The relationship between foot traffic and commercial land prices

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ABSTRACT Foot traffic data allow business operators and government officials to assess the degree of pedestrian activity on a street and thus play an important role in optimizing retail strategies and enhancing urban planning. This study uses foot traffic data from Seoul and its surrounding regions to examine the relationship between foot traffic and land prices. Three study areas were selected and investigated using spatial regression models. The results showed that the interplay between foot traffic and land prices was influenced by geographical location. While a linear association between the two variables was found in one study area, diminishing returns to scale of land prices to foot traffic were identified in the other two. This nonlinear relationship can be attributed to the mismatch between land-use intensity and zoning. These findings are expected to provide insights for stakeholders in various industries, including property valuation, urban planning, and real estate development.

KEY WORDS foot traffic – land price – spatial regression model – diminishing returns to scale – zoning – Seoul region

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1. Introduction

Foot traffic is a metric of great interest and value to many businesses, especially retail stores (Trasberg, Soundararaj, Cheshire 2021). Furthermore, in urban planning, generating more foot traffic on a new street, or safeguarding pedestrians on heavy traffic streets, have been of great concern for government officials. With traffic tracking software and Wi-Fi sensing infrastructure increasingly available in various industries, traffic data are now readily accessible to researchers and practitioners.

In both industrial and academic communities, it is acknowledged that increased foot traffic is generally associated with higher real estate value (Cortright 2009, Washington 2013). However, the specific relationship may vary depending on factors, such as geographical location and property type. The relationship between foot traffic and real estate value may be linear, nonlinear, or even inversely proportional, depending on whether the property in question is situated in an urban or rural setting and whether it is commercial or residential in nature. This research aims to investigate the impact of foot traffic on commercial properties in metropolitan areas and seeks to identify how this relationship is affected by geographical considerations.

This study uses foot traffic data from Seoul and its surrounding regions in South Korea and examines the relationship between foot traffic and land prices. We employed spatial regression models to capture the complex non-linear relationship that may exist between the two variables. The results were reviewed and interpreted to provide insights to stakeholders across relevant industries.

This study contributes to the literature by extending established findings. While it is well-known that land prices tend to increase proportionally as foot traffic on the street grows, our study takes this one step further, by attempting to discover if a previously unidentified nonlinear relationship exists between these two variables. The results of this study are expected to offer insights into the dynamic relationship between foot traffic and commercial land prices.

The remainder of this paper is organized as follows. Section 2 reviews the literature on foot traffic measurement, the application of such measures, and their impact on property value. Section 3 describes the dataset, study area, and method employed to identify the connection between foot traffic and land prices. The results are presented and interpreted in section 4. Finally, a summary of the study and future research directions are provided in the conclusion.

2. Literature review

2.1. Measuring foot traffic

Foot traffic indicates the number of pedestrians that move around in a store or location; it is a metric that is constantly monitored by property owners and store managers to gauge the maturity of a given street. Because foot traffic is a typical indicator of store performance and street activity, various measurement methods have been proposed in the literature.

Traffic tracking software, such as thermal or laser-sensing people-counters, is an early example of a method of counting customer entries into a store or mall (Wang et al. 2017). With the advancement of network technology, Wi-Fi sensing can be utilized to capture human activities, such as walking and running, as discussed in several studies (Abdelnasser, Youssef, Harras 2015; Guo et al. 2016; Habaebi, Rosli, Islam 2017; Ma, Zhou, Wang 2019).

Recently, big data techniques and computer vision algorithms have been extensively employed to determine current pedestrian and vehicular traffic and predict their future patterns (Dobler, Vani, Dam 2021; Feng, Fay 2022; Ning et al. 2022; Sevtsuk, Kalvo 2022). These methods commonly exploit publicly available data, such as aerial images and street-view photographs to build traffic estimation models. As traffic data become cheaper and easier to obtain, studies on their applications also increase.

2.2. Applications of foot traffic data

Increasing foot traffic is critical to the success of retail businesses; many studies on the relationship between store traffic and sales performance (e.g., sales volume and conversion rate) have been conducted (Perdikaki, Kesavan, Swaminathan 2012; Chao et al. 2013; Lee Jang 2014). These studies have suggested various strategies for increasing foot traffic, such as hosting special events and redesigning store layouts.

