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Determination of Urban Land Value: A Systematic Literature Review

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Determination of Urban Land Value: A Systematic Literature Review[1]

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Abstract: We apply the Systematic Literature Review (SLR) approach to surveying empirical studies on urban land value. We show that research attention is directed by market size and data availability towards developed economies and residential land. Two distinct patterns of literature evolution emerge, which can be explained by methodological homogeneity adopted in the literature. Following these observations, we compare different types of methods and compile an extensive catalog of databases for land value research. Drawing from 644 factors in the empirical literature, we conduct a thematic analysis to establish a hierarchical understanding of how urban land value is determined.

Keywords: Land Value; Systematic Literature Review; Thematic Analysis

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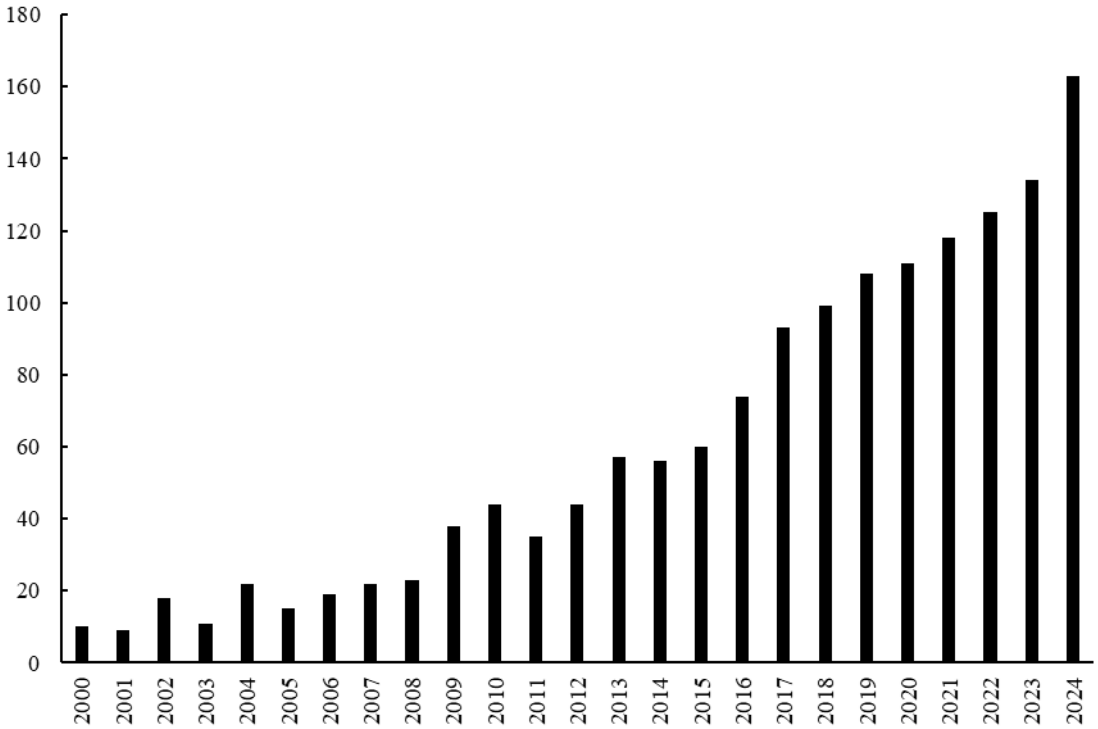
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1 Introduction

Land value is the dominant component of property value, which is essential for households to decide where to live (Merry et al., 2008) and invest (Bokhari & Geltner, 2019), for businesses to choose where to operate (Kowalski & Paraskevopoulos, 1990), and for governments to identify whom to tax (Chapman et al., 2009). As a result, scholars have a long interest in land value, dating back to Adam Smith, who regarded land as one of the three basic factors of production (labor, capital, and land) and advocated land value tax as the "perfect tax" (*The Wealth of Nations*, 1776, Book V, Chapter 2). Research on urban land value has been a growing field in recent decades (Figure 1).

Figure 1 Volume of publications on the determinants of urban land value



Source: Scopus. Search term: see Table 1.

The burgeoning academic interest in land value also echoes the rising volatility of housing prices since 2008 (Atalay & Edwards, 2022) and the exacerbating inequality of land ownership in recent decades (Piketty, 2014). The proliferation of literature on land value inevitably leads to refined divisions of the field. They ask different questions and adopt different methods as land value can be both an effect and a cause in the economic system. Some literature focuses on how land value is determined, initially under perfect market conditions (Alonso, 1964) and subsequently extended under imperfect market conditions such as elasticity of housing demand (Kau & Sirmans, 1979), government legislation (Goodall, 1970), and bargaining power (Wilson, 1978). Other literature investigates how land value affects a wide range of socio-economic

variables such as urban costs and agglomeration (Combes et al., 2019), production function for housing (Combes et al., 2021), housing prices (Huang & Tang, 2012), tax revenue (Lutz et al., 2011), remittances (Mack et al., 2023), wealth inequality (Piketty et al., 2019), and social welfare (Teulings et al., 2018).

Nevertheless, the boundary between the two strands is not always clearcut, and ignoring mutual causalities can lead to the endogeneity problem. For example, migration flows induced by unbalanced land value can feed back to land value (Foreman-Peck & Zhou, 2019), so the estimated effects of land value based on fixed land value are likely to be biased (Irwin et al., 2014). Thus, the upstream of the causality, i.e., how land value is determined, is more fundamental and is the focus of this review. Studies that treat land value as a cause are too loose (and too many) to be summarized in one reasonable review as they embark on diverse research questions. Despite their significance and interest, they are beyond the scope of our review. Furthermore, we limit our scope to urban land value where "urban" is defined as land within areas primarily characterized by residential, commercial, and industrial uses typical of urbanized environments as opposed to rural settings where land use and valuation are shaped by markedly different factors (The Appraisal Institute, 2020). Following these arguments, our literature review aims to answer the following primary research questions (RQs) in real estate economics. RQ1 and RQ2 summarize the spatial distribution and temporal evolution of the literature. RQ3 compares the prevailing methods, while RQ4 synthesizes the empirical findings.

> RQ1: How is the literature on urban land value distributed across geographic locations and land types?
>
> RQ2: How does the literature on urban land value evolve over time?
>
> RQ3: What methods are developed to determine urban land value?
>
> RQ4: What factors are identified to determine urban land value?

To answer these RQs, we need an appropriate approach to ensure the validity of the review. Researchers in Accounting, Finance, and Economics (AFE) are well-trained in quantitative research using structured statistical data, but less familiar with qualitative research involving unstructured textual data such as literature. Therefore, literature reviews in these fields are traditionally reserved for experienced, reputable researchers to ensure quality. As a result, literature reviews are particularly underrepresented in AFE research. According to the Scopus database, the proportion of review-type publications in AFE (4.48%) is much lower than that in other social sciences, such as management (5.17%) and psychology (6.23%), and even more so than in medical sciences (9.05%). Lack of review is a sign of insufficient use of existing research. This paper introduces and applies the Systematic Literature Review (SLR) approach, which provides rigorous guidelines for researchers to make better use of literature. Moreover,

it can facilitate theory building by analyzing unstructured textual data, similar to the research practice of "grounded theory" in social science (Locke, 2000).

Our systematic review has the following contributions. Empirically, we compile a comprehensive data catalog, a practical model guide, and a toolbox of identification strategy for empirical researchers. Conceptually, we develop a hierarchical framework of land value determinants with 25 subthemes, and 8 themes along 2 aggregated dimensions. It is the first comprehensive review to summarize factors identified by existing literature on urban land value. Methodologically, our paper is one of the early attempts to apply the SLR approach to survey AFE research themes. Adapted from medical sciences and management studies, we develop general principles, procedural guidelines, and analytical tools of SLR. They are applicable to other contexts in AFE.

Following the introduction, Section 2 introduces the SLR approach. Section 3 presents unbalanced research attention in the literature on land value (RQ1). Section 4 discusses the two patterns of literature evolution (RQ2). Section 5 compares the two empirical methods of land value estimation (RQ3), and Section 6 reports the thematic analysis of land value factors (RQ4). Section 7 concludes.

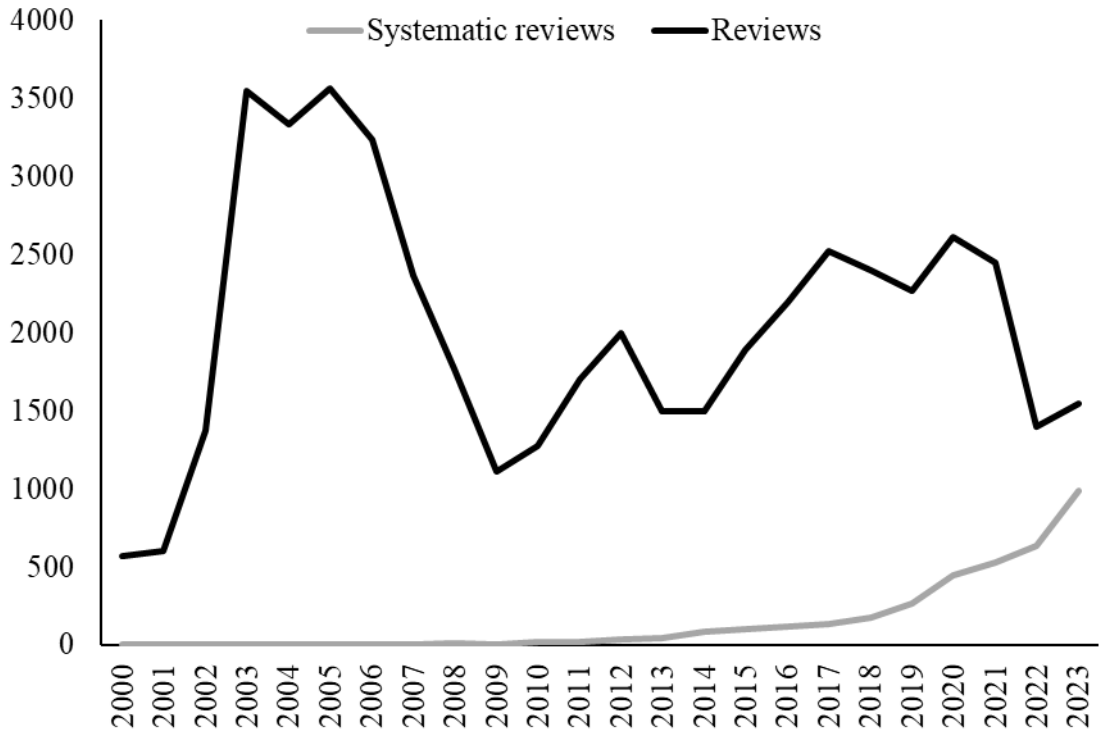
2 Systematic Literature Review

Most researchers in AFE follow a snowballing approach to literature review—start with some seminal papers, extract references of these key papers, and then retrieve further references of the references to form a self-made literature database for the review. An advantage of this snowballing approach is its efficiency in identifying relevant publications, because seminal papers usually establish basic questions and methods of a field. The drawback, however, is that it can be confined by the authors' knowledge and may overlook "hidden gem" papers and emerging trends in literature. To avoid this drawback, reviews are typically authored by experienced, reputable scholars. However, the limited supply of these researchers consistently falls short of the increasing demand for reviews in expanding research themes. Land value is one such example. It has a long history and has been developing rapidly (Figure 1), but to the best of our knowledge a comprehensive review of land value is still absent. To fill this gap and to systematically minimize possible biases in the review, our paper applies the SLR approach which is protocol-based and evidence-based rather than experience-based (Adjei-Mensah et al., 2024; Bhuiyan et al., 2024; Morrison et al., 2024; Zhao et al., 2024; Schnieder, 2022).

