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Spatial Analysis of Economic and Transit-Driven Land Value in a District-Level City in Thailand: A Case Study of Ban Pong Municipality, Ratchaburi, Thailand

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Abstract

Despite extensive Transit-Oriented Development (TOD) research in major metropolitan areas, critical knowledge gaps persist regarding how rail infrastructure impacts vary spatially across different land value segments in non-metropolitan district-level urban centers. This gap severely constrains the formulation of evidence-based policies for optimizing rail infrastructure investments and managing transit-induced spatial transformation in emerging urban contexts. Our study investigated the spatially heterogeneous impacts of heavy rail infrastructure on land values across property types and value segments in Ban Pong Municipality, Ratchaburi Province, Thailand, while examining spatial spillover effects to inform context-appropriate TOD strategies for district-level urban centers. Applying Hedonic Pricing Model (HPM) and TOD principles, this research employed Spatial Lag Quantile Regression (SLQR) to analyze 6,506 land parcels consisting of commercial (1,727), residential (3,705), and vacant (1,074) properties. It examined accessibility impacts across low-value <77.06 USD/sq.m. (<2,500 THB/sq.m.), mid-value 77.06-154.11 USD/sq.m. (2,500-5,000 THB/sq.m.), and high-value >154.11 USD/sq.m. (>5,000 THB/sq.m.) quantiles to capture market heterogeneity. The findings revealed pronounced quantile-specific variations in rail accessibility capitalization. Low- and mid-value segments demonstrated significant favorable premiums for proximity to rail stations, access to the Central Business District, and arterial road connectivity. Commercial and vacant parcels exhibited the strongest responsiveness, supporting bid-rent and agglomeration theories. Conversely, high-value residential properties exhibited weak or adverse transit proximity effects, indicating a preference for low-density, amenity-rich environments. Spatial lag coefficients remained consistently significant, confirming substantial neighborhood spillovers across all models. Results indicated the necessity for differentiated TOD implementation strategies: intensive development targeting in low-to-mid value zones where transit premiums were strongest, coupled with inclusionary zoning and anti-gentrification measures, while maintaining environmental quality in high-value areas. This research advances TOD theory by demonstrating systematic spatial heterogeneity in district-level urban contexts through the SLQR application, offering evidence-based guidance for sustainable urban transformation in non-metropolitan district-level cities in Thailand.

Keywords

Heavy rail transit; Land value; Transit-Oriented Development (TOD); Spatial Quantile Regression; Central Business District (CBD); Hedonic pricing

1. Introduction

1.1 Background

Economic development drives profound urban transformation, triggering labor migration, urban expansion, and investments in infrastructure, such as transportation, electricity, water supply, and public facilities, to meet the population's growing demands and improve the quality of life. Sustainable urban development strategies are critical, with Transit-Oriented Development (TOD) emerging as a key approach. TOD integrates residential and commercial areas around transportation hubs to maximize land use efficiency, reduce car dependence, and encourage the use of public transportation (Curtis et al., 2009).

While urban development in low-density regions, such as the United States and Australia, often follows major highways, Asian cities typically grow around high-density railway or metro hubs. In Hong Kong and Tokyo, constrained by geography, vertical land use and seamless integration of commercial and residential spaces dominate TOD practices (Knowles, 2012). These strategies mitigate environmental impact, support sustainable economic growth, and enhance quality of life.

The Central Business District (CBD) model plays a crucial role, functioning as the economic and commercial core of urban areas, marked by high-density development and strong connections to public transportation (Cervero & Kang, 2011). For instance, Tokyo's Marunouchi District demonstrates these characteristics through its direct linkage to Tokyo Station. Similarly, Hong Kong's Central District features an integrated network of the MTR subway and tram systems, which supports its dense commercial activities (Cervero & Murakami, 2009).

Thailand mirrors these approaches by prioritizing rail-based urban development, particularly in Bangkok, with the BTS Skytrain and MRT systems enhancing accessibility and TOD around major stations (Padon & Iamtrakul, 2022). Beyond Bangkok, the national railway system (heavy rail) supports regional connectivity, as seen with Hua Lamphong Station (Anantsuksomsri & Tontisirin, 2015). Heavy rail expansion aligns with Thailand's Industrial Development Master Plan (2011–2031), integrating rail networks into Special Economic Zones (SEZs) to boost industrial investment and logistics efficiency (National Statistical Office, 2017).

Western Thailand plays a pivotal economic role, with a focus on energy, agro-industries, border trade, and tourism. Ratchaburi Province, especially, excels in agriculture, food industries, and power generation, with a Gross Provincial Product (GPP) per capita of 7,630.38 USD (247,560 THB)[1] in 2022, ranking first in the western region (Office of the Provincial Governor of Ratchaburi, 2024). In particular, the Ban Pong Municipality exemplifies this economic dynamism through its role as Ratchaburi Province's primary transportation node, where strategic positioning has catalyzed agro-industrial development and in-migration, generating concentrated urbanization pressures around railway infrastructure (Office of the Provincial Governor of Ratchaburi, 2024). The district is undergoing a major economic restructuring, as shown in Figure 1, where the number of registered businesses is consistently increasing. Figure 2 further demonstrates that industrial facilities are increasing

[1] Amounts in Thai baht (THB) were converted to U.S. dollars (USD) at the exchange rate of 1 THB = 0.0308 USD (Bank of Thailand, October 6, 2025)

steadily in Ratchaburi Province, with Ban Pong leading industrial development in the province. Figure 3 illustrates the trend of increasing population growth which has been accompanied by infrastructure and industrial development. Within this context, Ban Pong Municipality is a critical case study for understanding Transit-Oriented Development (TOD) and land value dynamics in Thailand's transportation hub towns and district-level urban centers. In addition, the district's urban development challenges, including spatial inequality, land speculation near transport nodes, and mounting pressure on local infrastructure (National Economic and Social Development Council [NESDC], 2022), necessitate context-specific TOD implementation strategies that account for limited local administrative capacity while addressing rapid spatial transformation. Consequently, findings from Ban Pong's experience can inform TOD policy frameworks applicable to similar transportation hub districts throughout Thailand.

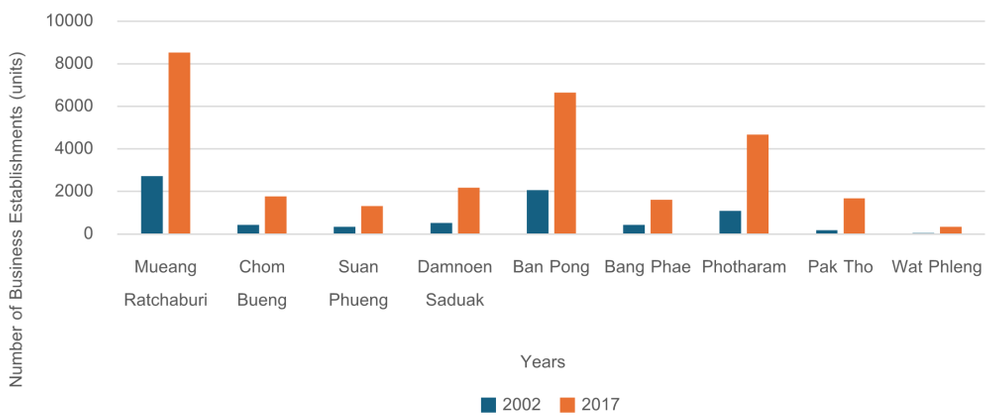


Figure 1. Number of business establishments in Ban Pong Municipality, 2001–2017.
Source: National Statistical Office (2017).

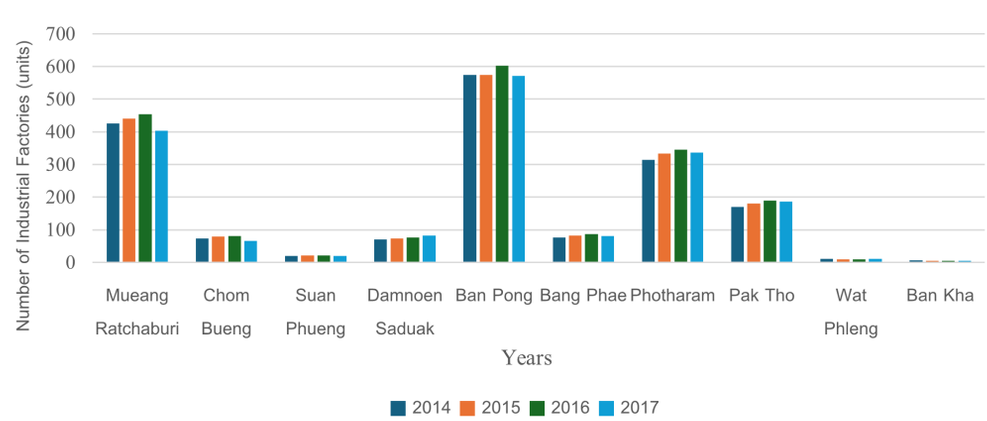


Figure 2. Number of industrial factories in Ratchaburi Province, 2001–2017.
Source: Office of the Provincial Governor of Ratchaburi (2018).