Online strategies to increase foot traffic have also been suggested as the boundaries between offline and online shopping channels become blurry (Ayodeji, Kumar 2019; Sun, Fan, Tan 2020; Dolega, Rowe, Branagan 2021; Sun, Chen, Fan 2021). Especially, Sun, Chen, Fan (2021) argued that online sellers' use of live chats could increase platform traffic through the mechanism of information and persuasion.

Foot-traffic information is also critical for urban planning. Several factors influence the level of foot traffic on a street scale, for example, street width, block length, planting strips, lighting distance, and street cleanliness. Researchers have argued that among these street elements, designing efficient street intersections plays a key role in enhancing the urban pedestrian experience and street safety, thereby leading to increased pedestrian volume (Hosford, Cloutier, Winters 2020; Gerike et al. 2021; Chen et al. 2022). Another perspective on the use of foot traffic in urban planning is the mitigation of traffic congestion in cities. By designing a relevant transportation infrastructure, such as a subway network or public bus route, governments can efficiently manage the transportation volume and travel convenience of its citizens. These studies measured existing pedestrian and passenger volumes and recommended relevant policies for rail and bus transport services (Patra, Sala, Ravishankar 2017; Dubroca-Voisin, Kabalan, Leurent 2019; Tan et al. 2019; Wang et al. 2020).

2.3. Impact of foot traffic on property value

The impact of foot traffic on property value has been examined from various perspectives in the literature. Traffic flow is closely related to urban growth, and thus, the relationship between urban growth and land rent has been analyzed in earlier literature (Capozza, Helsley 1989). The predominant methodology employed in such studies was the hedonic pricing model (Bartholomew, Ewing 2010).

In the literature, it is widely acknowledged that well-designed pedestrian streets or walkable neighborhoods generally increase the value of real estate (Pivo, Fisher 2011; Sohn, Moudon, Lee 2012; Pham 2023). However, the main drivers influencing property value were identified differently depending on the study. For example, Rauterkus and Miller (2011) demonstrated that land value increases as street walkability improves but cautioned that this effect might be undermined if the street becomes car-dependent. Lam and Chau (2012) underscored shopping mall ownership structure and management strategy as key factors in increasing pedestrian flow, thereby increasing rental value. Qian, Zhang, Zhang (2023) showed that the opening of new stores, such as grocery stores, amplifies foot traffic and is ultimately capitalized into rent.

In a more recent study, Shin and Woo (2024) applied a popular deep learning technique, the semantic segmentation method, to street-view images and examined the effect of walkability on property value. Although the methods employed for analyzing foot traffic and property value have evolved over time, a positive relationship between these two variables has been consistently observed.

In short, foot traffic has mainly been investigated to identify its relationship with sales performance in retail marketing and to provide urban planning practitioners with insights, such as effective street layouts and transport services. In the property valuation literature, it is generally observed that high-foot traffic tends to increase property prices linearly; however, few studies have examined the specific dynamics, such as nonlinear or reverse patterns, in the relationship

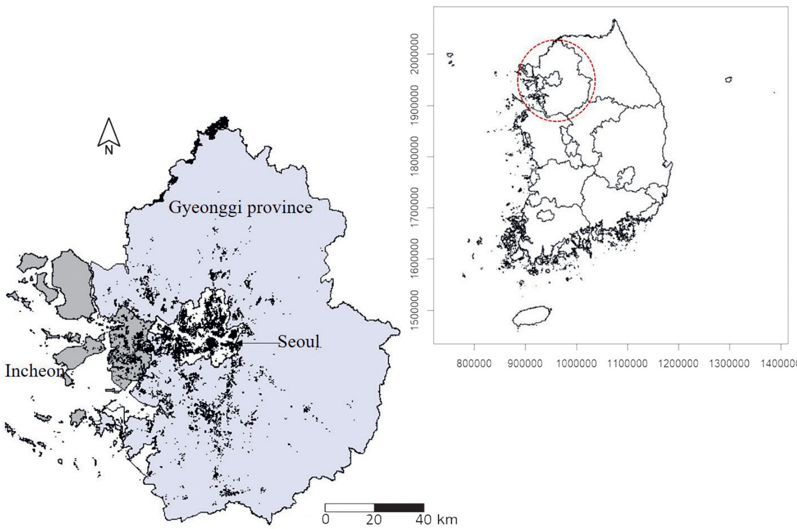

Fig. 1 – Study area and distribution of commercial properties

between the two factors. This study attempts to bridge this research gap by comparing foot traffic levels with the prices of nearby land lots, thus, offering insights to stakeholders in the relevant industries.