SLR was originally developed in medical science (Higgins & Green, 2008), but it has witnessed meteoric popularity in the social sciences in recent decades (Chapman, 2021). As shown in Figure 2, the overall volume of reviews remains stagnant whereas the SLR approach experiences growth in AFE. Nevertheless, the SLR approach has yet to gain significant recognition

and awareness within mainstream economics. Notably, no SLR has been published in the Journal of Economic Literature (the counterpart of the Journal of Accounting Literature) as of January 2025. One of the ambitions of our paper is to demonstrate the application of the SLR approach to economic researchers by applying it to the interdisciplinary topic of land value, which integrates perspectives from accounting (e.g., valuation methods), finance (e.g., investment implications), and economics (e.g., market dynamics). We must clarify that our purpose is *not* to substitute traditional reviews, but to supplement it with a systematic approach.

Figure 2 Volumes of all reviews and systematic reviews



Source: Scopus. Subject area: Accounting, Finance, and Economics.

SLRs are designed to survey existing literature in a bias-minimizing way (Snyder, 2019), in which a strict protocol is developed for search strategies, screening criteria, data extraction, and information synthesis (Moher et al., 2010). One desirable feature of protocol-based SLRs is their trustworthiness thanks to reproducibility and transparency (Greenhalgh et al., 2004). In this paper, we adopt and adapt the famous three-stage SLR of Tranfield et al. (2003) and Mahmud et al. (2022). Table 1 simply states the procedures without justifications. Detailed discussions of the procedures are provided in the **Supplementary Material**. Figure 3 follows the PRISMA guideline (Page et al., 2021) to summarize the identification and screening stages. 76 articles are finally kept, which form the basis for subsequent analyses.

Table 1 Procedures of the three-stage SLR

Stage 1: Planning

• From the review panel and establish the review protocol.
• Conduct an exploratory pilot review.
• Define research scope: urban (residential/commercial/industrial) land evaluation:
  ○ Inclusion Criteria:
  ▪ Include studies on determination or estimation of land value.
  ▪ Include studies on urban (residential/commercial/industrial) land.
  ○ Exclusion Criteria:
  ▪ Exclude studies on the effects of land value.
  ▪ Exclude studies that discuss agricultural/recreation/transportation land.

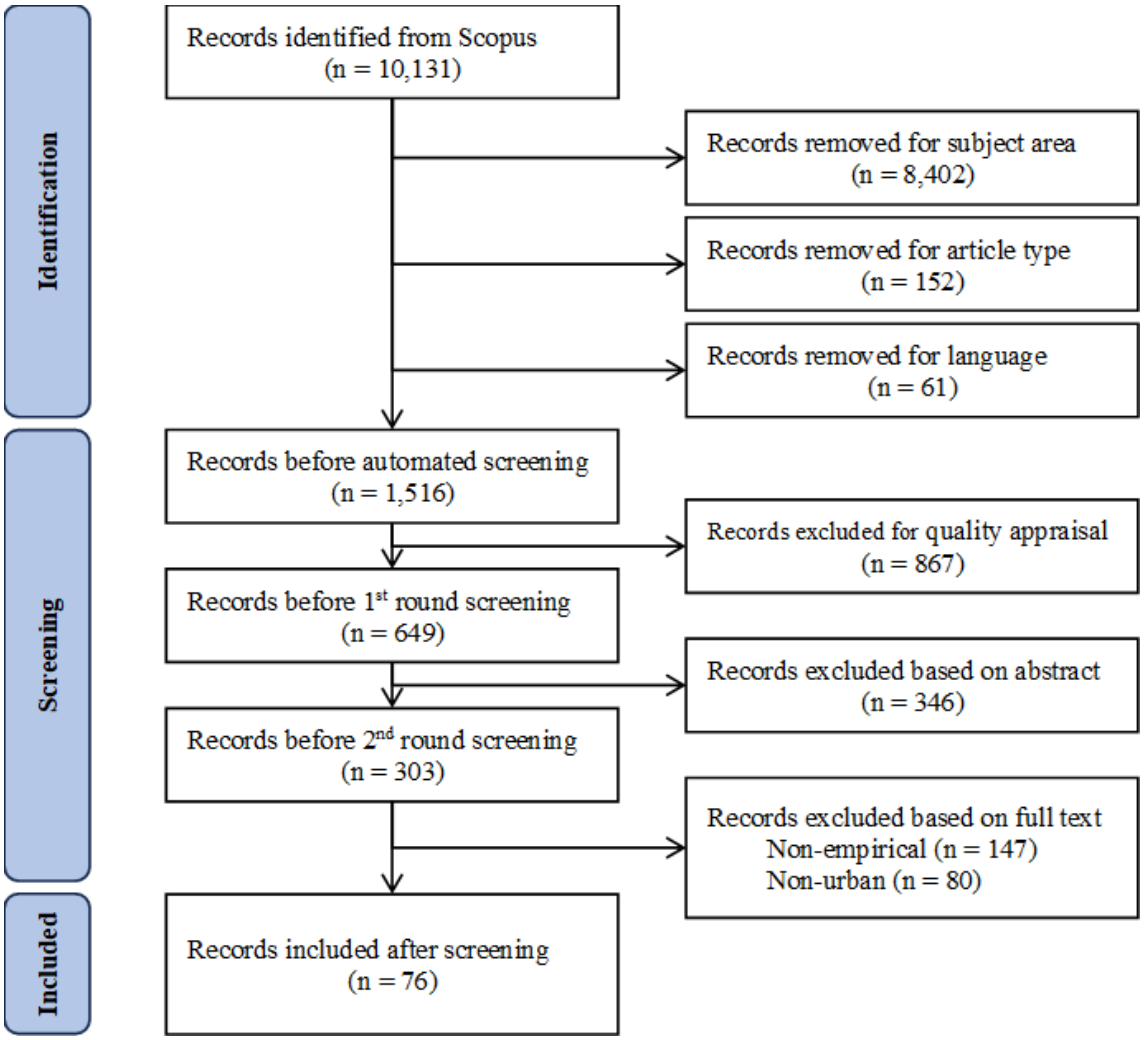
Stage 2: Conducting

Stage 2.1: Identification
• Search database: Scopus.
• Search fields: TITLE-ABS-KEY.
• Search term: "land *valu*" OR "land pric*" OR "location *valu*" OR "location pric*" OR "*valu* of land" OR "pric* of land" OR "*valu* of location" OR "pric* of location".
• Search restrictions:
  ○ Published year: no restriction.
  ○ Document type: article and review.
  ○ Subject area: Accounting, Finance, and Economics.
  ○ Language: English.

Stage 2.2: Screening
• Automated screening: publication quality (ABS 3, 4 and 4*).
• 1st round manual screening: based on TITLE-ABS-KEY.
• 2nd round manual screening: based on full text.
  ○ The results are checked by three raters independently.
  ○ Disputes are resolved by discussions and votes.

Stage 2.3: Analysis • Quantitative analysis: e.g., bibliometric analysis • Qualitative analysis: e.g., thematic analysis
Stage 3: Reporting
• PRISMA: e.g., Page et al. (2021) • Synthesis: e.g., narrative, tabular, graphical, etc. (Grant & Booth, 2009)

Figure 3 The PRISMA flowchart

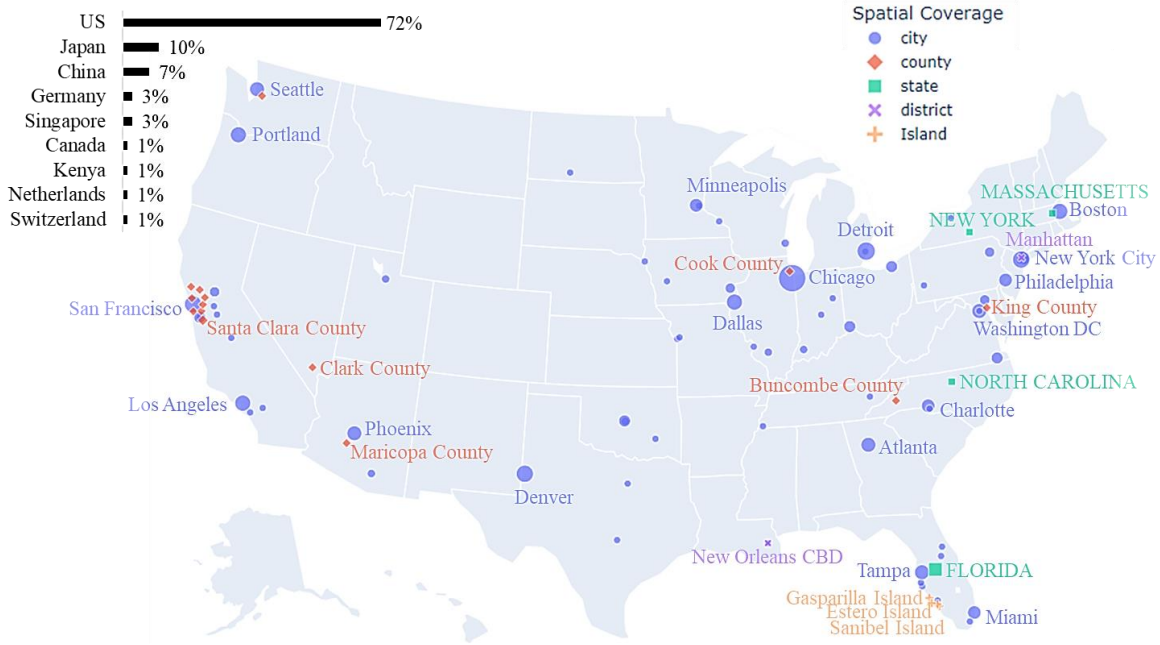


3 Distribution of Literature: Directed Research Attention

This section presents and explains the unbalanced research attention in the literature on urban land value (RQ1). As discussed below, the distribution of literature on land value is unbalanced in terms of land type, geographic distribution, spatial coverage, temporal coverage, and empirical strategy.