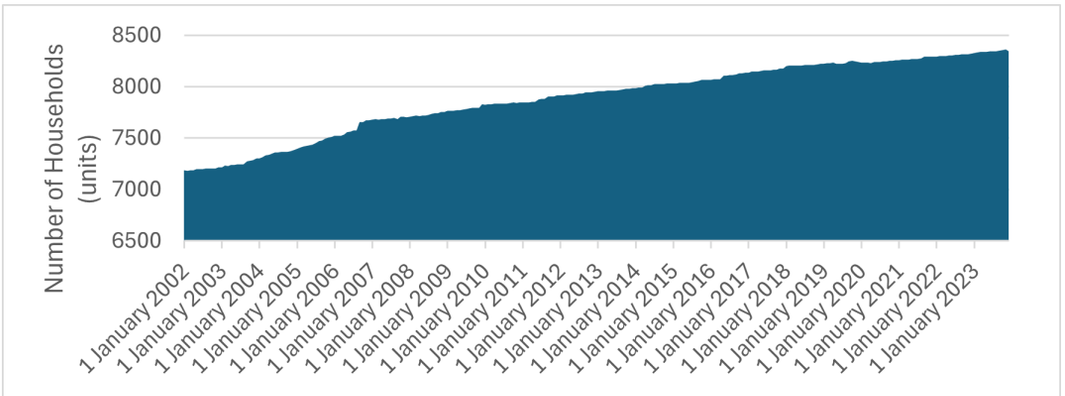


Figure 3. Number of household in Ban Pong Municipality, 2002–2017.
Source: Office of the Provincial Governor of Ratchaburi (2018).

Despite growing recognition of TOD as a sustainable urban planning strategy, existing research reveals theoretical and empirical limitations that constrain our understanding of transportation-land value relationships in developing economies. Current TOD literature demonstrates a pronounced metropolitan bias, with studies predominantly focusing on light rail systems in major urban centers such as Bangkok's BTS Skytrain and MRT networks (Chalermpong, 2007; Malaitham et al., 2020). The spatial economic effects of heavy rail in Thailand's district-level urban centers remain largely unexplored. This gap is particularly problematic given that heavy rail infrastructure represents the primary transportation connectivity for most of Thailand's emerging urban centers.

To address these research gaps, this study examines the distinctive impacts of transportation-driven urbanization in district-level towns, where concentrated development along a single railway corridor generates unique patterns of land speculation, spatial expansion, and value appreciation that differ markedly from those observed in metropolitan TOD contexts. Two conceptual frameworks were employed and adapted explicitly for district-level analysis. First, the study adopted TOD principles to evaluate how land use patterns are integrated with heavy rail infrastructure in a non-metropolitan setting. Second, the study applied the Hedonic Pricing Model (HPM) as the analytical framework to measure the spatial economic influence of heavy rail proximity on land values, allowing for a systematic separation of transportation accessibility effects from other locational and environmental factors. Without empirical evidence on heavy rail's land value effects in district contexts, policymakers lack the analytical foundation necessary for implementing effective TOD strategies in Thailand's emerging urban centers.

This study makes significant contributions to TOD research and urban planning practice in developing economies. Theoretically, a district-level analytical approach that considers institutional restraints, governance constraints, and single-corridor urbanization dynamics typical of Thailand's growing urban centers expands TOD frameworks beyond metropolitan contexts. Empirically, the findings provide quantitative evidence on how heavy rail proximity affects land values in transportation-induced urbanization contexts, addressing an important gap in understanding the impacts of heavy rail outside major urban centers. Methodologically, the research advances spatial econometric approaches by adapting the Hedonic Pricing Model (HPM) for district-level analysis, thereby enabling a systematic decomposition of the impacts of heavy rail accessibility from other location-specific factors. This methodological framework establishes a replicable analytical approach for similar district contexts throughout Thailand and other developing economies.

2. Literature Reviews

2.1 Development of areas surrounding transit stations and economic growth

Transit-Oriented Development (TOD) is acknowledged widely as being crucial for economic growth and increasing urban land values. However, global evidence shows its effects vary greatly depending on physical, institutional, and policy contexts. In developed cities, TOD success often hinges on supportive land use regulations and existing urban density (Bowes & Ihlanfeldt, 2001; Debrezion et al., 2007). While TOD has transformed cities like Seoul and Shanghai (Cervero & Kang, 2011), Mu and Jong (2012) highlight that without effective policy frameworks and land use coordination, TOD benefits remain limited.

This growing literature shifts focus from whether TOD creates value to understanding the contexts that maximize its effectiveness. In particular, the TOD role in reshaping Central Business Districts (CBDs), the economic cores of cities, remains underexplored, presenting an important avenue for future research.

2.2 Connection between TOD and CBD development

TOD enhances the competitiveness of CBDs by integrating efficient transit with compact land use (Cao & Schoner, 2014; Cervero & Murakami, 2009). This synergy supports higher land values and urban agglomeration. Alonso (1964) bid-rent theory explains that land users willing to pay more for proximity to the CBD benefit from reduced transport costs, creating a land value gradient from the center outward. This results in concentric land use patterns, which remain a core reference in TOD frameworks. In this study, the model helps interpret land value differences shaped by accessibility in Ban Pong District.

Agglomeration effects further intensify CBD value through clustering of economic activity (Fujita & Thisse, 2002), while transit investment strengthens these dynamics (Mohammad et al., 2013). However, TOD also may drive gentrification, requiring policies such as inclusionary zoning (Bartholomew & Ewing, 2011; Huang & Yin, 2015). As accessibility is central to both TOD and CBD vitality, the following section explores its broader role in shaping urban land values.

2.3 Impacts of accessibility and transportation infrastructure on urban land values

Accessibility to employment centers and transit nodes critically shapes land values. According to Alonso (1964), bid-rent theory, land near the CBD commands a higher value due to reduced transportation costs. Empirical studies validate this: Gibbons and Machin (2005) found rail network expansions positively influenced property values in London, U.K. while Debrezion et al. (2007) confirmed that proximity to commuter and light rail stations generally raises property values. Studies also highlight context sensitivity; Bowes and Ihlanfeldt (2001), for example, observed that transit proximity increases property values primarily in low-crime areas.
Today, accessibility encompasses not only proximity to the CBD but also connections to multimodal systems, such as BRT, subways, and highways (Pan, 2019). Improvements in connectivity increase household mobility and firm productivity and such benefits are capitalized into land values. Beyond general accessibility, specific transportation hubs, such as rail junctions, play an even more critical role in shaping urban land values, as examined next.

2.4 Impacts of rail junctions on urban land value

Rail junctions enhance accessibility by serving multiple transit lines, which substantially increases nearby land values (Alonso, 1964). Research indicates that junctions foster dense commercial activities and transit-oriented development. Similarly, Debrezion et al. (2006) identified higher hedonic price effects at interchange stations in suburban Netherlands.

In Japan, Nakagawa and Larson (2011) demonstrated that Tokyo's Shinjuku and Ikebukuro junctions command the highest land values, acting as urban magnets for investment. Toronto's Union Station has similarly spurred significant appreciation in commercial and residential values (Diao et al., 2017). These cases highlight how rail junctions support polycentric urban structures and economic densification. To rigorously analyze these spatially varied effects, specialized econometric models tailored to the characteristics of spatial data are necessary.

2.5 Spatial regression models in urban and land value analysis

Traditional regression often overlooks spatial dependence in land values. Spatial models such as the Spatial Lag Model (SLM) and Spatial Error Model (SEM) help reduce bias (Anselin, 1988; Lesage & Pace, 2009). The "First Law of Geography," often credited to Tobler (1970), emphasizes the presence of spatial dependence, though its classification as a true "law" is contested. In this study, the concept is used descriptively to justify the application of spatial analytical techniques. Geographically Weighted Regression (GWR), as developed by Fotheringham et al. (2002), enables spatial variation in model parameters, thereby capturing local contextual effects rather than assuming uniform global relationships. Empirical work also shows accessibility effects on land values, including subway/rail access (Efthymiou & Antoniou, 2013; Mohammad et al., 2013).