3. Data and methodology

3.1. Dataset and the study area

Foot traffic data were obtained from a government research institute.[1] This dataset was created by a South Korean telecommunications company by analyzing the voice calls and text messages of smartphone users. Foot traffic in this dataset indicates the average number of daily pedestrians within a 38-meter distance from a property of interest. It was measured for one year between January 2021 and December 2021.[2] Land data, that is, land prices of individual lots, were collected

[1] The Korea Institute of Local Financing manages this data for the purpose of tax assessment.

[2] The telecommunication company analyzes voice calls, text messages, and data usage for each mobile device. It then examines the density of calls and data usage in specific areas and estimates the number of pedestrians. For example, if property A has foot traffic of 1,200, it indicates that the average daily number of pedestrians within a 38-meter distance from the property A is 1,200. The 38-meter radius is determined by the internal policy of the telecommunication company.

Table 1 – Descriptive statistics (n = 20,457)

	Min.	Median	Mean	Max.
Land price (mil. KRW/m²)	0.2	4.6	6.3	49.9
Daily foot traffic (persons)	8	453	616	12,680
Region	Seoul: 9,870 (48.2%), Gyeonggi province: 8,612 (42.1%), Incheon: 1,975 (9.7%)			

from a government website.[3] Land prices in this dataset indicate the prices surveyed by valuation experts in January 2021.

In general, metropolitan areas have large numbers of commercial properties, but the same is not true for rural regions. In South Korea, the Seoul Metropolitan Area is a representative urban region with a population of approximately 25 million people. The Seoul Metropolitan Area consists of Seoul, Gyeonggi province, and Incheon. These three administrative regions were chosen for analysis because the commercial properties are located close to each other, frequently forming retail store clusters and generating a decent amount of foot traffic. By contrast, rural regions are not suitable for this study because stores are scattered across a wide area; thus, the number of daily pedestrians is likely to be small. Table 1 shows the descriptive statistics of the data used in this study, and Figure 1 displays the three study regions and locations of the 20,457 commercial properties.

3.2. Spatial regression model

Spatial regression models were employed to analyze the relationship between foot traffic and land prices. These models are particularly useful in geography because they consider spatial autocorrelation. The most common types of spatial regression models, the spatial autoregressive model and spatial error model (Pineda-Ríos, Giraldo, Porcu 2019; Bayode et al. 2022), were adopted for the analysis. The spatial autoregressive model deals with spatial autocorrelation by explicitly considering the impact of neighboring land prices on the target land price. The spatial error model handles this by introducing a spatially autocorrelated error term. The spatial autoregressive model (SAR) and spatial error model (SER) can be expressed as follows:

$$\text{SAR: } Y = \rho WY + \textit{foot traffic}_i + \textit{foot traffic}_i^2 + \textit{county code}_i + \varepsilon \quad (1)$$

$$\text{SER: } Y = \textit{foot traffic}_i + \textit{foot trafficc}_i^2 + \textit{county code}_i + \varepsilon,\ \varepsilon = \lambda W\varepsilon + \eta \quad (2)$$

[3] The Korean government releases land price information annually on the website https://www.data.go.kr/data/15004246/fileData.do.

Table 2 – Akaike Information Criterion values and selected models

Region	OLS*	SAR	SEM	Final model
Seoul	56,591	56,286	56,392	SAR
Gyeonggi province	30,563	30,485	30,413	SEM
Incheon	5,778	5,765	5,749	SEM

* Ordinary least squares model

Y is the land price per square meter, *foot traffic* is the number of daily pedestrians pertaining to property *i*, and *county code* is a code corresponding to the sub-level administrative unit to which property *i* belongs. The squared *foot traffic* was added to the model to examine the complex relationship between foot traffic and land prices. The county code is a categorical variable employed to capture the differences in land price levels between counties. In formula (1), ρ is the spatial autoregressive parameter, and W is the spatial weight matrix[4]. In formula (2), λ is the spatial autoregressive parameter, W is the spatial weight matrix, and is a white noise error.[5]

4. Results and interpretation

4.1. Model selection and results

The spatial regression models specified in Equations (1) and (2) were fitted separately to each region. The Akaike Information Criterion was used to determine the final model for each region, and Table 2 shows the selected results. From the table, it is confirmed that both the spatial autoregressive model and SEM perform better than the baseline model (ordinary least squares model), which warrants using spatial regression models.