Among the 76 included papers, an overwhelming proportion is dedicated to residential land (83%), followed by commercial and industrial land. Most of the research is done for developed economies (92%). Studies on the US alone account for 72% of all included papers (Figure 4). Furthermore, geographic distribution within the US is also unbalanced. Research mainly concentrates on big cities along the coastlines and the Great Lakes region (Figure 4).

Figure 4 Geographic distributions and spatial coverages of research on land value



Notes: The marker size indicates the number of papers.

In addition, the spatial coverage of research is mainly at the city level. Fewer papers study land value covering larger spatial units (e.g., county, state) or smaller spatial units such as Manhattan districts in New York City (Barr et al., 2018) and specific barrier islands in Florida (Burge, 2014). These studies provide a finer-scale view of urban land values, but such highly localized research is underrepresented. The lack of different spatial scales is a missed opportunity to identify how the scale of analysis affects the conclusions drawn about land value dynamics. For example, while city-level studies capture broad urban trends, district-level, or neighborhood-level analyses can reveal granular variations driven by localized factors like zoning or infrastructure. Similarly, studies at the county or state level could better capture regional dynamics or external influences such as migration patterns and economic shocks.

In terms of temporal coverage, the reviewed studies span a wide range of years, from the 1970s (Clapp, 1980) to the 2020s (Kanno & Shiohama, 2022), but there is no longitudinal study for a longer scope. Older studies tend to examine the effects of policies (Dehring, 2006) or economic conditions (Peiser, 1987) on land value, while more recent papers focus on modern issues like sustainability (Albouy et al., 2018) and urban resilience (Kanno & Shiohama, 2022). A key limitation in this body of work is the lack of cohesive methodological frameworks that bridge these temporal divides. It hinders our understanding of how historical dynamics inform current land value determinants.

A detailed breakdown of different data types and models reveals unbalanced empirical strategies in land value research. 77.6% in our sample employ a cross-sectional approach, which focuses on land value patterns across different geographic locations at a single point in time (Fitzgerald et al., 2020). This method dominates the literature, offering insights into spatial heterogeneity and drivers of land values within specific timeframes. In contrast, only 9.2% in the screened literature adopt a time-series approach, analyzing how land values change over time in specific locations (Davis et al., 2017). These studies capture temporal trends, cycles, and impacts of policy changes or economic shifts. The remaining 13.2% use other approaches, such as panel data, spatial analysis, or combining different approaches (Davis & Palumbo, 2008; Kuminoff & Pope, 2013; Davis et al., 2021; Huang & Du, 2022). The overwhelming reliance on cross-sectional methods leads to a fragmented understanding of land value determinants, as it emphasizes spatial diversity at the expense of temporal depth. This imbalance in empirical strategy limits the ability to draw robust conclusions about causality, trend analysis, or implications of policy interventions.

These observed imbalances can be explained by "directed research attention", which is inspired by "directed technical change" (Acemoglu, 2002). In Acemoglu's theory, innovations are directed towards larger markets ("the market effect"). For example, more medical innovations have taken place in diabetes and cancer than Amyotrophic Lateral Sclerosis due to the differences in market size of the diseases. Likewise, academic research, as a special type of innovation, also aims at larger "markets" such as big countries (e.g., US, Japan) and megacities (e.g., New York, Chicago).

Meanwhile, data availability affects the difficulty of research ("the cost effect"), which can also direct the research attention to data-rich countries, cities, and land types. For example, despite China having a big real estate market, research on the land value of China is hindered by a lack of data. Similar explanations apply to the Midwest in the US. To show this point, we collect information on databases from the empirical sections of the 76 papers. A database falls into one of the three types: government databases, government sponsored databases, and private databases. They have different frequencies (daily, monthly, quarterly, yearly) and coverage (property, district, city, state, nation). We compile a catalog of land value databases in Table 2 and demonstrate the popularity of these databases in Figure 5. Note that the databases are not predetermined but identified through a systematic screening process following the SLR procedure. Therefore, the resulting list reflects their prominence in hosting peer-reviewed literature rather than a circular justification based on the handpicked papers.

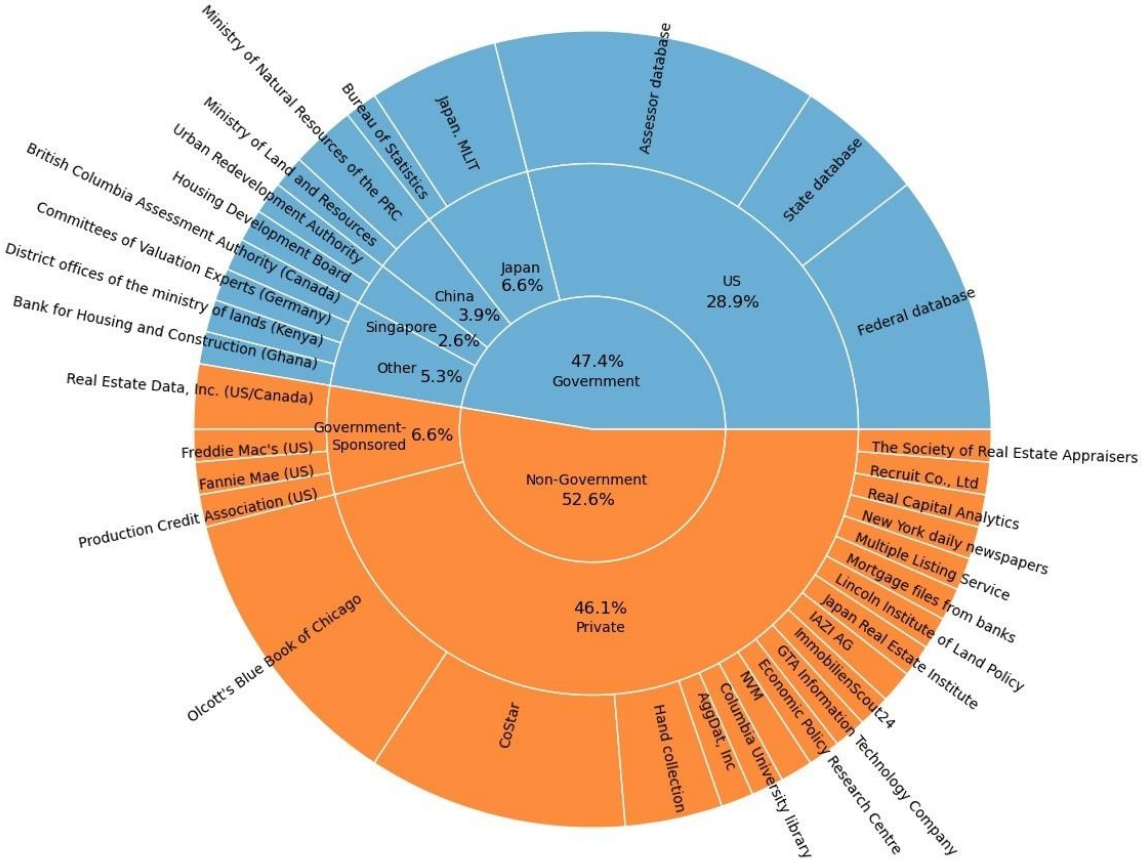
Table 2 Databases for Land Value

Database	Source	Country	Frequency	Coverage	Notes
CoStar	Private	US, UK, Canada	Daily	Property	Property-level information on location, size, age, type, ownership, and leasing activity.
Warren Group	Private	US	Daily	Property	Detailed property and transaction information.
Real Capital Analytics	Private	160 countries	Daily	Property	Various property types including office, industrial, hotels, retail, development sites, multi-family, senior housing, and self-storage.
Freddie Mac HPI	Government sponsored	US	Weekly	City	Housing price indices, loan-level dataset, and federal cost of funds index.
Real Estate Data, Inc.	Private	US, Canada	Monthly	City	Real estate analysis, reports, and forecast.
Production Credit Association & Federal Land Bank	Government sponsored	US	Monthly	City	A farm credit system to provide financing and data services to farmers and rural communities.
City-Data.com	Private	US	Monthly	District	Indices for every city in the US from crime rates to weather patterns.
Lincoln Institute of Land Policy	Private	US	Monthly	City	The FiSC database makes it possible to compare local government finances for 200 of the largest US cities across revenues, expenditures, debt, and assets.
Assessor's Databases	Government	US	Monthly	District	e.g., Buncombe, Lee, King, Dallas, Detroit, Deeds, New York City.
State Databases	Government	US	Monthly	State	e.g., Florida Department of Revenue, State of Maryland's Tax Assessment Database.
Federal Databases	Government	US	Quarterly	City	e.g., Bureau of Land Management, Federal Reserve Economic Data, Bureau of Economic Analysis, National Collateral Database, US Department of the Treasury.
British Columbia Assessment Authority	Government	Canada	Yearly	City	Annual data on property assessments for all property owners in British Columbia.

Land Registry	Government	UK	Daily	Property	Property-level information on location, age, type, ownership, and transaction price for both residential and commercial properties.
Local Committees of Valuation Experts	Government	Germany	Daily	Property	Valuation data on real estate properties.
ImmoScout24	Private	Germany	Daily	Property	Transaction and valuation data on residential and rental properties.
Informations und Aus-bildungszentrum fur Immobilien	Private	Switzerland	Monthly	City	SWX IAZI, Swiss real estate offer index, and regional indices.
NVM	Private	Netherlands	Daily	Property	Largest real estate database on transaction prices in the Netherlands.
MLIT	Government	Japan	Quarterly	City	Land prices and real estate securitization data.
JREI	Private	Japan	Daily	Property	Property-level information on appraisal.
Urban Redevelopment Authority	Government	Singapore	Yearly	Nation	Data on physical planning and development.
Ministry of Land and Resources	Government	China	Monthly	City	Official indices of house prices and land use at city level.
GTA Data	Private	China	Yearly	City	The CSMAR database includes housing price index.
Bank for Housing and Construction	Government	Ghana	Monthly	City	Housing price indices.
District Offices of the Ministry of Lands	Government	Kenya	Yearly	City	Official database in Kenya.

The US has a variety of data sources, including governments (e.g., federal, state, and assessor databases), government-sponsored agents (e.g., Freddie Mac, Fannie Mae, Production Credit Association), and private institutes (e.g., New York Daily Newspapers, Columbia University Library). These databases have facilitated research on land value in the US.