The Hedonic Pricing Model (HPM) continues to serve as a key analytical framework for examining how physical and locational attributes influence property values (Rosen, 1974). When combined with Quantile Regression, the approach allows for the assessment of heterogeneous effects across different points in the land value distribution (Koenker, 2005; Koenker & Bassett, 1978) The Spatial Lag Quantile Regression (SLQR) method further advances this by incorporating spatial spillover effects and distributional heterogeneity, providing a more nuanced understanding of spatial interdependence (Chasco & Gallo, 2013; Kim et al., 2003; Wang et al., 2024). Although most applications of SLQR have concentrated on large metropolitan regions, district-level cities influenced by heavy rail infrastructure exhibit unique characteristics, including market segmentation and the reconfiguration of central business districts. Accordingly, this study applies the SLQR framework to Ban Pong Municipality to analyze spatial and economic dynamics in a non-metropolitan, rail-oriented context.

2.6 TOD and land value impacts in non-metropolitan and district-level urban centers

While most of the TOD research has focused on metropolitan regions, especially megacities with established mass transit systems, recent studies have begun to explore the dynamics of TOD in non-metropolitan and district-level urban centers. These contexts differ markedly in terms of urban morphology, land market maturity, and infrastructure readiness, resulting in unique patterns in how transit infrastructure affects land values.

In district-level urban centers, land markets exhibit greater heterogeneity and the impact of transit infrastructure on land values is influenced by baseline accessibility, existing urban morphology, and latent development capacity (Suzuki et al., 2015). For instance, Pan (2019) examined the METRORail system in

Houston's low-zoning environment and found that light rail led to uneven land value appreciation, particularly in underserved and underutilized neighborhoods. Supporting this, Debrezion et al. (2007) and Mohammad et al. (2013) demonstrated that the capitalization of transit accessibility into land values varies significantly based on urban size, land use density, and broader economic structures.

In the Southeast Asian context, Chalermpong (2007) observed that rail-based accessibility in Bangkok contributed to increased land prices, with more potent effects in suburban areas. Similarly, Mu and Jong (2012) emphasized the importance of integrated land use policies and institutional coordination in their analysis of TOD implementation in Dalian, a non-metropolitan industrial city in China, for realizing transit-induced land value gains.

For Thailand's emerging non-metropolitan cities, such as Chiang Mai and Khon Kaen, empirical research remains limited. Nevertheless, preliminary case studies suggest that potential land value uplift may occur near proposed rail stations, albeit with more gradual and delayed effects compared to Bangkok, due to lower urban density and slower market responsiveness (Office of Transport Traffic Policy Planning, 2021).

In the case of Ban Pong, with its interplay of industrial growth and rail-induced density, there is alignment with other district-level centers where TOD functions as a development catalyst, unlike in already capitalized metro cores (Arrington & Cervero, 2008; Curtis et al., 2009). Evidence suggests these non-metropolitan areas see the strongest relative land value gains in low- to mid-value quantiles, underscoring the need for differentiated and targeted TOD policies to optimize transit investment benefits (Suzuki et al., 2015). Collectively, the reviewed literature confirms that transportation accessibility exerts profound and spatially varied impacts on urban land values, necessitating sophisticated spatial econometric modeling.

3. Methodology

3.1 Study Site: Ban Pong Municipality, Ratchaburi Province, Thailand

The study site is the urban center of Ban Pong, delineated by the Ban Pong Municipality administrative boundary within Ban Pong District, Ratchaburi Province, Thailand (Fig. 4a). The study is framed at the district level while operationalizing the urban extent with the municipality boundary to provide a clear, policy-relevant delineation of the built-up core. The dataset comprises 6,506 parcels within this boundary, assembled at the parcel scale (Department of Lands, 2024; Treasury, 2024). These data support spatial econometric and quantile-regression analyses.

Ban Pong Municipality is a district-level urban center located in the northwestern part of Ratchaburi Province, approximately 80 kilometers west of Bangkok and around 40 kilometers from Nakhon Pathom. Covering an area of approximately 8.45 square kilometers, it serves as a vital economic and transportation hub within Thailand's Western Economic Corridor (WEC) (Fig. 4b) (Office of Transport and Traffic Policy and Planning Thailand, 2024). The municipality's compact and transit-oriented urban form has been shaped historically by the presence of the Ban Pong Railway Station, which lies along the Southern Line of the State Railway of Thailand (SRT). Its strategic location at the intersection of major regional routes enables Ban Pong to serve as a secondary growth pole, connecting the Bangkok Metropolitan Region with the western provinces of Kanchanaburi, Ratchaburi, and Phetchaburi (Fig. 4c). Accessibility to the municipality is supported by Highway No. 323 and Asian Highway 2 (AH2), forming a regional logistics spine that facilitates both interprovincial passenger travel and freight distribution. The ongoing expansion of Thailand's double-track railway project is

expected to enhance the city's connectivity further, reinforcing its regional role and stimulating land value appreciation along transit corridors and arterial routes (Ministry of Transport Thailand, 2022).

Demographically, Ban Pong Municipality has a population of approximately 15,564 residents, according to The Department of Provincial Administration (2023). The population structure reveals a predominance of the working-age group, which accounts for about 64 percent of the total population, followed by 18 percent elderly and 18 percent youth under 15 years of age (Ban Pong Municipality, 2025). This demographic pattern characterizes Ban Pong as a mature and stable urban community with moderate aging and limited natural population growth. Despite this, the municipality continues to attract in-migration due to employment opportunities in manufacturing, trade, and logistics (Office of the National Economic and Social Development Council, 2023). The local economy is diverse, encompassing industries such as food processing, packaging, furniture production, and the manufacture of automotive parts. Many of these industrial activities are concentrated in the Ban Pong Industrial Zone and its surrounding peri-urban areas, where land availability and transportation access facilitate industrial expansion (Ratchaburi Provincial Industrial Office, 2017). The urban core operates as the principal commercial and service center, hosting traditional markets, retail shops, and small enterprises that cluster around the railway station and along main road corridors (Ban Pong Municipality, 2025).

Land use in Ban Pong Municipality comprises five major categories: residential, commercial and mixed-use, industrial, institutional and public, and open space or transportation infrastructure (Ban Pong Municipality, 2025). Residential areas account for approximately 38 percent of the total municipal area, comprising a mix of traditional wooden houses, townhouses, and modern detached dwellings, situated along collector roads and in suburban neighborhoods. Commercial and mixed-use zones account for about 22 percent. They are concentrated along Sukhaphiban Road, Ban Pong–Kanchanaburi Road, and in the vicinity of the railway station, demonstrating the strong relationship between accessibility and land utilization. Industrial land use accounts for roughly 15 percent, primarily located along the eastern fringe near Tha Pha Subdistrict, where small and medium-sized enterprises are predominant. Institutional and public uses, including temples, schools, hospitals, and administrative offices, account for approximately 10 percent, while transportation and open space cover the remaining 15 percent (Fig. 4a) (Ban Pong Municipality, 2025). The pattern of land values in Ban Pong exhibits a transparent spatial gradient, decreasing outward from the central railway and major road corridors. The highest appraised values, ranging from 460.21 to 613.61 USD/sq.m. (15,000 to 20,000 THB/sq.m.) , are concentrated near the central commercial zone, declining to 115.05-191.75 USD/sq.m. (3,750–6,250 THB/sq.m.) in the outer residential and industrial areas (Fig. 4a) (Department of Treasury, 2024).

Transportation connectivity is a defining feature of Ban Pong's spatial structure. The municipality is supported by two primary systems—rail and road—that together form the foundation of its economic and spatial development. The Ban Pong Railway Station, one of the oldest and busiest along the SRT's Southern Line (Ministry of Transport Thailand, 2022), connects the municipality directly to Bangkok in the east and Kanchanaburi in the west, serving both passenger and freight transport. The railway corridor has long acted as a catalyst for commercial growth, encouraging the clustering of retail, service, and residential activities. Running parallel to the rail line, Asian Highway 2 (AH2) functions as Thailand's central north–south artery linking Bangkok with the western and southern regions. At the same time, Highway No. 323 connects Ban Pong to Kanchanaburi and extends toward the Myanmar border. These arterial routes enhance regional connectivity and have stimulated the development of industrial estates, warehouses, and logistics facilities along the municipal outskirts. Within the town, Sukhaphiban Road and Ban Pong–Kanchanaburi Road serve

as collector routes, connecting residential areas, markets, and industrial zones to support efficient local movement (Ban Pong Municipality, 2025). The integration of the rail and road systems positions Ban Pong as a multimodal transport hub, where high accessibility is strongly correlated with rising land values and the concentration of commercial and industrial development around major junctions and transit-oriented zones (Fig. 4c).

