) are heavily influenced by the fluctuations present in the data, how they are modeled, and the heavy-tailed distribution of city sizes.

A study on human mobility by Alessandretti et al. (2020) highlights a contradiction in our current understanding of individual and collective mobility patterns. On one hand, extensive analyses of large datasets suggest that human movements are scale-free, indicating that there are no distinct spatial scales governing mobility. On the other hand, the concept of scale--referring to meaningful levels of description from individual buildings to neighborhoods, cities, regions, and countries--is crucial for comprehending various aspects of human behavior, including socioeconomic interactions, political dynamics, and cultural influences.

To reconcile this apparent paradox, Alessandretti et al. (2020) demonstrate that daily human mobility does exhibit meaningful scales, represented by spatial "containers" that constrain mobility behavior. The scale-free findings arise from aggregating displacements across these containers. The study presents a straightforward model that identifies an individual's neighborhood, city, and larger geographical contexts based on their trajectory, as well as the sizes of these geographical containers. Analysis of over 700,000 individuals confirms that these containers have typical sizes, revealing that meaningful scales indeed play a role in understanding human mobility patterns.

A recent paper by Arvidsson et al. (2023) suggests that the significant inequalities within cities should not be overlooked in the relevant studies. Human networking and productivity often follow heavy-tailed distributions, meaning that a few individuals contribute disproportionately to overall city metrics. Leveraging micro-level data from Europe and the United States concerning interconnectivity, productivity, and innovation within cities, the study uncovers that the tails of within-city distributions and their expansion with city size explain a substantial portion (36-80%) of previously observed scaling effects. Moreover, these factors account for a significant portion (56-87%) of the variation in scaling among indicators of differing economic complexity. Arvidsson et al. (2023) identify a mechanism known as city size-dependent cumulative advantage to show that urban scaling largely reflects the inequalities within cities, highlighting the importance of considering the socio-economic dynamics that drive the disparities within urban environments. They find that agglomeration effects primarily benefit urban elites, leaving a significant portion of city residents partially excluded from the socio-economic advantages associated with urban growth. The effect of social and economic segregation on the scaling coefficient is also found in Keuschnigg(2019) in which Swedish geocoded microdata suggest that trajectories of superlinear growth are highly robust only for cities assuming dominant positions in the urban hierarchy, echoing the rich-get-richer process on the system level.

In sum, while the empirical findings for Korea that do not align closely with the urban scaling law predicting superlinear growth can be understood in the context of evolutionary theory, other explanations are possible as discussed above. Recent studies can shed light on the issue. Indeed, this aspect also remains a task for future research.

ACKNOWLEDGMENT

This work was supported by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (NRF-2023S1A5A2A01074457).

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