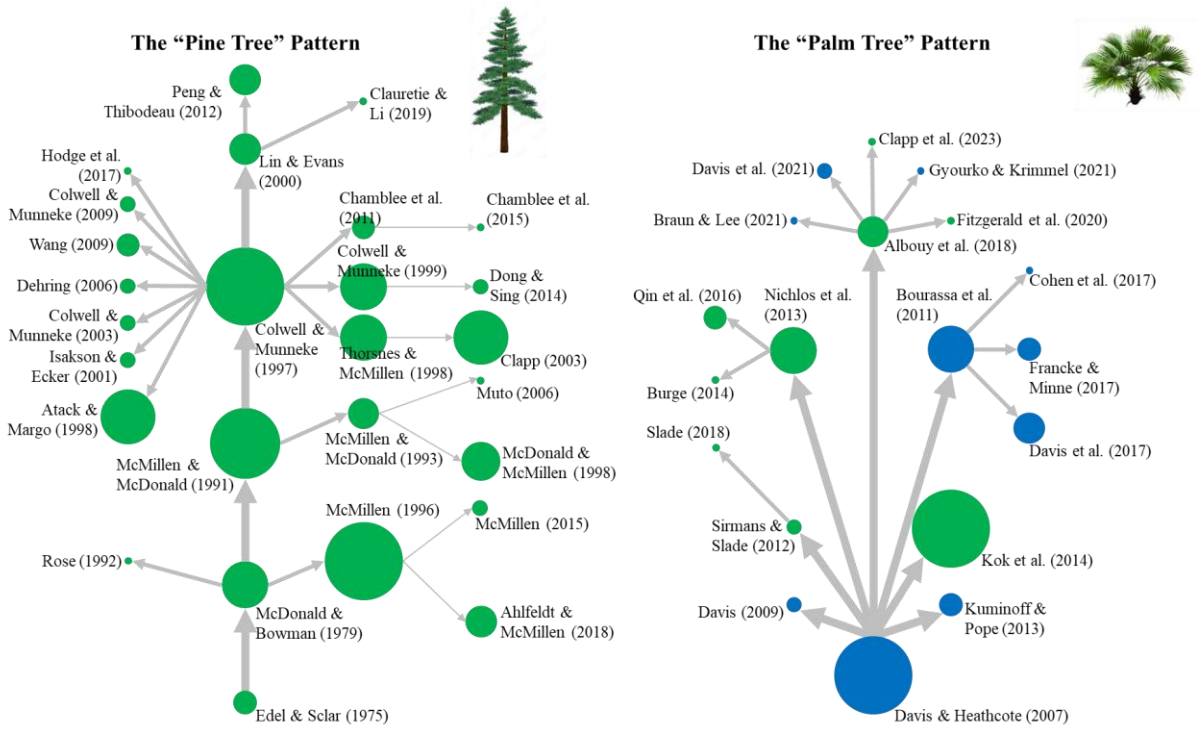
Figure 5 Databases on land value used in the literature



4 Evolution of Literature: Knowledge Tree Pattern

The distribution of literature is a static snapshot of research attention, while the evolution of literature offers a dynamic view of research development. To visualize the chronological development of literature, we employ the Edmonds algorithm (Edmonds, 1965) to automatically detect links among papers based on citations. This algorithm is originally designed to find maximum cardinality matching in a "tree", which is a set of directed "edges" with no common "vertices". In our case, a vertex (or node) represents a paper, and an edge indicates the most immediate influence between two papers based on citations. Exactly one node of the tree, called the "root" (a seminal paper), has no edge directed toward it. Papers may cite many papers in the sample, but the algorithm optimally determines the strongest links to highlight the primary storyline of the literature.

Figure 6 Trees of literature based on the Edmonds algorithm



Notes: The size of a node indicates the number of citations of the paper. Color code: green = regression method, blue = residual method (to be defined in the next section).

As shown in Figure 6, there are two "trees" growing out of the literature on land value. The left-hand side tree is rooted in Edel & Sclar (1975), who started the tradition of land value estimation using regression methods. Subsequently, the method is applied to different datasets (McDonald & Bowman, 1979), land types (McMillen & McDonald, 1991), model specifications (Colwell & Munneke, 1997), and time ranges (Lin & Evans, 2000). Each of these vertices then spawns other branches of literature, but the overall pattern of the tree is straight up. In contrast, the knowledge tree on the right-hand side has quickly developed many branches directly from the root Davis & Heathcote (2007). They were the earliest to propose the residual method, but they also influenced many papers using regression methods (Kok et al., 2014).

The French philosopher René Descartes also viewed the development of human knowledge as "a tree of knowledge", where new knowledge grows out of old when old frameworks fail to solve new problems (Ariew, 1992). Nevertheless, Descartes did not discuss how trees of knowledge grow into different shapes. Grounded in the evolution of land value research, we elaborate on patterns of trees and determination of patterns.

Taking the analogy of tree further, the left-hand side tree in Figure 6 has a "pine tree" pattern with a tall stem, while the right-hand side tree has a "palm tree" pattern with a short stem. We

notice that patterns of literature depend on the homogeneity of methods adopted in the literature. The methods used in the left-hand side tree are homogeneous (regression methods), so papers in this string of literature can easily cite and influence each other in an accumulative pattern (a pine tree feature). For example, the seminal paper (Edel & Sclar, 1975) contains basic factors of all dimensions. Building on these basic factors, later papers then add more sophisticated measures of hedonic factors (Colwell & Munneke, 1997) or spatial factors (Pace et al., 1998; McMillen, 2015).

On the contrary, the methods used in the right-hand side tree are heterogenous (including both regression methods and other methods), so this string of literature develops in a sprawling pattern (a palm tree feature). For example, the seminal paper (Davis & Heathcote, 2007) conceptualizes a house as "*a bundle comprising a reproducible tangible structure and a non-reproducible plot of land*". This novel principle inspires many papers in the field, but disparate applications are undertaken by different authors independently (Sirmans & Slade, 2012; Cohen et al., 2017; Clapp et al., 2023).

It is worth noting that the two literature tree patterns in Figure 6 are based on a screened set of 76 articles on land value. Therefore, these trees are not exhaustive enumerations of all potential pathways or linkages within the literature. For instance, "hybrid" trees can naturally emerge as researchers integrate methodologies or theoretical perspectives from one thread of literature into another. These dynamics reflect the evolving nature of the field, where "cross-pollination" or "transplantation" of methods can contribute to literature development and interdisciplinary insights. As we will demonstrate in the next section, some studies primarily employing the residual method also embed regression techniques in their analytical processes.

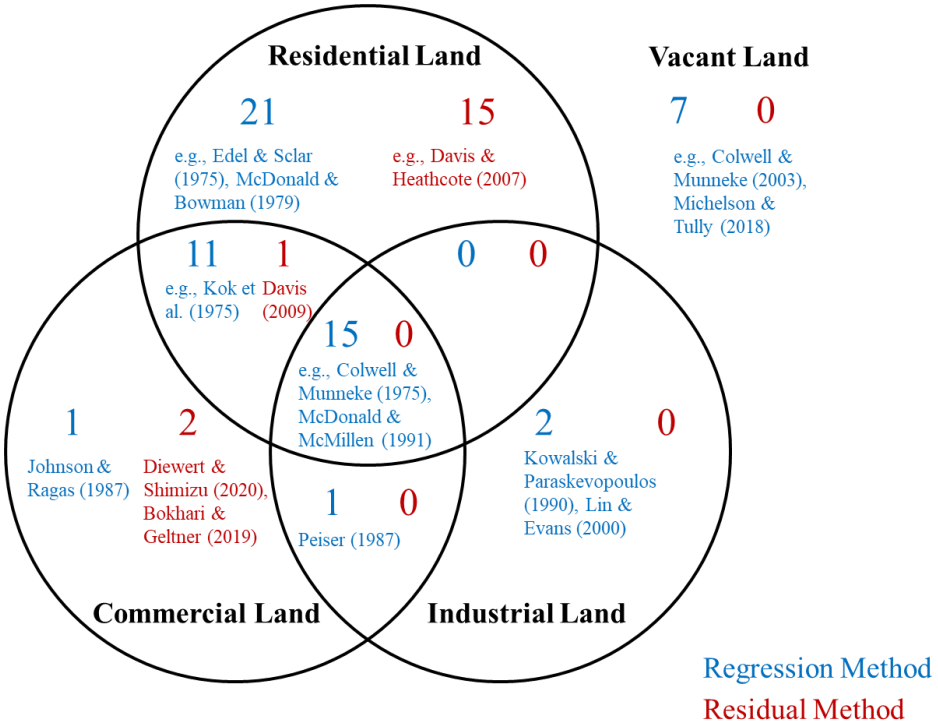
5 Methods of Estimation: A Tale of Two Methods

Having shown the importance of methodological homogeneity in shaping literature evolution, this section discusses methods of land value estimation (RQ3). As mentioned earlier, there are two general types: regression method and residual method. The following two subsections are devoted to reviewing the two methods. Before that, we briefly summarize how to decide which type of method to use.

In general, the method adopted is often influenced by the data available, particularly in the context of land value research where datasets are predominantly secondary rather than primary. If data on vacant land transactions are available, then regression methods can be directly applied to estimate factors of land value (Michelson & Tully, 2018). If only data on property transactions are available, then the residual method is usually used to extract land value from the property value (Diewert & Shimizu, 2020). The Venn diagram in Figure 7 demonstrates the connections between land types and method types. It is also noted that regression methods

are mainly used for mixed types (e.g., any combinations among residential, commercial, and industrial) of land, while the residual method is more popular for residential and commercial land.

Figure 7 Venn diagram of land types and method types



Overall, regression methods (76%) are more popular than residual methods (24%), but some studies adopt a mixed method by combining both. For example, Francke & Minne (2017) first apply the residual method to extract land value and then use the (hedonic) regression method to identify factors of the extracted land value. Similarly, Clapp (2003) uses the (spatial) regression method after applying the residual method. These cases are counted as the residual method since regressions are a secondary feature.

In addition, many up-to-date data science techniques, such as big data and machine learning, have been utilized to enhance the empirical power of both types of method (Clapp & Lindenthal, 2022). Therefore, the method used in a specific research field (land value) can be directed by the development of general-purpose methods. This resembles the disruptive effects of general-purpose technology in the innovation literature (Goldfarb et al., 2023).

5.1 Regression Method

The **regression method** is based on the econometric equation (1) or a special case of it (e.g., $\beta = 0$ or $\gamma = 0$ or both).

$$L_{it} = \alpha \times control + \beta \times land + \gamma \times spatial + \epsilon_{it}. \quad (1)$$

Vector *control* is a set of factors excluding land attributes and spatial factors. Examples of *control* include amenities (Diamond, 1980), distance to CBD (Atack & Margo, 1998), exposure to natural disasters (Fang et al., 2021), and transportation (McDonald & Osuji, 1995). Many studies (about 26% of regression methods) do not include control factors in their regressions, especially in the early literature (Edel & Sclar, 1975; McDonald & McMillen, 1998). We term this subtype as the "basic regression method".