Tables 3–5 present the spatial autoregressive model and SEM results for Seoul, Gyeonggi province, and Incheon, respectively. The lower and upper bounds used in creating the spatial weight matrices were determined by ensuring that each data point had at least one neighbor and by considering the overall goodness-of-fit. The variable *traffic* and its squared term, which are pertinent to this study, were found to be significant in all three regions. Additionally, all spatial parameters such as ρ and λ were also estimated to be significant. Thus, the inferences based on the results in Tables 3–5 would have no serious problems.

[4] Distance-based (row-standardized) weight matrices were used in this study.

[5] Refer to Anselin (2002) and Ward and Gleditsch (2018) for details related to the spatial autoregressive model and spatial error model.

Table 3 – Results for Seoul (SAR)

Coefficients				
Variable	Estimate	Standard error	z-value	p-value
Intercept	4.81	0.6754	7.13	0.0000
Traffic	4.87	0.1048	46.45	0.0000
Traffic²	−0.33	0.0178	−18.55	0.0000
County #1	−5.24	0.3876	−13.52	0.0000
County #2	−6.30	0.4908	−12.84	0.0000
…	…	…	…	…
County #24	−6.15	0.4825	−12.74	0.0000
Other parameters				
ρ	0.62 (p-value = 0.0000)			
Distance bound in spatial weight matrix	Lower: 0 m, Upper: 5,000 m			

Table 4 – Results for Gyeonggi province (SEM)

Coefficients				
Variable	Estimate	Standard error	z-value	p-value
Intercept	1.83	0.7083	2.59	0.0096
Traffic	2.22	0.0560	39.64	0.0000
Traffic²	−0.10	0.0182	−5.64	0.0000
County #1	3.56	1.7472	2.04	0.0414
County #2	−2.80	1.7468	−1.60	0.1093
…	…	…	…	…
County #30	2.03	0.6538	3.11	0.0019
Other parameters				
λ	0.96 (p-value = 0.0000)			
Distance bound in spatial weight matrix	Lower: 0 m, Upper: 12,000 m			

Table 5 – Results for Incheon (SEM)

Coefficients				
Variable	Estimate	Standard error	z-value	p-value
Intercept	1.59	0.0573	27.70	0.0000
Traffic	1.52	0.1008	15.14	0.0000
Traffic²	−0.10	0.0396	−2.41	0.0158
County #1	0.44	0.0476	9.22	0.0000
County #2	−0.74	0.3340	−2.21	0.0273
…	…	…	…	…
County #8	0.72	0.0683	10.48	0.0000
Other parameters				
λ	−1.57 (p-value = 0.0000)			
Distance bound in spatial weight matrix	Lower: 0 m, Upper: 5,000 m			

Note (Tables 3–5): County variables are shown partially for better readability.

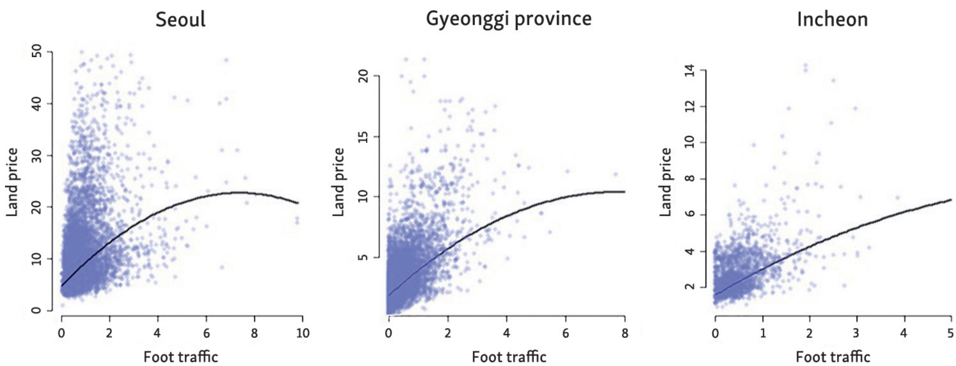

Fig. 2 – Relationship between foot traffic (100 pedestrians) and land price (mil. KRW/m²)

Figure 2 shows the relationship between foot traffic and land prices. The curves in the figure were created using the coefficients of the variable traffic and its squared term from Tables 3 to 5. The dots in the figure represent the actual data points observed in each region. The general expectation is that more foot traffic will lead to higher sales volumes, eventually increasing land prices in the area. This linear relationship was confirmed only in Incheon. In Seoul and Gyeonggi province, land prices increase linearly up to a specific point as foot traffic increases, but prices stop increasing and appear to reach a saturation point after a certain threshold. These diminishing returns to scale of land prices with respect to foot traffic are more noticeable in Seoul than in Gyeonggi province. In short, the relationship between foot traffic and land prices was revealed to vary depending on regions. Some regions, such as Incheon, show a linear pattern, while other regions, such as Seoul and Gyeonggi province, show a pattern of diminishing returns to scale.