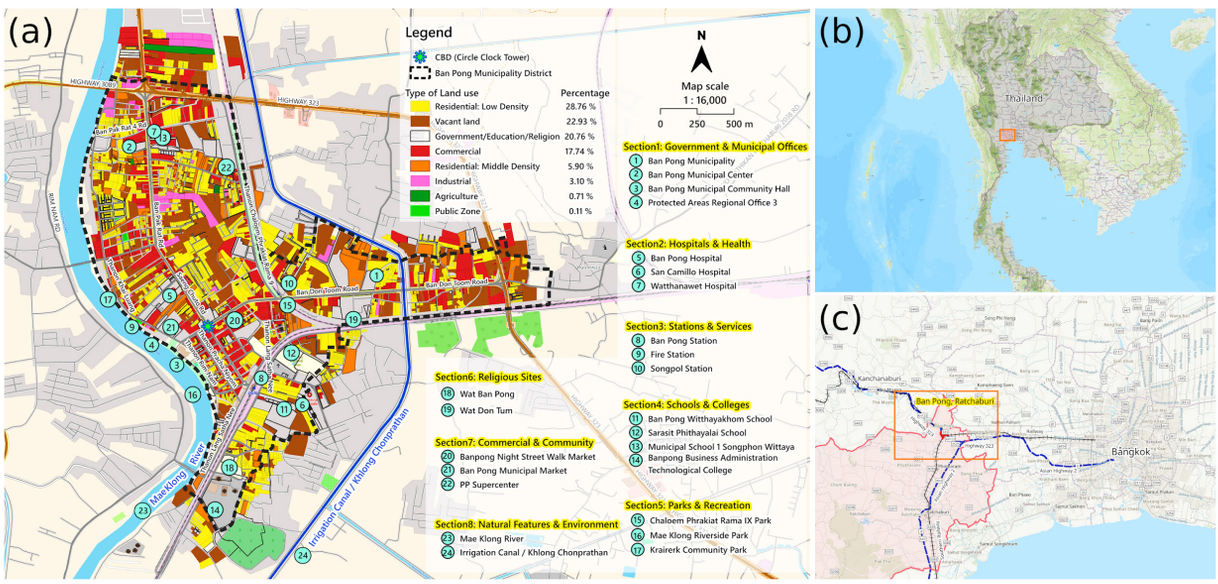


Figure 4. (a) Land use map of Ban Pong Municipality; (b) regional setting of Ban Pong Municipality in Thailand; and (c) regional–provincial context of Ban Pong Municipality.

Source: Authors (2025)

3.2 Data and variables

This study investigated the determinants of land value at the district-level urban center of Ban Pong, Ratchaburi Province, by integrating spatial econometric techniques with quantile regression. The analysis utilized a parcel-level dataset consisting of 6,506 land plots within the Ban Pong Municipality, categorized into commercial (1,727), residential (3,705), and vacant (1,074) parcels. The dependent variable, land value (LV), measured in Thai Baht per square meter (THB/sq.m), was obtained from the Department of Lands and the Treasury Department. For international comparison, values were also converted to U.S. Dollars (USD) based on the Bank of Thailand exchange rate of 1 THB = 0.0308 USD as of October 6, 2025. The Treasury Department's assessed land values, used for official purposes such as taxation, are not based on market transactions and often underrepresent actual market value, especially in rapidly developing areas, because they are not updated frequently (Ministry of Finance, 2023).

Despite these limitations, Treasury data were chosen for use in this study because they provide standardized, georeferenced, and comprehensive coverage and are a widely accepted proxy in Thai research where transparent market data are lacking (Anantsuksomsri & Tontisirin, 2015); the data also remain suitable for the study's goal of analyzing relative spatial variations in land value, rather than predicting precise prices. The independent variables were selected based on the theoretical framework of the Hedonic Pricing Model (HPM),compiled from credible national and municipal sources. These variables were grouped into four distinct categories to systematically analyze their influence on land value.

The first category, Accessibility and Distance Variables, captures proximity to major urban infrastructure, as greater accessibility generally is linked to higher land values (Bowes & Ihlanfeldt, 2001; Cervero & Duncan, 2002). Variables included distances (in meters) to the CBD, Ban Pong railway station (SBP), main roads (TMR), secondary roads (TSR), and the nearest shopping mall (PP).

The second category, Demographic and Economic Variables, represents population characteristics influencing land demand, based on data from the Bureau of Registration Administration and Ban Pong Municipality. Higher density and income levels are positively correlated with land prices (Bartholomew & Ewing, 2011). This group included household density (HD), per capita income (IPAVG), average household income (IHAVG), and the proportion of working-age population (POP15_59).

The third category, Land Parcel Variable, consists of parcel size (SIZE, in m^2). While larger parcels may have lower unit prices, their total value can be higher due to development potential (Alonso, 1964). Finally, the Amenity Variable includes distance to the nearest river (RMK), as proximity to natural features may enhance land value, albeit with potential risks like flooding (Efthymiou & Antoniou, 2013). All geospatial data, including distances, were computed using QGIS 3.32, based on official parcel shapefiles, and cross-validated with Google Earth Pro. Statistical analyses, including descriptive statistics, multicollinearity diagnostics (Pearson correlation and VIF), and the final Spatial Lag Quantile Regression (SLQR) models, were conducted using Stata 17 and R (spgwr, spdep, and quantreg packages). A summary of the variables is presented in Table 1.

Table 1. Selected Variables and Data Sources

Category	Expected sign	Variable Code	Full Variable Name	Description	Source
Dependent Variable		LV	Land Value	Land value (THB/sq.m.)	Land plot: Dept. of Lands; Valuation: Treasury Dept.
Independent Variables					
Accessibility and Distance Variables	-	CBD	Central Business District	Distance to Ban Pong's main economic hub (meters)	Land plot data: Dept. of Lands; Distance: QGIS; Location: Google Earth Pro
	-	SBP	Distance to Train Station	Distance to Ban Pong train station (meters)	Distance calculation: QGIS
	-	TMR	Distance to Main Road	Distance to the main road (meters)	
	-	TSR	Distance to Secondary Road	Distance to the nearest secondary road (meters)	
	-	PP	Shopping Mall	Distance to nearest shopping mall (meters)	
Demographic and Economic Variables	+	IPAVG	Average Population Income per Year	Average annual income per individual (THB)	Ban Pong Municipality Registration Office
	+	IHAVG	Average Household Income per Year	Average annual household income (THB)	
	+	HD	Household Density	Household density per square meter	Household data: Ban Pong Municipality; Area size: Dept. of Lands
	+	POP15_59	Population in 15-59 Years of Age	Percentage of population aged 15-59 (%)	Bureau of Registration Administration, Dept. of Provincial Administration
Land Parcel Variables	+	SIZE	Land Parcel	Size of land parcel (square meters)	Department of Lands
Amenity Variables	+/-	RMK	Distance to River	Distance to the nearest river (meters)	Distance calculation: QGIS

Notes: Distance measurements were conducted using GIS spatial analysis and socioeconomic data were sourced from municipal and national registration offices.

3.3 Hedonic Pricing Model (HPM)

This study is grounded in the Hedonic Pricing Model (HPM), a widely accepted framework for examining how property characteristics influence land value. Originating from utility theory and extended by Rosen (1974), the HPM posits that the value of a property is derived from a composite of its attributes, physical, neighborhood, locational, and transportation-related. Traditionally, this model is estimated using Ordinary Least Squares (OLS), which focuses on the conditional meaning of the dependent variable.

The general form of the HPM is represented as:

$$P_i = f(X_i, A_i, L_i, T_i) + \epsilon_i \quad (1)$$

Where P_i is the price of land parcel i; X_i, A_i, L_i, and T_i denote vectors of physical attributes, neighborhood factors, locational characteristics, and transportation accessibility, respectively; and X_i is an error term representing unmeasured influences. However, OLS estimation of the HPM is limited. It only captures average effects, masking variations across the price distribution and fails to account for spatial dependence, which, combined with skewed data and heteroskedasticity, can lead to biased estimates.

3.4 Spatial Quantile Regression in Hedonic Pricing Model

This study builds upon the Hedonic Pricing Model (HPM) framework (Rosen, 1974). While traditionally estimated using Ordinary Least Squares (OLS), which focuses on the conditional mean, land values often exhibit skewed distributions and heterogeneous effects across the price spectrum. To address this issue, we adopted Quantile Regression (QR), an extension of HPM that estimates the effects of explanatory variables at different points (quantiles) of the land value distribution (Koenker, 2005). Unlike OLS, which minimizes the sum of squared errors, QR typically is estimated using the Least Absolute Deviation (LAD) method.

The quantile regression model is formulated as:

$$Q_\tau(P_i) = X_i\beta_\tau + \epsilon_i \quad (2)$$

Where $Q_\tau((P_i))$ represents the conditional quantile of the land value at quantile τ, and βτ varies across quantiles. This allows us to examine how the impact of a variable, such as distance to a train station, differs between low- and high-value parcels. However, while QR effectively addresses heterogeneity, it does not, in its standard form, account for spatial dependence (Koenker, 2005; Koenker & Bassett, 1978). To address this limitation, we incorporated Spatial Lag Quantile Regression (SLQR), which combines QR with spatial econometrics to account for spatial spillover effects, i.e., the influence of nearby land values on a given parcel (Kostov, 2009).