Vector *land* is a set of factors related to attributes of land per se such as size (Clauretie & Li, 2019), tenure (Agarwal et al., 2018), and land regulations (Albouy et al., 2018). Regressions with land attributes are also known as the "hedonic regression method" since land attributes are regarded as the intrinsic component of land value (Shimizu & Nishimura, 2007). This subtype accounts for the majority (about 67%) of regression methods.

Vector *spatial* is a set of factors such as spatial autoregression and spatial geometric dependence. Regressions with spatial factors are termed as the "spatial regression method" (McMillen, 2015), which accounts for about 7% of regression methods.

Empirical studies involving factors (62 papers in our sample) provide a long list of determinants of land value (644 factors in our sample). These 62 papers include those which use regression methods and those which use residual methods complemented by regression methods. Pure residual methods do not identify factors. Themes, prominence, and significance of these identified factors are to be analyzed in Section 6, so this subsection only discusses how to choose the appropriate regression model if regression methods are adopted. Like the choice between regression and residual methods, data availability influences methodological feasibility. For example, if property-level datasets are available, then cross-sectional (Gyourko & Krimmel, 2021), panel models (Davis et al., 2021), or spatial (Clapp et al., 2023) can be used. However, if only higher-level datasets are available, then time-series models (Davis, 2009) are usually adopted. In this case, the aim is to forecast future land value at the aggregate level rather than to estimate past land value at the property level or to identify factors of land value.

5.2 Residual Method

The second type is the **residual method**. It is based on the accounting identity (2), which treats land value (L_t) as a residual of housing value (H_t) after deducting the value of the structure attached to the land (S_t). Equivalently, the equation can also be expressed by unit prices (p_t^L, p_t^H, p_t^S) and units (l_t, h_t, s_t) of land, house, and structure.

$$L_t = H_t - S_t, \text{ or } p_t^L l_t = p_t^H h_t - p_t^S s_t. \tag{2}$$

The residual method is appropriate when the dataset at hand does not separate land value from structure value. It is usually adopted when the study aims to estimate a broad range of land values at a refined spatial unit. Essentially, the method translates the task of estimating land value into estimating depreciated structure value (replacement cost). An evident advantage of the method is utilization of large-scale property transaction datasets. Nevertheless, Clapp et al. (2023) criticize the underlying assumption of the residual method that "structures are easily replaced". A possible consequence is that high and rising land value ratios identified in the literature are an artifact.

The current residual method has developed two subtypes of separating land value from structure value: one is based on regressions, while the other relies on accounting identities. The regression-based residual method, according to Jackson (1984), rearranges equation (2) into a hedonic regression equation (3) of house value.

$$H_t = \underbrace{\boldsymbol{\beta}^L \cdot \mathbf{x}_t^L}_{L_t} + \underbrace{\boldsymbol{\beta}^S \cdot \mathbf{x}_t^S}_{S_t} + \epsilon_t. \tag{3}$$

The dependent variable is house value (H_t) and the independent variables include structure-related attributes $\mathbf{x}_t^S$ (e.g., type, size) and land-related attributes $\mathbf{x}_t^L$ (e.g., location, amenities). The effects of land-related regressors are then aggregated to form the estimated land value $L_t = \boldsymbol{\beta}^L \cdot \mathbf{x}_t^L$. Later studies use more comprehensive sets of $\mathbf{x}_t^S$ and $\mathbf{x}_t^L$ such as quality of building materials (Kuminoff & Pope, 2013), garden features (Francke & Minne, 2017), distance to subway stations (Diewet & Shimizu, 2016), and latitude/longitude (Clapp, 2003). The regression-based residual method is technically similar to the regression method, only that the dependent variable is house value instead of land value.

The accounting-based residual method begins with Davis & Heathcote (2007), who transform the static accounting identity of levels (2) to the dynamic identity of growth rates (4). The growth rate $\frac{L_{t+1}}{L_t}$ can then be used to generate land value indices at the chosen spatial unit from the base period $t = 0$.

$$\frac{L_{t+1}}{L_t} = \frac{1}{\omega_t}\left[\frac{H_{t+1}}{H_t} - (1 - \omega_t)\frac{S_{t+1}}{S_t}\right]. \tag{4}$$

In equation (4), the growth rates of both housing price index $\frac{H_{t+1}}{H_t}$ and structure price index $\frac{S_{t+1}}{S_t}$ are observable. The problem boils down to the share of land value ($\omega_t \equiv \frac{L_t}{H_t}$). The estimation of ω_t is usually based on the reconstruction cost of newly built structures S_T in period $T > t$

discounted backward to period t when the structure was built (Davis et al., 2017): $\hat{S}_t = S_T \times \left(\frac{p_t^S}{p_T^S}\right)$, where P_t^S is the overall reconstruction index in period t. The share of land value in period t can then be estimated by $\widehat{\omega}_t = \frac{H_t - \hat{S}_t}{H_t}$. However, this approach can only calculate the land value in the period when the structure was built, so a large volume of transaction prices of old houses is not utilized. To address this limitation, another string of the residual method investigates the depreciation rate of structures (δ), so they can capture a full dynamic history of land value at different ages of structures (A_t). Instead of discounting backward from future value S_T to present value S_t as in Davis et al. (2017), the so-called "builder's model" (Diewet & Shimizu, 2016, 2020) iterates forward from a past value S_0 to present value S_t by the law of depreciation $S_t = S_0(1-\delta)^{A_t}$. The depreciation rate is assumed to be fixed $\delta = 1.5\%$ (i.e., straight-line depreciation in accounting) in some studies (Davis & Palumbo, 2008), while others allow for age-dependent depreciation rate δ_A (Braun & Lee, 2021). Hedonic regressions are sometimes used to estimate δ_A after controlling other structure attributes and location (Bokhari & Geltner, 2019), so this method integrates both econometric regressions and accounting identities. A substantial body of literature employs the same method to create land value indices for various spatial units, ranging from the national level down to the census tract level (Davis et al., 2017; Davis et al., 2021).

It should be clarified that our categorization of methods is not the only possible approach. For example, hedonic regression is widely employed in both the regression method and the residual method. If the focus is on the technique itself, both can be grouped under "regression-based methods", while the accounting-based residual method stands as a distinct category. However, this review prioritizes the fundamental assumption underlying land value estimation rather than the technical process involved. Therefore, we categorize "regression-based residual method" as part of the residual method because regression serves only a secondary role in operationalizing equation (2) of the residual method.

5.3 Identification Strategy

A critical issue in empirical literature is the identification problem, i.e., the challenge of establishing a causal relationship between variables in a way that allows researchers to draw meaningful and unbiased conclusions about the impact of one variable on another (Manski, 1993). Identification problems in the land value research can arise from: (i) endogeneity bias (e.g., amenities, land use, and land regulations can be influenced by land value), (ii) selection bias (e.g., observable data of land value can be selective), (iii) spatial dependence (e.g., the land value of one parcel can be influenced by that of neighboring parcels), and (iv) temporal dynamics (e.g., common cycles and trends underlying land value and regressors). To deal with these problems, two types of identification strategies are used in the literature. It is worth noting that, in most cases, papers use a combination of both types rather than relying on one.

The first type of strategy is to establish a theoretical model to pin down the causal relationships between land value and other variables. Theories provide foundational principles and conceptual insights that explain underlying mechanisms or relationships. They differ from modeling assumptions, which are specific premises adopted to operationalize a theory into an empirical model for testing, and from methodologies, which refer to the procedures or techniques used to analyze data. Popular theories include hedonic theory (Barr et al., 2018), auction theory (Dong & Sing, 2014; Agarwal et al., 2018), real option theory (Cunningham, 2006), information frictions theory (Broxterman & Zhou, 2023), and New Keynesian monetary theory (Liu et al., 2013). Specifically, the hedonic theory is the most popular theory in our sample (accounting for about 61% among all theories). The central idea of the hedonic theory is that land value is determined by the perceived utility that individuals derived from the characteristics associated with the land. The theory assumes that individuals make optimal choices based on their preferences and budget constraints, usually resulting in a hedonic pricing regression of land. Factors in the regression must be theoretically founded land characteristics which bring financial, physical, or mental benefits.

The second type is to resort to empirical designs to identify causal relationships. For example, Difference-in-Differences (DiD) can be applied if an exogenous event exists (Agarwal et al., 2018). As an extension, Slade (2018) utilizes a spatial DiD to mitigate the omitted variable bias and spatial dependence. Instrumental variables and regression discontinuity are popular methods of correcting for endogeneity biases (Ahlfeldt & McMillen, 2018). The Heckman model is usually adopted to deal with selection biases (Hodge, 2017). For cross-sectional data, propensity score matching can facilitate identification of the treatment effect (Michelson & Tully, 2018). For time-series data, Granger causality and cointegration tests are standard tools of identification (Fitzgerald et al., 2020). Most commonly, fixed effects are used to control for time-invariant unobserved factors in panel data settings (Kuminoff & Pope, 2013).

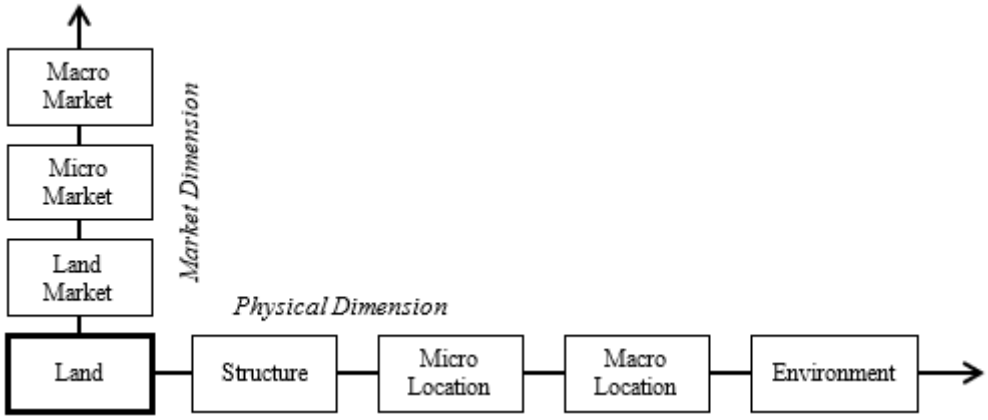
These strategies are particularly relevant to studies involving regressions because identification problems stem from the uncertain nature of factors in regression analyses. The estimated relationship can be attributed to either causality or correlation. In contrast, the residual method is based on accounting identities, making it immune to the causality-correlation distinction. As pointed out by Francke & Minne (2017), "*disengaging house prices into structure values and land values solve the identification problem in itself*."