4.2. Mismatch between land-use intensity and zoning

The causes of the diminishing returns to scale of land prices with respect to foot traffic need to be examined. A mismatch between land-use intensity and zoning might be a plausible explanation. Land lots with maximum foot traffic were identified in Seoul and Gyeonggi province and further investigated: these lots are Hwagok-dong 343-2 in Seoul; Pungdukcheon-dong 1080-4 in Gyeonggi province.

The two identified land lots are shown in Figure 3. The lots are adjacent to a subway station exit and, thus, experience abundant nearby foot traffic. In the figure, the residential and commercial zones are indicated in yellow and pink, respectively. Both the lots are in residential zones, which is unusual because most subway station areas tend to be designated as commercial zones. Additionally, the figure shows that some neighboring lots have already been designated as commercial

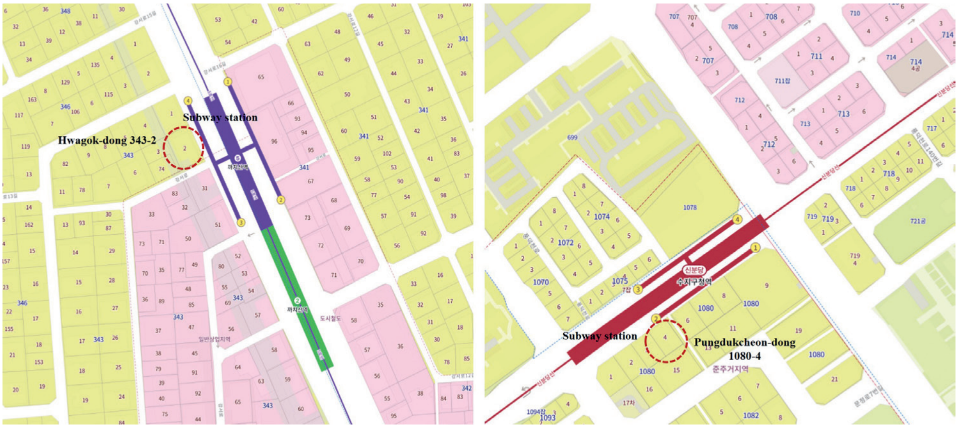

Fig. 3 – Land lot with the maximum foot traffic in Seoul and Gyeonggi province
Map source: https://map.naver.com

zones. In principle, a governor is required to alter existing zones promptly by the *National Land Planning and Utilization Act* when land-use intensity and neighborhood landscapes in jurisdictions change significantly. It seems necessary that the two lots in question and adjacent lots be upgraded to commercial zones.

As more severe restrictions, such as a lower floor-area ratio, are applied to land lots in residential zones compared to those in commercial zones, sites in residential zones command lower market prices than those in commercial zones. Therefore, the diminishing returns to scale in Seoul and Gyeonggi province can be attributed to the low land prices of the two lots that are zoned as residential, despite their substantial foot traffic and mature street infrastructure.

5. Conclusion

Three regions in the Seoul Metropolitan Area were selected for analysis, and the relationship between foot traffic and land prices was examined. The spatial regression models were employed to capture the relationship between the two variables while controlling the spatial autocorrelation. The results showed that diminishing returns to scale of land prices with respect to foot traffic exist in two regions. Many elements may combine to cause such a non-linear pattern. One explanation is that the zone designation and alteration systems in changing neighborhoods have not been updated in a timely manner.

Property valuers estimate the price of commercial land by considering various site characteristics, including foot traffic. Thus, the non-linear relationship identified in this study needs to be incorporated into the valuation process when land lots with high foot-traffic are appraised. Local government officers should monitor changes in jurisdictions carefully for current zoning to align with changing reality. Real estate developers and agents can improve their performance by acquiring under-zoned land lots in advance, such as those identified in this study.

Owing to data unavailability, this study could not segment foot traffic further, for example, based on age and gender. Future research should analyze the relationship between land prices and segmented foot traffic data. Additionally, the non-linear relationship between foot traffic and land prices can be argued to be valid in Seoul and Gyeonggi province. Thus, future studies need to investigate the generalizability of the current findings to different geographical settings.

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