The SLQR model is specified as:

$$Q_\tau(P_i) = \rho W(P_i) + X_i\beta_\tau + \epsilon_i \quad (3)$$

Where $Q_\tau(P_i)$ is the conditional τ-th quantile of the land value; W is a spatial weights matrix derived using inverse distance, a standard approach that assigns greater influence to closer parcels and reflects the localized nature of spatial spillovers in urban land markets; ρ measures the spatial lag effect; X_i is the vector of explanatory variables; and β_i denotes the coefficients that vary across quantiles. The spatial lag term $\rho W(P_i)$ captures the influence of neighboring land values on the outcome in each parcel, allowing for spatial feedback effects (Kostov, 2009).

For analytical purposes, a log–log functional form was employed due to elasticity-based interpretability and statistical advantages. Many variables, including land value, parcel size, and income, are right-skewed and heteroskedastic, violating OLS assumptions. Logarithmic transformation of both dependent and independent variables helps normalize distributions, stabilize variance, and mitigate outlier effects (Wooldridge, 2010). Although back-transforming a log-transformed dependent variable can introduce prediction bias (Ferguson, 1986; Koch & Smillie, 1986), the focus here is on relative effects and elasticities rather than point predictions of land values. The log–log specification is appropriate because it provides unbiased estimates of percentage relationships that are central to understanding land-value dynamics in Ban Pong. Such models are particularly suitable for land-value studies where percentage-based and multiplicative relationships dominate (Wooldridge, 2010).

The final model specification is as follows:

$$\begin{aligned} Q_\tau(ln\ ln\ (LV_i)\ ) = {} & \rho W ln(LV_i) + \beta_1\ ln\ ln\ (SIZE_i)\ + \beta_2\ ln\ ln\ (HD_i) \\ & + \beta_3\ ln\ ln\ \left(POP15_{59_i}\right)\ + \beta_4\ ln\ ln\ (IPAVG_i) + \beta_5\ ln\ ln\ (IHAVG_i) \\ & + \beta_6\ ln\ ln\ (TSR_i)\ + \beta_7\ ln\ ln\ (CBD_i)\ + \beta_8\ ln\ ln\ (SBP_i) \\ & + \beta_9\ ln\ ln\ (TMR_i) + \beta_{10}\ ln\ ln\ (RMK_i) + \beta_{11}\ ln\ ln\ (PP_i) + \epsilon_i \end{aligned} \tag{4}$$

In this model, the dependent variable is the log-transformed land value ($\ln(LV_i)$), and the explanatory variables include physical characteristics such as land parcel size ($\ln(SIZE_i)$); demographic indicators such as household density ($\ln(HD_i)$), proportion of working-age population ($\ln(POP15_59_i)$), and income levels ($\ln(IPAVG_i)$) and ($\ln(IHAVG_i)$); accessibility measures such as distance to secondary roads ($\ln(TSR_i)$), main roads ($\ln(TMR_i)$), the central business district ($\ln(CBD_i)$), and the train station ($\ln(SBP_i)$); and amenity factors such as proximity to the river ($\ln(RMK_i)$) and shopping malls ($\ln(PP_i)$). The spatial lag term ρWln(LVi) captures the spillover effects of land values in surrounding locations (Anselin, 1988; Bartholomew & Ewing, 2011; Chasco & Gallo, 2013; Koenker, 2005; Rosen, 1974).

4. Results

4.1 Model diagnostics and justification for SLQR

Preliminary diagnostic tests justified the adoption of the Spatial Lag Quantile Regression (SLQR) framework. Initial tests for heteroskedasticity (Breusch-Pagan: $\chi^2 = 58.61$, $p < 0.001$) and model misspecification (RESET: $F = 35.20$, $p < 0.001$), as detailed in Table 2 indicated that standard OLS was unsuitable, leading to the selection of Quantile Regression (QR) for its robustness to distributional heterogeneity (Koenker, 2005). Furthermore, the spatial dependence diagnostics presented in Table 3 confirmed significant positive spatial autocorrelation (Moran's I and Geary's C: $p < 0.01$), and Lagrange Multiplier tests showed the Spatial Lag Model to be more appropriate than the Spatial Error Model. Collectively,

these findings demonstrated the need for a model that could simultaneously address both heterogeneity and spatial dependence, making SLQR the most appropriate analytical framework for this study (Getis & Ord, 1992; Moran, 1950).

Table 2. Results of Heteroskedasticity and RESET test

Results Heteroskedasticity & RESET			
Heteroskedasticity and RESET test			
Breusch-Pagan Test	58.61	-	< 0.001
RESET tests	35.20	-	< 0.001

Note: Breusch-Pagan tests for heteroskedasticity; RESET tests for model specification.

Table 3. Results of Spatial Dependence

Results of Spatial Diagnostics			
Test Spatial Diagnostics			
Evaluate	**Statistic**	**Expectation**	**p-value**
Moran's I Test	0.1229	-0.000022	< 0.001
Geary's C Test	0.8596	1.0	< 0.001
LM Lag Test	4438.8	-	< 0.001
LM Error Test	4088.7	-	< 0.001

Notes: Moran's I and Geary's C test spatial autocorrelation; LM tests check for spatial lag/error dependence.

4.2 SLQR estimates by land value segments

Table 4 summarizes the SLQR estimates, revealing significant heterogeneity across land use types and value segments, which reflects the complex market dynamics of a non-metropolitan urban center. A consistently positive and significant spatial lag term (ρ) also indicates strong spillover effects from surrounding parcels. To facilitate a detailed discussion of these varied impacts, land parcels were divided into three distinct groups based on their price distribution: a low-value group (10th–30th quantiles; <77.06 USD/sq.m. (<2,500 THB/sq.m.), a mid-value group (40th–60th quantiles; 77.06-154.11 USD/sq.m. (2,500–5,000 THB/sq.m.), and a high-value group (70th–90th quantiles; >154.11 USD/sq.m. (>5,000 THB/sq.m.), as illustrated in Figure 5.

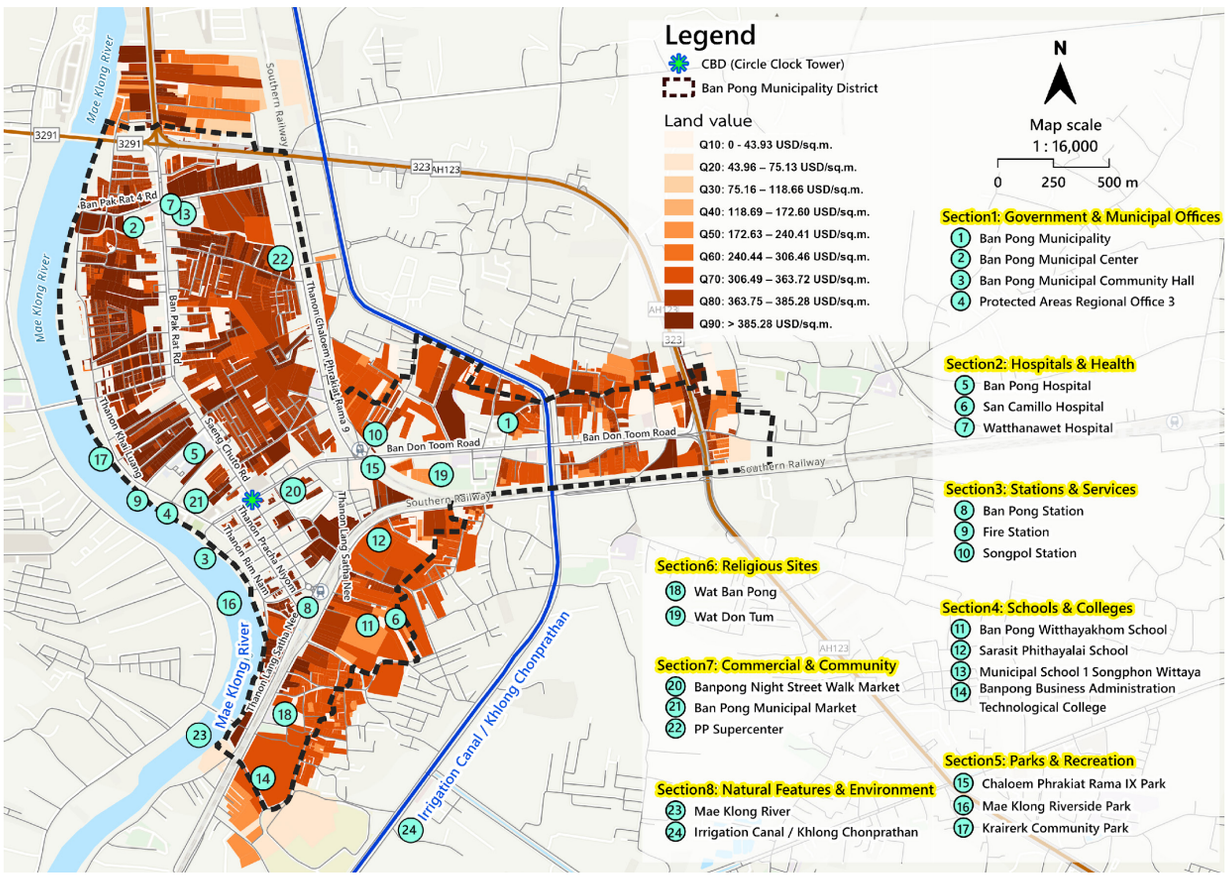


Figure 5. Quantile mapping of land values (in USD/sq.m.) across the study area.