6 Factors of Land Value: Hierarchical Thematic Analysis

The identified factors are crucial for understanding land value determination. To portray the findings (RQ4), this section applies the "six-phase thematic analysis" (Braun & Clarke, 2006) to identify, analyze, and synthesize the identified factors of land value. As mentioned in Section 5, there are 644 raw factors collected from the 62 papers involving regressions. Many of these

factors are semantically the same under different names (e.g., “close to CBD” and “close to commercial center”). In other cases, the definitions of some factors are opposite but basically the same (e.g., “there is a superstore in the neighborhood” and “there is no superstore in the neighborhood”). To facilitate comparison and analysis, the review panel unifies the names of factors. Further synthesis is done to categorize factors into subclusters (subthemes) and clusters (themes). It results in a structured narrative from factors to themes (Guest & McLellan, 2003). The 644 raw factors are grouped into 25 unique subthemes and 8 themes.

Figure 8 Dimensions of land value factors



The eight themes either belong to the **physical dimension** or the **market dimension**. The analysis of land value starts with land attributes. As physical space extends outward from land, structures built on land are included in the analysis. Next, as physical space expands further, micro location, macro location, and the environment of land are further considered. On the other hand, land market, micro market, and macro market are extensions along the market space, which describes the supply side, demand side, and macroeconomic conditions of land transactions. Land attributes lie in the intersection of the two dimensions (Figure 8), so we discuss these factors separately in the following analysis.

The hierarchical thematic map (Table 3) categorizes raw factors to subthemes and themes along the physical and market dimensions. Building on these identified themes, the following two subsections quantify the prominence and significance of land value factors. The former focuses on the literature attention (thematic prominence), while the latter focuses on the empirical findings (thematic significance).

Table 3 Thematic analysis of factors of land value

Themes	Subthemes	%	Factors
Land: attributes of a land	size	7.8	area (Bourassa et al., 2011), lot area squared (Barr et al., 2018), square feet (Clapp et al., 2023), acres (Clauretie & Li, 2019), parcel size (Nichlos et al., 2013)
	tenure	0.1	60-year tenure (Agarwal et al., 2018)
	land surface	0.9	oddly shaped, difficult topography (Cunningham, 2006), irregular (Gedal & Ellen, 2018)
	land conditions	2.8	Elevation (Ahlfeldt & Wendland, 2016), buildable (Hodge et al., 2017), rough graded, fully improved, previously developed (Kok et al., 2014), cultivated (Shonkwiler & Reynolds, 1986)
	land regulation	7.6	proposed use (Albouy et al., 2018), classification (Qin et al., 2016), impact fees (Burge, 2014), zoning plan (McMillen & McDonald, 2002; Clauretie & Li, 2019)
Structure: attributes of the structure attached to the land	structure attributes	2.2	Height (Ahlfeldt & McMillen, 2018), capacity constraint (Agarwal et al., 2018), floor area ratio (Bourassa et al., 2011), % of dwelling units in apartments (Clapp, 1980), property type (Nichols et al., 2013), assessed value of structure, site served by public water and sewer (Leggett & Bockstael, 2000)
	building regulation	0.6	property restrictions (Francke & Minne, 2017), required resistant level of wind and wave loads (Dehring, 2006), fire prevention (Kanno & Shiohama, 2022)
Micro Location: specific location and immediate neighborhood of a land	relative micro location	1.1	corner lot (Atack & Margo, 1998), cul-de-sac (Clapp et al., 2023)
	close to scenery	1.7	within walking distance to river (Ahlfeldt & McMillen, 2018), lake, bay, gulf, canal (Dehring, 2006), park (Gedal & Ellen, 2018)
	close to public transport	5.1	within walking distance to main road (Asabere, 1981), subway (Barr et al., 2018), commuter railroad line (McMillen & McDonald, 1998)
	close to specific places	5.0	within walking distance to high-class residential zone (Asabere, 1981), greenbelt (Clapp et al., 2023), commercial zone (Slade, 2018), sewage treatment plant (Leggett & Bockstael, 2000)
Macro Location: broader location of a land within the city or region	coordinates	0.9	latitude and longitude (Ahlfeldt & Wendland, 2016; Cohen et al., 2017)
	distance to scenery	3.0	distance to river (Ahlfeldt & Wendland, 2016), lake (Ahlfeldt & McMillen, 2018), coast (Albouy et al., 2018), gulf (Dehring, 2006), canal (Johnson & Ragas, 1987)
	distance to CBD	11.3	distance to CBD (Ahlfeldt & McMillen, 2018), city hall (Edel & Sclar, 1975), downtown (Colwell, 1997)

	distance to public transport	15.2	distance to primary roads (Clapp et al., 2023), freeway (Thorsnes & McMillen, 1998), tollways (Colwell & Munneke, 1999), airport (Qin et al., 2016), nearest station (Shimizu & Nishimura, 2007)
	distance to specific places	9.8	distance to Broadway (Barr et al., 2018), golf (Clapp et al., 2023), city boundary (Colwell & Munneke, 1999), major shopping center (McDonald & Osuji, 1995), high income zip (Fitzgerald et al., 2020)
Environment: non-location factors describing the environment in the neighborhood	demographic environment	3.0	population density (McDonald & Osuji, 1995), education (Ahlfeldt & Wendland, 2016), race (Clapp, 1980), age (Thorsnes & McMillen, 1998)
	economic environment	4.3	employment (Ahlfeldt & Wendland, 2016), family income (Clapp, 1980), median income (Ihlanfeldt, 2007), average light at night (Qin et al., 2016)
	social environment	3.1	crimes (Diamond, 1980), teacher ratio (Burge, 2014), school crowding (Ihlanfeldt, 2007), fecal coliform concentration (Leggett & Bockstael, 2000)
	natural environment	2.8	particulate pollution (Clapp, 1980), erosion danger, seismic danger, risk of landslide (Cunningham, 2006), flood elevation (Dehring, 2006), air particulate count (Diamond, 1980), PM2.5 (Huang & Du, 2022)
Land Market: supply and demand side of the land market	land market demand	2.5	number of bids, joint bid, bidding experience (Agarwal et al., 2018), developer (Clauretie & Li, 2019), bid spread (Dong & Sing, 2014), type of the bid (Michelson & Tully, 2018)
	land market supply	2.8	previous launch within the neighborhood (Agarwal et al., 2018), sold by a chief (Asabere, 1981), type of the auction (Clauretie & Li, 2019; Qin et al., 2016), land supply (Rose, 1992)
Micro Market: markets associated with or inseparable from the land market	housing market	1.7	housing price index (Peiser, 1987), lagged housing price index (Clauretie & Li, 2019), anticipated housing prices, price uncertainty (Cunningham, 2006)
	rental market	0.3	rental rate (Peiser, 1987; Ihlanfeldt, 2007)
Macro Market: macroeconomic conditions	macroeconomic indicator	3.3	per capita income (Burge, 2014), interest rate (Clauretie & Li, 2019), recession year (Kowalski & Paraskevopoulos, 1990), GDP per capita (Wang, 2009), unemployment rate (Peiser, 1987)

Note: Column 3 lists the percentages of the screened literature (76 articles) using the corresponding subthemes.

6.1 Thematic prominence

We first describe the prominence of factors along the $N_T = 8$ thematic dimensions. Note that different papers have different numbers of factors. For example, in Atack & Margo (1998) there are only two factors, while Shimizu & Nishimura (2007) consider 70 factors. To take this disparity into account, we distinguish between paper-based shares (s_t^P) and factor-based shares (s_t^F) to measure thematic prominence. Denote the total number of papers as N_P and the total number of factors for theme t in paper p as $N_{p,t}$ where $t = 1,2,\dots,N_T$ and $p = 1,2,\dots,N_P$. The total number of factors is therefore $N_F = \sum_{t=1}^{N_T}\sum_{p=1}^{N_P} N_{p,t}$. The factor-based share (s_t^F) of theme t is defined as the raw proportion of factors falling into the theme t without considering paper as the calculation units:

$$s_t^F \equiv \frac{1}{N_F}\sum_{p=1}^{N_P} N_{p,t} \text{ for } t = 1,2,\dots,N_T. \quad (5)$$

In contrast, the paper-based share (s_t^P) is defined as the average proportion (over N_P papers) of factors falling into the theme using papers as the calculation units:

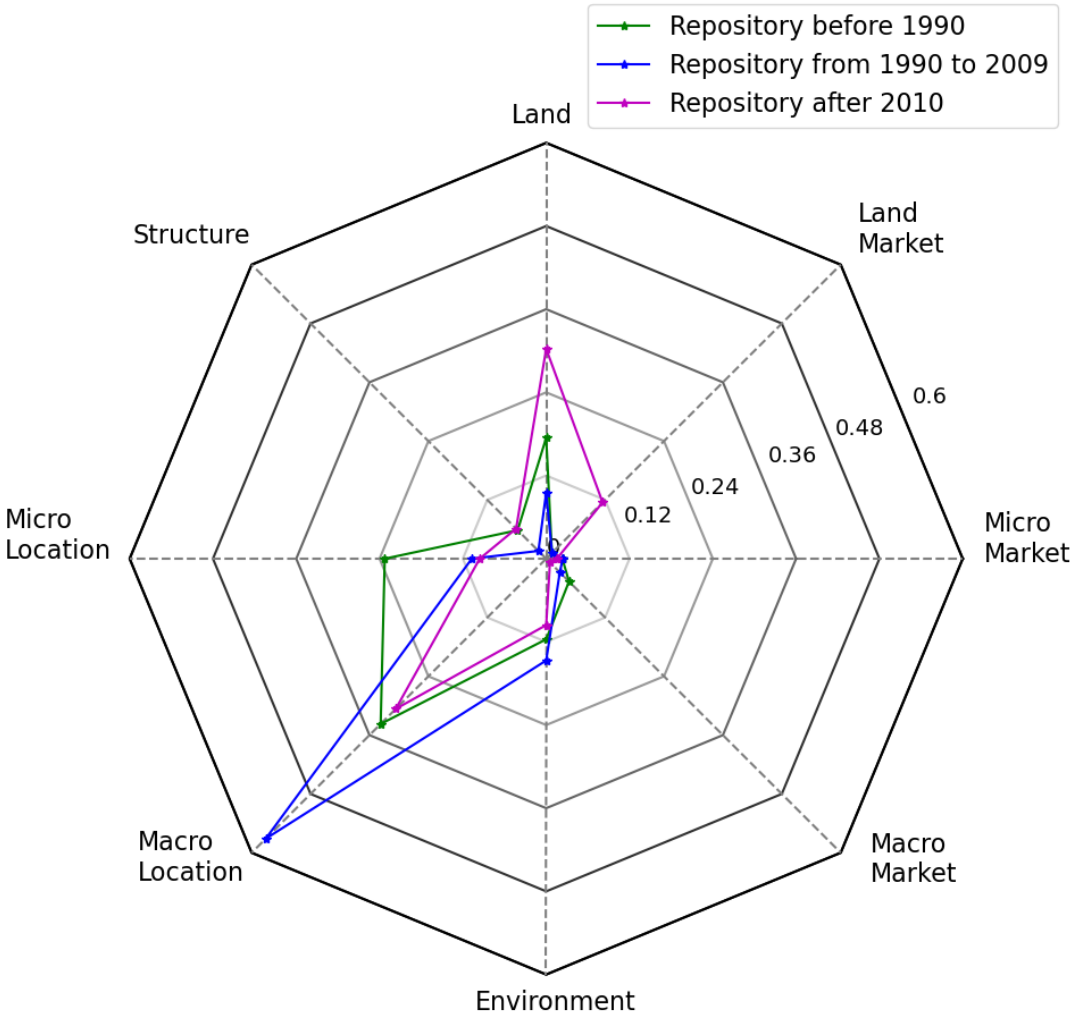
$$s_t^P \equiv \frac{1}{N_P}\sum_{p=1}^{N_P} \frac{N_{p,t}}{\sum_{\tau=1}^{N_T} N_{p,\tau}} \text{ for } t = 1,2,\dots,N_T. \quad (6)$$

Table 4 presents two measures of prominence. Three stylized facts stand out. First, factor-based and paper-based shares are almost identical. From the proximity between (5) and (6), we can infer $s_t^F \approx s_t^P \to \frac{N_F}{N_P} \approx \sum_{\tau=1}^{N_T} N_{p,\tau}$, i.e., the numbers of factors across papers are close enough. Hereinafter, we stick to the factor-based shares in the analysis, but the conclusions are robust if paper-based shares are used. Second, the attention paid to "where it is" outweighs the attention to "what it is" in land value determination. Among all themes, *macro location* is the most prominent determinant for land value, accounting for about 40% of all factors. This finding aligns with the old wisdom of "location, location, location". However, it is worth noting that the *macro location* of a land with reference to the city matters more than the *micro location* with reference to the neighborhood. *Land* attributes (e.g., size, shape, orientation) are the next most prominent theme accounting for about 20% of all factors. Third, themes in the market dimension are relatively less prominent compared to those in the physical dimension. This unbalanced prominence suggests that authors assume or believe that land markets (and housing markets) are highly competitive and efficient, so various bidding arrangements only contribute small perturbations of land value. Land can be treated as an asset, so the "Efficient Market Hypothesis" should also apply (White, 1978).

Table 4 Measures of thematic prominence

Dimension	Theme	Factor-based share (s_t^F)	Paper-based share (s_t^P)
Physical	Land	0.197	0.216
	Structure	0.042	0.049
	Micro Location	0.120	0.129
	Macro Location	0.422	0.388
	Environment	0.120	0.114
Market	Land Market	0.057	0.059
	Micro Market	0.020	0.016
	Macro Market	0.022	0.028

Figure 9 Changes of thematic prominence over time



To further capture chronological changes of the literature, we use a radar chart (Figure 9) to compare shares of factors in the eight thematic dimensions over time. The identified patterns of thematic prominence are generally maintained, but the waxing-and-waning of shares over time suggests that the prominence of factors related to *macro location* and *land* tends to move in opposite directions. As shown in Figure 9, the share of factors related to *macro location*

shrinks from about 50% before 2009 to less than 30% after 2010, while the share of factors related to *land* expands from about 10% to about 25% during the same time. One explanation is that literature co-evolves with reality. The burst of the housing bubble in 2008 has decreased the share of extrinsic "speculative value" (related to *macro location*) and increased the share of intrinsic "use value" (related to *land*) of land (DeFusco et al., 2022), reflected by a similar change of thematic prominence in land value literature. After 2010, *macro location* and *land* become almost equally prominent themes. Therefore, the attention of literature is partly directed by real-world changes.

6.2 Thematic significance

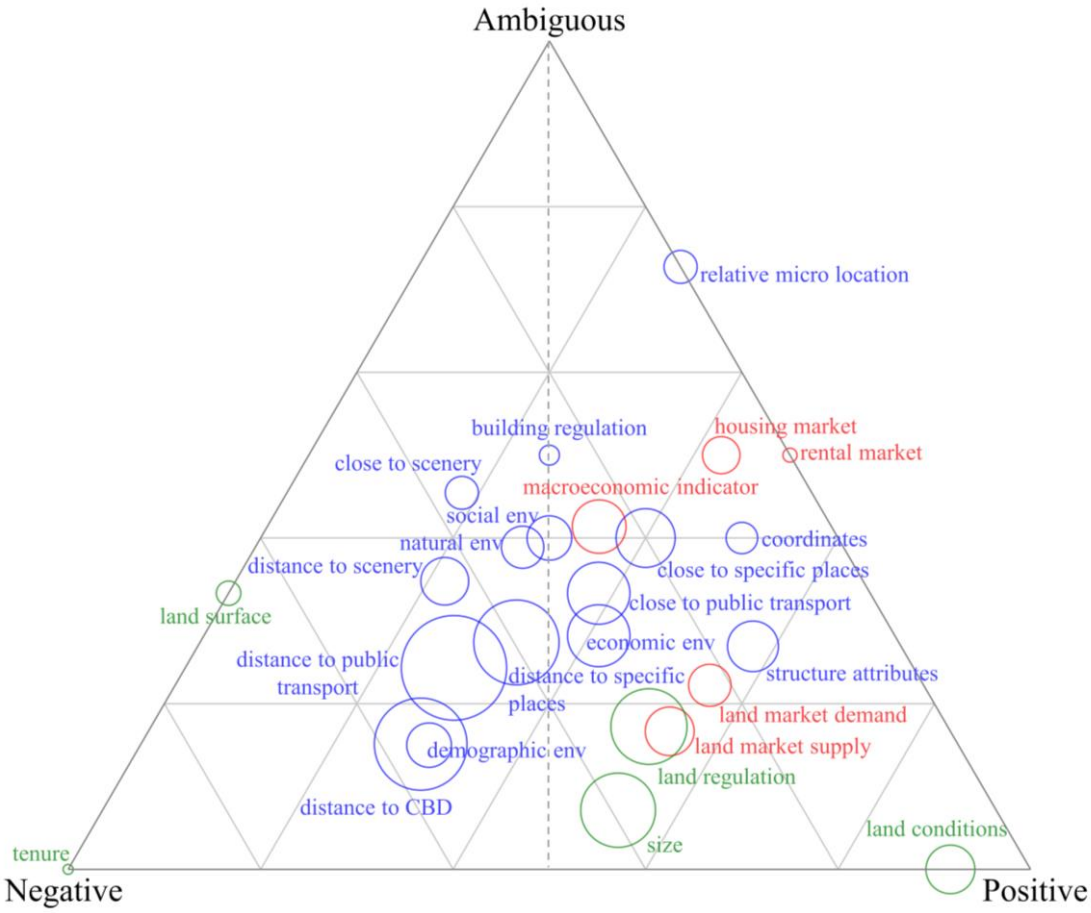
In the thematic analysis, we categorize the raw factors into 25 subthemes, so that the signs of factors can be meaningfully and consistently compared. The effect of a factor on land value can be negative (N), ambiguous (A), or positive (P). Based on factors belonging to the same subtheme, we can calculate the average ratios of N, A, and P. These ratios determine the coordinates of factors in a NAP ternary plot, which can intuitively demonstrate thematic significance. This NAP framework is inspired by the barrier-enabler-ambiguous framework in technology adoption literature reviews (Zhang et al., 2024). Based on the ternary plot (Figure 10), three patterns can be drawn.

First, more factors lie on the positive side. All factors in the market dimension (red) and most factors of land attributes (green) have positive effects on land value. Measures of these factors are usually time-varying with a prospect of rising (e.g., macroeconomic indicator), so they contribute to the growing trend of land value.

Second, factors in the physical dimension (blue) and the market dimension (red) are more ambiguous than those related to land (green). It is because land attributes (e.g., size, tenure) influence the intrinsic components of land value, so the effects are more stable. In contrast, factors in the physical and market dimensions influence the extrinsic components of land value, so the effects are less stable due to the uncertainties in the two dimensions.

Third, thematic prominence is positively correlated with thematic significance. In Figure 10, the thematic prominence of a factor is measured by the size of the circle, while the thematic significance can be measured by the distance from the A-vertex. The correlation between size and A-ratio is -0.35, which suggests that a more prominent factor is less ambiguous (or more significant).

Figure 10 Thematic prominence and thematic significance



Notes: For each vertex (N, A, and P), draw parallel lines to the opposite edge of the vertex. A closer parallel line to the vertex indicates a higher ratio of that vertex. Blue = physical dimension. Red = market dimension. Green = land. Size of circles = number of factors.

Arguably, this pattern may simply reflect a statistical construct—major factors like size and distance to CBD are prominent because they are significant, while minor factors like building regulations are less considered because they are proven to be insignificant. However, if prominence is primarily driven by statistical significance, there is a risk of perpetuating research bias. Scholars may disproportionately focus on factors with established significance, thereby neglecting less prominent but potentially impactful determinants. This could result in an incomplete understanding of land value dynamics and missed opportunities to identify underexplored causal relationships. Moreover, policy decisions based on such patterns may overemphasize prominent factors, such as proximity to CBD or lot size, while overlooking the cumulative impact of less-studied elements like zoning laws or environmental regulations. This could lead to ineffective or unbalanced policies that fail to address the full spectrum of influences on land value.

7 Conclusions

This paper employs a systematic approach to examine the empirical literature on urban land value determination. The SLR presents an unbalanced distribution of literature focus (RQ1), which is explained by "directed research attention" (e.g., market size, data availability, real-world changes, and general-purpose techniques). We then provide a chronological narrative of literature evolution (RQ2) which is explained by methodological homogeneity. Given the importance of data and methods, we compile an extensive catalog of databases utilized in the reviewed literature and compare the two methods of land value estimation (RQ3). Thematic analysis is then applied to establish a hierarchical framework to synthesize various factors of land value (RQ4)—644 factors, 25 subthemes, 8 themes, and 2 aggregated dimensions.

The systematic review provides a bias-minimizing summary of existing literature and an evidence-based forecast of future research. Based on the findings, we propose three potential research directions in the future research of land value.

First, we have shown that there has been an unbalanced growth in the literature on developed economies and residential land. It is partly due to the lack of academic interest in developing economies and non-residential land ("the market effect"), and partly due to the lack of available data ("the cost effect"). To address this unbalanced distribution, future research can invest in creating new databases on land and property transactions. One promising source of data is web-scraping from real-estate websites such as Zoopla and Rightmove (Bricongne et al., 2023), which can provide high-frequency, property-level observations on both transacted and listed properties.

Second, we have seen that the most popular method is still regressions (particularly hedonic regressions), which can be dated back to 1970s (Edel & Sclar, 1975). With the fast progress of data science in recent years, new methods are expected to emerge such as big data methods (Livingston et al., 2021) and machine learning algorithms (Shen & Ross, 2021). The development of a specific research field (e.g., land value) can be directed by the development of general-purpose techniques (e.g., AI).