Source: Authors (2025)

Note: The map categorizes parcels into nine value segments (Q10–Q90), ranging from below Q10 is 43.93 USD/sq.m. (1,425 Baht/sq.m.) to above Q90 is 385.28 USD/sq.m. (12,500 Baht/sq.m.).

Table 4. Spatial Lag Quantile Regression Results

Influential Factors / Land Use and Price Tier			Accessibility and Distance Variables					Demographic and Economic Variables				Land Parcel Variables	Amenity Variables	Spatial Explanatory Variable	Constant
			ln(CBD)	ln(SBP)	ln(TMR)	ln(TSR)	ln(PP)	ln(IPAVG)	ln(IHAVG)	ln(HD)	ln(POP15_59)	ln(SIZE)	ln(RMK)	ln(lagLV)	
Commercial	Low	q10	0.579	-1.122	**1.572***	-0.673	-1.053	2.259	1.165	334.2	-0.0462	0.174	-0.883	**0.597***	-9.498
		q20	**-0.432*****	-0.212	**-0.298****	-0.119	-0.152	0.3	0.561	-15.80	0.00922	0.0337	**-0.193***	**0.0992***	5.289
		q30	**-0.361*****	**-0.196***	**-0.241*****	0.0523	**-0.229*****	0.249	**1.387*****	13.56	0.00603	0.00269	**-0.155****	**0.108*****	-5.016*
	Medium	q40	**-0.203*****	-0.0947	-0.0894	0.0922	-0.0395	**0.254***	**0.561*****	4.898	**0.0236*****	-0.00999	0.021	**0126*****	-0.663
		q50	**-0.151****	-0.0807	-0.00684	0.0261	0.05	**0.298*****	**0.292***	-2.307	**0.0242*****	0.00416	**0.175*****	**0.102*****	0.136
		q60	**-0.236*****	-0.0435	-0.0100	0.0101	**0.0553****	**0.193*****	**0.534*****	-8.330	**0.0172*****	0.0116	**0.160*****	**0.0606*****	-0.464
	High	q70	**-0.194*****	-0.0445	**0.0456***	-0.00222	**0.0598****	0.074	**0.478*****	-0.231	**0.0183*****	**0.0257***	**0.137*****	**0.0847*****	0.334
		q80	**-0.150*****	**0.223*****	**0.114*****	-0.0150	0.0384	0.0237	**0.333*****	**75.11*****	**0.0181*****	**0.0367****	**0.152*****	**0.0930*****	0.685
		q90	-0.0376	0.0439	**0.0937****	-0.0324	**-0.127****	-0.0485	**0.338****	**77.32*****	**0.0118****	**0.0523***	**0.158*****	**0.0992*****	4.167**
Residential	Low	q10	**0.145*****	-0.0562	**0.0824*****	**-0.132*****	**-0.133*****	0.00978	-0.0401	-2.296	**0.327*****	**0.0911*****	**-0.149*****	**0.105*****	9.238***
		q20	**0.115*****	-0.0356	**0.0452****	**-0.0886*****	**-0.141*****	**0.0623***	**-0.235*****	-10.98	**-0.549*****	**0.0818*****	**-0.150*****	**0.0925*****	12.50***
		q30	**0.111*****	0.0151	0.0976***	**-0.0814*****	**-0.146*****	0.0549	**-0.425*****	**-19.96****	**-0.865*****	**0.0712*****	**-0.176*****	**0.0879*****	15.93***
	Medium	q40	0.00065	0.0544**	**0.0887*****	**-0.0722*****	**-0.155*****	**0.0784****	**-0.560*****	**-33.21*****	**-0.952*****	**0.0707*****	**-0.203*****	**0.0734*****	18.63***
		q50	**-0.109*****	**0.0718****	**0.144*****	**-0.0627*****	**-0.111*****	**0.0588***	**-0.611*****	**-74.21*****	**-1.002*****	**0.0545*****	**-0.190*****	**0.0633*****	21.33***
		q60	**-0.130*****	0.0645	**0.136*****	**-0.0667****	**-0.0809****	**-0.168*****	**-0.571*****	**-85.92*****	**-0.917*****	**0.0523*****	**-0.196*****	**0.0610*****	21.99***
	High	q70	**-0.339*****	0.0478*	-0.0278	**-0.0673*****	**-0.0859*****	**-0.427*****	**-0.558*****	**-125.9*****	**-0.700*****	**0.0385*****	**-0.264*****	**0.0540*****	27.48***
		q80	**-0.528*****	0.0831	**-0.0986***	-0.0408	-0.0495	**-0.479*****	**-0.579*****	**-146.3*****	**-0.660*****	**0.0515***	**-0.305*****	**0.0421****	29.82***
		q90	**-0.691*****	**0.179*****	0.0304	0.0107	0.0497	**-0.378*****	**-0.749*****	**-208.7*****	**-0.512****	-0.0355	**-0.269*****	-0.0136	30.04***
Vacant	Low	q10	**3.446***	-0.524	-0.462	-0.420	-1.130	**-3.292***	-1.148	-185.3	**-10.69*****	0.263	-0.0452	**0.667***	89.00***
		q20	-0.0533	-0.120	-0.167	-0.290	-0.260	-0.300	-0.0188	16.94	-1.322	0.128	-0.109	0.0829	20.98
		q30	-0.0794	-0.0979	**-0.116*****	**-0.277*****	**-0.202*****	-0.132	-0.0627	6.638	**-0,794*****	**0.100*****	**-0.106*****	**0.0524*****	17.12***
	Medium	q40	**-0.169***	0.0300	**-0.113*****	**-0.271*****	**-0.170*****	0.0159	**-0.328*****	15.7	**-0.599****	**0.0779*****	**-0.132*****	0.028	17.81***
		q50	**-0.277****	0.0881	**-0.146*****	**-0.243*****	**-0.167*****	**0.213***	**-0.681*****	0.155	**-0.473***	**0.0614****	**-0.180*****	0.0229	20.37***
		q60	**-0.382*****	0.183	**-0.188*****	**-0.229*****	**-0.170*****	**0.372*****	**-0.950*****	-22.13	-0.0624	**0.0818*****	**-0.217*****	0.0151	20.77***
	High	q70	**-0.553*****	0.101	**-0.224*****	**-0.163*****	-0.0879	**0.223***	**-1.125*****	**-78.73****	0.184	**0.0582***	**-0.219*****	0.00602	25.45***
		q80	**-0.457*****	0.0746	**-0.200*****	-0.0432	-0.0266	**0.276****	**-1.195*****	**-63.82****	0.340	**0.0411***	**-0.236*****	-0.0116	24.03***
		q90	-0.192	0.236	-0.133	-0.0442	0.155	-0.153	**-0.736****	15.43	-0.168	0.0986	**-0.266*****	0.0233	20.71***

Note: ***p < 0.001, **p < 0.01, *p < 0.05

The SLQR estimates disaggregated by land value segments revealed significant insights into how different variables influence land values across quantiles. Spatial spillovers, represented by the spatial lag coefficient (ρ), were positive and statistically significant ($p < 0.001$) across all land use types and quantiles, indicating that land values in Ban Pong were influenced by the values of neighboring parcels, confirming the presence of spatial dependence.

For the low-value range (Q10-Q30), the results showed that commercial land values displayed mixed accessibility patterns. In Q10, the distance to major roads (TMR) showed a positive impact with a coefficient of 1.572 ($p < 0.05$), while spatial effects (lagLV) were significant at 0.597 ($p < 0.05$), indicating positive spatial spillover effects. By Q20, the distance to CBD became significant with a coefficient of -0.432 ($p < 0.001$), indicating that land value decreased with distance from CBD. These results are supported by Alonso's bid-rent theory (1964), which suggests commercial land users are willing to pay more for the land to be near the CBD due to higher accessibility and the price of land tends to decline with distance from the urban core. Additionally, a major road (TMR) had a negative impact on commercial land values, with a coefficient of -0.298 ($p < 0.01$). At the Q30 quantile, representing lower-middle land value areas, proximity to key urban amenities significantly influenced land prices. The negative coefficient for rail station proximity (-0.196, $p < 0.05$) indicated that parcels closer to the station were more valuable, reflecting the importance of transit access even in mid-tier zones. Similarly, distance to the CBD (-0.361, $p < 0.001$) and shopping centers (-0.229, $p < 0.001$) both showed negative effects, meaning land closer to these amenities commanded a higher value.