Third, the most prominent factors are those related to *macro location* (speculative component of land value), but *land* attributes (intrinsic component of land value) have become increasingly prominent since the global financial crisis in 2008. The "duet dance" between academia and market suggests that future research on land value continues to be directed by real-world fluctuations.

Our review sets a good example of applying the "systematic literature review" approach to an economic topic. We have made one of the earliest attempts to introduce this useful technique

to mainstream economic reviews. The qualitative and quantitative techniques applied in this paper can enrich AFE researchers' toolbox and keep abreast of the vast flow of literature. As a protocol-based and evidence-based procedure (rather than relying on experience-based judgement), the systematic approach to literature review can offer emerging researchers a greater opportunity to produce high-quality surveys—traditionally regarded as an exclusive skill of experienced, reputable scholars.

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Supplementary Material

by Peng Zhou, Yue Gai, and Chaowei Wang

Our three-stage Systematic Literature Review (SLR) is adapted from Tranfield et al. (2003) and Mahmud et al. (2022). This supplementary material provides a detailed discussion and justification of the procedures in Table 1. Note that, like other types of qualitative research, SLRs do not have distinctive, linear stages. Rather, the process is iterative and reflective, involving a constant moving back and forth (Nowell et al., 2017).

To ensure validity, the procedures pay attention to three potential biases (Castañer & Oliveira, 2020). First, *retrieval bias* can arise due to inappropriate search database, search term, and search restrictions. This bias is rooted in the sources of literature, so it affects the trustworthiness of the entire review from the very beginning. To mitigate retrieval bias, we experimented on different search strategies to avoid missing any relevant papers in Stage 2.1. Second, *selection bias* can result from ambiguous selection criteria and inconsistent selection process. It can lead to omission of relevant articles, inclusion of irrelevant articles, and using inconsistent selection criteria. In Stage 2.2, we conducted two rounds of manual screening collaboratively to minimize selection bias. Third, *expectancy bias* is caused by the researchers' conscious/unconscious preferences and existing paradigms. It gives rise to a subjective summary of the literature and undermines the validity of the review. In Stage 2.3, we approached the literature data inductively and followed well-established guidelines for both qualitative and quantitative analyses to attenuate expectancy bias.

Stage 1: Planning

Prior to the three stages, a review panel (the authors) was formed, a review protocol was developed, and an exploratory pilot review was conducted. These planning arrangements aim to enhance procedural rigor and to resolve disputes throughout the review (Tranfield et al., 2003).

The review protocol is developed to define clear research questions, to outline the review roadmap (i.e., who does what), and to agree on procedures of conflict resolution (discussion and vote). To pinpoint a relatively specific scope to make the SLR relevant, effective, and applicable, we initiate an *exploratory pilot review* using the sample articles (in total 340) obtained from searching "land value" in Scopus. To maintain the focus, we determine the inclusion and exclusion criteria and only review articles on urban land (residential and commercial) valuation. This is because valuation of agricultural land, recreational land, transportation land and other types of land are bundled with their respective purposes, which are entirely distinct from each other and from urban land. Moreover, further applications of land value on tax policies, housing prices, urban development, etc., are also beyond the scope of this SLR.

Stage 2: Conducting

Stage 2.1: Identification

Search database. Scopus is selected as the database, which is one of the largest academic archives of peer-reviewed literature. Alternative databases include Web of Science and ScienceDirect, but the former covers a narrower range in the subject area of "Business, Economics, and Management" (Martin-Martin et al. 2018) and the latter has a narrower coverage due to its commercial scope. Another popular choice, Google Scholar, contains too much non-peer-reviewed literature, so the validity and reliability are difficult to judge. Therefore, we use Scopus as the sole database for the SLR following recent practices.

Search fields. It is a general practice in SLR to set search fields within "article title, abstract, keywords" (TITLE-ABS-KEY), rather than "all fields" because of two reasons. On the one hand, many dated articles do not have body texts in the database, so it can cause retrieval bias against older publications. On the other hand, "land value" or "land price" are common phrases which can appear in general statements in the body text of an article. It is, however, unlikely to be omitted from TITLE-ABS-KEY if land value is the focus of the research.

Search term. To determine the search terms, we followed an iterative procedure. The review panel first conducted a pilot search using the term "land value" in TITLE-ABS-KEY of Scopus. After applying the automated screening, we obtained 340 results. We then performed a text analysis on the search outcome using Python algorithm to identify the most frequently used phrases. It is noted that some variants of "land value" are used such as "land price", "location value", "price of land", "evaluation of land", "price of land", etc. Therefore, this simple, highly restrictive search term may miss many papers using these variants. Following that, we ran another pilot search using a highly flexible term ("land" OR "location") AND ("*valu*" OR "pric*"). This is to capture the two necessary features of the research, one on land/location and the other on value/price. After the automated screening, we had 3,532 papers left.

One unanticipated type of words appearing in the search result is place names ending with "land", such as England, Scotland, Ireland, and Iceland. This problem of false inclusion can be solved by adding a space in front of land, i.e., " land". Yet, this search term is still too flexible that "land/location/…" and "value/price/…" can well be far away apart. Some quick inspections suggest that most papers are indeed irrelevant to land value.

To reconcile between an over-restrictive term and an over-flexible term, we craft a search syntax to exhaustively list all possible variants: " land *valu*" OR " land pric*" OR "location *valu*" OR "location pric*" OR "*valu* of land" OR "pric* of land" OR "*valu* of location" OR "pric* of location". This is to restrict the two parts of the search term, "land/location/…"

and “value/price/…”, to appear in one phrase. The search returns 649 articles after automated screening. This eclectic search term strikes a good balance on the tradeoff between retrieval bias and search efficiency.

Search restrictions. To minimize retrieval bias, we do not restrict the time frame (the search date was 30/03/2023). The document type is limited to “journal articles” and “reviews”, because other research output like books and book chapters may not be peer reviewed or quality assured. The subject areas are restricted to “economics, econometrics, and finance” to focus on the most relevant studies. Following the convention of SLR literature, publication language is restricted to English (Follmer & Jones, 2018). Nowadays, most academic publications are written in English, while articles published in other languages usually provide English translations of titles, abstract, and keywords. Thus, the language restriction should not lead to retrieval bias.

Stage 2.2: Screening

This stage starts with automated screening of paper quality followed by two rounds of manual screening based on inclusion/exclusion criteria.

Automated screening. An important parameter set in automated screening is paper quality. Some scholars advocate paper-specific rating (Mahmud et al., 2022), but this method is susceptible to subjectivity. Others use year-adjusted citations as an indicator of paper quality, but standard errors for recent publications are much bigger than older publications (Davis, 2009). The two methods can lead to systematic selection bias. In contrast, we use the ABS journal ranking[1] as an indicator for paper quality. The ABS journal ranking is a popular indicator for paper quality (Battisti et al., 2021; Pereira et al., 2021). It is also widely believed that papers published in ABS 3+ journals are of better quality and have more significant contributions than those in other journals. Hence, we set automated screening criterion as ABS 2021 journals ranked as grades 3, 4 and 4-star. Although the ABS journal and ranking lists are re-evaluated every 3-5 years, the selection bias is negligible as changes in the list are trivial (Spiewanowski & Talavera, 2021).

Manual screening. In the first round (based on title, abstract, and keywords), the inclusion criteria and exclusion criteria are discussed and determined by the review panel. The purpose is to set transparent and clear criteria to avoid inconsistency. In the second round (based on full text), screening is refined and criteria per se are iteratively revised to reflect on the accumulated evidence and experience. For example, the review panel initially aimed to summarize all types of land value, but later decided to exclude agricultural land, recreational land, and

[1] The Chartered Association of Business Schools (ABS) regularly produce a guide to academic journals published within economics and business management fields. ABS 3-star journals are internationally excellent in terms of quality, while ABS 4-star journals are world leading. The ABS journal ranking is a de facto guide in academic job markets of many countries such as the UK.

transportation land, because the valuation processes are completely disparate from those of residential land and commercial land. Disputes in the screening stage are resolved by votes according to the preset protocol.

Stage 2.3: Analysis

There are many tools available for analysis. Our SLR combines both quantitative methods (e.g., bibliometric analysis) and qualitative methods (e.g., thematic analysis), so it is a mixed method.

Bibliometric analysis. Building on the data on citations, we apply the Edmonds algorithm (Edmonds, 1965) to visualize the directed networks among influential papers in a tree diagram. There are many other tools available to conduct bibliometric analysis, but one advantage of the Edmonds algorithm is that it guarantees an optimal solution for the minimum weight matching problem. It ensures that the selected edges form a matching that has the smallest possible total weight among all possible matchings. So, instead of visualizing all citation connections among all articles in the sample, the algorithm works out the most prominent literature links.

Thematic analysis. To avoid expectancy bias, we apply thematic analysis developed in other disciplines like management (Lane et al., 2002), psychology (Braun & Clarke, 2006), and medical science (Côté & Turgeon, 2005). One important benefit of thematic analysis is its flexibility, which is suitable for analyzing textual data like literature. In the meantime, to avoid being too flexible and the "anything goes" critique (Antaki et al., 2003), a methodologically sound thematic analysis must make the assumptions explicit and procedures transparent (Holloway & Todres, 2003). Ideally, a trustworthy thematic analysis must be credible (Guba & Lincoln, 1989), transferrable (Tobin & Begley, 2004), dependable (Lincoln & Guba, 1985), confirmable (Koch, 1994), and auditable (Sandelowski, 1986). To establish trustworthiness, we follow a well-known six-phase thematic analysis guideline (Stage 2.3 of Table 1) initially developed by Braun & Clarke (2006).

(i) *Familiarizing with the data* (i.e., the screened literature in Stage 2).
(ii) *Coding the texts*: extraction and labelling of textual data in the literature.
(iii) *Searching for themes*: synthesis of coded texts.
(iv) *Reviewing themes*: triangulation of emerging subthemes and themes.
(v) *Defining themes*: naming and refining subthemes and themes.
(vi) *Writing up the review*: summarizing themes in a hierarchical structure.

We determine coding fields based on the RQs. To perform a trustworthy and thorough review, we ensure that coding fields reflect a comprehensive set of dimensions in land valuation. Meanwhile, we must not produce excessive coding that does not contribute to the integration of the literature. Hence, we iterate a few rounds of reading and discussion, and decide the following

coding fields: title, authors, contribution, land types, temporal coverage, spatial coverage (countries, cities, districts, etc.), spatial unit (parcel level, property level, etc.), factors of land value, data source, valuation method.

Stage 3: Reporting

The reporting stage usually follows the PRISMA guideline (Liberati et al., 2009; Page et al., 2021). In different subject areas, the reported contents vary substantially, but well-written SLRs usually include narrative and tabular syntheses according to the SALSA framework (Grant & Booth, 2009).