These findings highlight that accessibility to transportation, employment, and retail remains a key driver of land value across broader market segments, not just in high-end areas. Residential land parcels exhibited a significant positive relationship with CBD proximity (0.145, $p < 0.001$) in the Q10 segment, indicating that proximity to the city center was associated with higher land prices. However, access to secondary roads (TSR) had a negative effect (-0.132, $p < 0.001$), suggesting that these roads may reduce desirability in lower-value residential areas, possibly due to traffic or noise. In Q30, household density became a significant negative factor (-19.96, $p < 0.01$), implying that higher density may reduce land value in these mid-range zones, perhaps due to overcrowding or lower quality of life. For vacant land parcels, the CBD surprisingly showed a strong positive coefficient in Q10 (3.446, $p < 0.05$), possibly reflecting speculative value near the city center. Meanwhile, a higher share of the working-age population (POP15_59) had a strongly negative effect (-10.69, $p < 0.001$), which may indicate labor-driven outmigration or socioeconomic stress in these areas.

In the mid-value range (Q40-Q60), commercial parcels remain influenced by income and accessibility variables. For instance, the average household income (IHAVG) had a positive impact on all quantiles, with coefficients of 0.561 ($p < 0.001$) for Q40, 0.292 ($p < 0.05$) for Q50, and 0.543 ($p < 0.001$) for Q60. Per capita income (IPAVG) had a positive impact of 0.254 ($p < 0.05$), 0.298 ($p < 0.001$), and 0.193 ($p < 0.001$) for all mid-value ranges. The distance to CBD remained negative and significant at -0.203 ($p < 0.001$) for Q40, -0.151 ($p < 0.01$), and -0.236 ($p < 0.001$) for Q60. Residential parcels exhibited evolving patterns, with CBD effects turning negative at -0.109 ($p < 0.001$) and -0.130 ($p < 0.001$) in Q50 and Q60, respectively. Meanwhile, secondary road access (TSR) played a significant role in negatively impacting these patterns, with coefficients of -0.0722 ($p < 0.001$), -0.0627 ($p < 0.001$), and -0.0667 ($p < 0.01$) from Q40 to Q60. Household density (HD) indicated increasingly strong negative effects on Ban Pong residential land values for all quantiles, reaching -33.21 ($p < 0.001$), -74.21 ($p < 0.001$), and -85.95 ($p < 0.001$) in the Q40 to Q60 range. Vacant parcels exhibited persistent resistance to development, with the average household income (IHAVG) maintaining significant negative coefficients of -0.328 ($p < 0.001$), -0.681($p < 0.001$), -0.950($p < 0.001$), and accessibility variables including CBD, main roads, and secondary roads showing consistently negative coefficients across all quantiles.

At the upper end of the distribution (Q70-Q90), the explanatory power shifted considerably. For commercial parcels, household income (IHAVG) remained significantly positive at 0.478 ($p < 0.001$), 0.333 ($p < 0.001$), 0.338 ($p < 0.01$) in the Q70 to Q90 range, while household density (HD) also exhibited a strong positive effect of 75.11 ($p < 0.001$) in Q80, and 77.32 ($p < 0.001$) in Q90, contrasting with residential patterns. Proximity to shopping areas (PP) became negative only at -0.127 ($p < 0.01$) in Q90. The CBD had a negative impact on commercial land prices in Q70 to Q80, with coefficients of -0.194 ($p < 0.001$) and -0.150 ($p < 0.001$). In residential parcels, household density (HD) continued to exhibit a strong negative effect, reaching -125.9 ($p < 0.001$), -146.3 ($p < 0.001$), and -208.7 ($p < 0.001$) from Q70 to Q90, while the distance to the CBD showed increasingly negative coefficients of -0.339 ($p < 0.001$), -0.528 ($p < 0.001$), -0.691 ($p < 0.001$). Notably, distance to the railway station (SBP) at Q90 showed a positive coefficient of 0.179 ($p < 0.001$), suggesting evolving valuation patterns due to neighborhood infrastructure improvements. Vacant land exhibited diminishing responsiveness to most variables, with only household income (IHAVG) remaining significantly negative at -1.125 ($p < 0.001$), -1.195 ($p < 0.001$), and -0.736 ($p < 0.01$) in Q70 to Q90, suggesting the presence of speculative or intangible drivers.

The stratified SLQR results revealed significant land market segmentation and spatial interdependencies in secondary cities like Ban Pong. Transit-oriented development strategies and urban policy interventions must account for distinct responses across value tiers and land use types. Commercial land values exhibited varying accessibility effects across quantiles, with major road access dominating lower-value segments (Q10), income variables becoming prominent in median values (Q50), and density effects emerging in high-value areas (Q90). Residential land values were consistently influenced by CBD proximity and household density across all quantiles, with density effects intensifying in higher-value segments. Vacant parcels showed limited responsiveness to observable variables with substantial negative population and income effects, suggesting speculative valuation patterns. These SLQR findings provide nuanced insights into how transportation accessibility, socioeconomic indicators, and spatial context interact to shape land markets in secondary urban areas.

5. Discussion and Interpretation

5.1 Accessibility and transit proximity

Accessibility is a multidimensional driver of land value that manifests differently across value tiers and land use types. In low-value zones (Q10–Q30), accessibility to Ban Pong's railway station, shopping centers, and the Central Business District (CBD) exhibited strong and consistent capitalization, particularly for commercial land. This suggests that in lower-tier markets, mobility improvements substantially enhance land attractiveness by reducing transportation costs and stimulating local economic activity (Cervero & Murakami, 2009). Retail proximity (PP) and CBD access emerged as value-enhancing features through their ability to attract foot traffic, encourage customer clustering, and leverage agglomeration economies (Debrezion et al., 2007). For residential land, the influence of CBD proximity and parcel size indicated that households in low-income areas valued spatial convenience to employment and services, as well as the availability of relatively larger, affordable plots.

In mid-value zones (Q40–Q60), the influence of accessibility became more differentiated. While rail access (SBP) remained relevant, its effects diminished in magnitude, suggesting that its value was contingent on additional infrastructure such as feeder roads and pedestrian connections. Secondary road access (TSR), consistently significant and negative, underscored the persistent "last-mile" challenge for rail connectivity alone, which is insufficient without supporting micro-scale infrastructure (Suzuki et al., 2013). Both commercial and residential users in this tier appeared to seek a balance between connectivity and livability, prioritizing moderate accessibility with reduced noise and congestion.

In high-value zones (Q70–Q90), the effects of accessibility diminished further, and in some cases, reversed. Residential parcels increasingly were averse to proximity to CBDs and rail stations, signaling a shift in locational preferences toward low-density, tranquil environments. This pattern mirrors those observed in suburban areas of cities like Tokyo and Penang, Malaysia, where affluent residents emphasize quality of life, exclusivity, and environmental amenities over direct connectivity (Yiu & Wong, 2005). Notably, rail station proximity turned positive again in Q90, likely reflecting targeted infrastructure improvements or neighborhood gentrification that renewed land value near transit hubs. These observations support the idea of threshold effects in transit capitalization, where the impact of accessibility depends not just on physical proximity but also on the broader urban context and complementary investments.

5.2 Economic conditions and demographic indicators

Economic and demographic factors also showed tier-specific patterns in shaping land value. In low-value segments, household and per capita income had a weak influence on land value, particularly for residential and vacant land. This factor likely was due to affordability constraints, limited purchasing power, and a predominance of speculative expectations over utility-based decision-making.

In contrast, mid-value zones showed stronger and more consistent responses to income indicators. Household income (IHAVG) and per capita income (IPAVG) significantly increased land values, especially for commercial parcels, reflecting an expanding consumer base and greater demand for upgraded infrastructure and services. These findings align with evidence from mid-tier cities, such as Dalian, where rising incomes, coupled with transit investments, catalyze land value appreciation (Wan et al., 2024). Additionally, residential land in this segment was negatively associated with household density, indicating a preference for lower-density, more comfortable environments, likely driven by emerging middle-class aspirations for better living standards. In high-value areas, the divergence between commercial and residential logic became more pronounced. Commercial land benefit from higher density, which supports agglomeration economies, retail concentration, and economic synergies. In contrast, residential land values dropped significantly with higher density, particularly in Q70–Q90, emphasizing that space, privacy, and low noise levels are perceived as luxury attributes. These results highlight the tension in mixed-use planning between clustering for commercial benefit and dispersal for residential amenity (Klinmalai & Kaewlai, 2024).

Across all land uses, the persistent negative effect of population variables (e.g., share of working-age population or household density) suggested deeper demographic transitions such as aging, out-migration, or unstable household composition that may affect the long-term sustainability of land value in certain neighborhoods. These effects also may reflect anticipatory behavior in the market where buyers price in expected future decline or limited growth.

5.3 Intangible factors and speculative expectations

Vacant land parcels demonstrated the weakest and most erratic associations with traditional explanatory variables. The high positive coefficient of CBD proximity in Q10, for example, suggested that speculative forces rather than current accessibility benefits may be driving valuation. This disconnect from fundamentals implies that vacant parcels often are priced based on perceived future potential, such as anticipated zoning changes, upcoming infrastructure, or developer interest, rather than existing utility or service provision (Healey, 1991).

At higher quantiles, this behavior became more evident, as vacant land values lost responsiveness to income, accessibility, and demographic factors. This highlights the role of land speculation and option value in shaping land prices for peripheral or underdeveloped urban areas. Such speculation can sometimes be productive, facilitating land assembly and unlocking development potential. However, it can also lead to land hoarding, price inflation, and development delays, particularly when institutions are unable to regulate or align private expectations with public planning goals. Policy tools, such as land value capture, staged development incentives, and regulatory zoning clarity, are essential for managing speculative dynamics in a way that ensures land remains available for productive use while discouraging rent-seeking behavior.

5.4 Comparative perspective from other cities

Experiences from cities such as Taichung (Taiwan), Penang, and Dalian demonstrated that transit-driven land value gains depend on more than infrastructure alone. Supportive zoning, coordinated infrastructure, and alignment with broader development goals are crucial. Differences in outcomes among cities with similar transit investments highlight the importance of institutional and regulatory contexts (Jen-Jia & Chi-Hau, 2004). The consistent segmentation of value impacts across cities suggests a structural pattern in urban land markets, driven by how different groups and land uses sort themselves spatially. Transit development can alter existing spatial patterns, generating new opportunities for urban growth while also introducing potential challenges such as displacement.

Ban Pong's speculative land trends contrast with Dalian's more active development, illustrating how institutional capacity shapes market responses. Where governance is strong, speculation can be guided toward productive use; where it is weak, it may stall development (Wan et al., 2024).

These insights emphasize that policy must go beyond improving accessibility. Effective TOD requires coordinated planning, tailored strategies for different market segments, and tools to manage speculation. Without this, secondary cities risk missing the full benefits of transit investments (Riratanaphong, 2024).

6. Conclusion and Policy Implications

This study examines the determinants of land value across various land use types and value segments in Ban Pong Municipality by employing the Spatial Lag Quantile Regression (SLQR) model. Rooted in the Hedonic Pricing Model (HPM), the research accounts for spatial dependence and distributional heterogeneity in urban land markets, thereby extending empirical and methodological insights into Transit-Oriented Development (TOD) in non-metropolitan areas. Findings highlight significant variation in how land values respond to factors such as accessibility, socioeconomic conditions, spatial context, and amenities, which provides a critical foundation for policy formulation.

The results confirm that proximity to rail infrastructure, especially Ban Pong's railway junction, significantly increases land values in the low- to mid-value land groups, particularly for commercial parcels, while effects on vacant land are statistically weak. This supports the bid-rent theory (Alonso, 1964) and aligns with extensive TOD literature emphasizing the value-enhancing effect of transit proximity in low- to mid-tier zones (Cervero & Murakami, 2009; Debrezion et al., 2006). Targeted TOD strategies in these zones such as upzoning, mixed-use zoning reforms, and reduced parking requirements can catalyze urban intensification and optimize public transit investment (Suzuki et al., 2015). Enhancing pedestrian infrastructure and streetscape quality can further support compact and livable communities (Nophaket et al., 2024; Padon & Iamtrakul, 2022; Thomas et al., 2018)

However, these gains bring the risk of transit-induced gentrification, particularly in low- to mid-value land groups. Price escalation near the rail station may displace vulnerable households and small businesses (Dawkins & Moeckel, 2016). Policy instruments such as inclusionary zoning, land banking, rent stabilization, and tenant protections are crucial to ensure that redevelopment benefits are equitably distributed. Support for small businesses through rent controls, financial incentives, and commercial preservation districts can help preserve local economic diversity (Baker & Lee, 2019).

The analysis also reveals contrasting effects of rail proximity by land use and value tier. Commercial land in mid- to high-value land groups benefits from strong agglomeration effects and business spillovers (Cervero & Duncan, 2002). These spillovers are evident not only for commercial parcels but also for residential land across various value segments, extending into the high-value land group (up to Q80), underlining neighborhood effects across housing markets. High-value land group residential land exhibits weak or negative responses to rail access, indicating a preference for low-density, amenity-rich environments (Bowes & Ihlanfeldt, 2001; Jim & Chen, 2009; Klinmalai & Kaewlai, 2024; Riratanaphong, 2024). A tiered planning framework is essential. In low-value land group zones, TOD-based land readjustment and infrastructure investment can unlock development. Mid-value land group areas require integrated road-transit planning and flexible zoning (Curtis et al., 2009). High-value land in residential zones demands the preservation of amenities, height restrictions, and environmental protection to maintain market value and neighborhood character (Curtis et al., 2009; OECD, 2012; Talen, 2012).

Another key finding is that secondary-road accessibility (TSR) raises residential values across low- to high-value land groups and vacant-land values in low- to mid-value land groups, underscoring the first- and last-mile role of local streets. By shortening walking and feeder-bus distances to the rail station, these streets expand the effective catchment of transit investment, especially for peripheral neighborhoods (Cervero et al., 2013). Ban Pong's urban strategy therefore should prioritize multimodal integration by linking rail stations to surrounding areas via feeder buses, pedestrian walkways, and cycling infrastructure (Bertolini & Le Clercq, 2003; Diao et al., 2017; Lund et al., 2004). Such networks extend the functional reach of transit infrastructure and promote inclusive value uplift (OECD, 2012).

Finally, the study shows that high-value land group residential zones are shaped more by environmental quality and amenity access than by transit proximity. Land value premiums in a high-value land group are associated with proximity to rivers, green space, and tranquil urban settings (Anderson & West, 2006; Crompton, 2001; Jim & Chen, 2009; Likitswat & Sung, 2025). This supports policy tools such as zoning overlays, urban conservation districts, and green infrastructure investments (Gill et al., 2007; Likitswat & Sung, 2025). As climate change risks grow, urban resilience planning including flood mitigation, air quality improvement, and heat reduction becomes crucial to maintaining long-term land value and quality of life (OECD, 2020; Likitswat & Sung, 2025).

In summary, the SLQR model effectively captures how spatial spillovers and local attributes affect land value across different contexts. These findings reinforce the need for differentiated context-sensitive planning in non-metropolitan areas. Ban Pong's urban policy should reflect land market heterogeneity by aligning TOD investments, zoning tools, and public infrastructure in ways that balance growth, equity, and environmental sustainability.

6.1 Limitations and future research

This study has limitations. It relies on Treasury Department land value data, which may not fully capture market transactions. It also lacks qualitative insights into stakeholder views, governance, and policy processes, limiting understanding of TOD's institutional aspects. Additionally, the findings are specific to Ban Pong and may not apply to other non-metropolitan areas with different contexts.

Although this study does not directly analyze stakeholder behavior, its findings can inform multiple groups. Municipal planners can use spatial land value patterns to guide TOD zoning and infrastructure priorities in low- to mid-value areas. Developers and investors may apply the results for site selection near the heavy rail

station and secondary roads. Policymakers can leverage insights to design equitable land readjustment and improve multimodal connectivity. While preferences were not surveyed, the study supports evidence-based decisions across sectors involved in Ban Pong's urban growth. Future studies should combine qualitative and quantitative methods better to explore stakeholder roles and institutional factors alongside spatial-economic modeling.

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Data Availability Statement

The data utilized in this study were obtained from several official sources, including the Department of Lands, the Property Valuation Bureau of the Treasury Department, the Bureau of Registration Administration within the Department of Provincial Administration, and Ban Pong Municipality. Restrictions apply to the availability of these data, which were used for the current study and are not publicly available. Data are, however, available from the authors upon reasonable request and with permission from these agencies.

Declaration of Generative AI and AI-assisted technologies

During the preparation of this work, the authors used ChatGPT V4o and Grammarly exclusively to improve readability and language. However, this only impacted a small portion of the text. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Author Contributions

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