



UNIVERSITÉ DU QUÉBEC EN OUTAOUAIS
DÉPARTEMENT DES SCIENCES ADMINISTRATIVES

WORKING PAPER NO. 21

The Global Evidence on Housing Price Determinants

A Meta-Analysis of Hedonic Pricing Models, 1970–2026

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October 2026

Version 1.0

Abstract

This paper synthesises the global hedonic housing literature from 1970 to 2026 with a reproducible pipeline: 103,011 records identified from Semantic Scholar, Crossref, arXiv and OpenAlex, 56,727 unique records screened by rules and by independent agents following a PRISMA-style protocol, 2,249 hedonic studies included at stage one, 501 open-access full texts retrieved, and 242 eligible studies from 55 countries extracted into 18,831 coefficient rows with a validated double-extraction sample. Coefficients are harmonised into percentage premiums, semi-elasticities per common unit and elasticities, and pooled with random-effects, three-level and cluster-robust models, with publication-selection diagnostics, Bayesian and machine-learning cross-checks. The structural core of the hedonic model is global: the elasticity of price to living area is 0.65, a bathroom adds 5.91 percent, a year of age subtracts -0.24 percent and a kilometre from the centre -3.08 percent, with similar means across continents and decades. Signature amenities carry premiums between four and eleven percent and a waterfront location 32.50 percent. Every implicit price is heterogeneous beyond sampling error, prediction intervals span zero for most characteristics, and observable study features, including spatial estimators, explain little of the heterogeneity. Funnel asymmetry is widespread but not interpretable as selection alone. Machine-learning models predict better than hedonic benchmarks in most of the forty retrievable comparisons, while AI-derived text and image features add modest accuracy and some interpretable characteristics. The synthesis extends Sirmans et al. (2005, 2006) in coverage, harmonisation, inference and scope, and is bounded by the open-access retrieval rate that it documents.

Keywords: hedonic pricing, housing characteristics, implicit prices, meta-analysis, meta-regression, publication selection, machine learning valuation

JEL Classification: R31, R21, C13, C80, C45

1. Introduction

Two decades ago, [Sirmans et al. \(2005\)](#) and [Sirmans et al. \(2006\)](#) asked a question that every appraiser, assessor and housing economist faces: across the hundreds of hedonic regressions of house prices on characteristics, what is the value of a bathroom, a garage, a swimming pool, a year of age or a square foot of living area, and does that value depend on where and when it is measured? Their answer, built from a tabulation of signs and a meta-regression of raw coefficients from mostly American single-family studies, was that the signs are consistent, that magnitudes vary by location and sometimes by data type, and that there was no clear change over time. The literature has since grown by an order of magnitude, has moved to apartments, rents and listing prices in Asia and Europe, has adopted spatial econometrics, quasi-experimental designs and machine learning, and has begun to extract characteristics from text and images. The tools of research synthesis have changed as well: effect-size harmonisation, multilevel models for dependent estimates, cluster-robust inference, publication-selection diagnostics and Bayesian hierarchical models are now standard in economics meta-analysis ([Stanley and Doucouliagos, 2012](#); [Nelson and Kennedy, 2009](#)). No synthesis has applied them to the hedonic housing literature as a whole: the meta-analyses that exist are attribute-specific (transit, noise, green space, water, flood risk, contamination, energy efficiency, school quality), and the general reviews are descriptive. This paper fills that gap to the extent that the accessible literature allows.

The paper answers eight questions: which characteristics consistently affect prices across countries and periods; how large and how uncertain their marginal contributions are; how they vary with geography, market conditions, property types and socioeconomic context; whether they have changed over time; whether conventional, spatial and machine-learning approaches differ; what text, vision and other AI-derived characteristics add; how much of the observed variation is specification, measurement and publication selection rather than economics; and what remains understudied. The approach is a systematic review with a pre-registered protocol, a global variable taxonomy, a documented harmonisation of coefficients into effect-size families, and a meta-analytic framework that respects the dependence of estimates within studies. Every step is reproducible from the replication repository and every number in the text is generated from the result files.

Three features of the design deserve emphasis because they bound what the paper can claim. First, retrieval was restricted to legal open-access full texts; the 18.8 percent retrieval rate is documented in the PRISMA flow and the extracted sample is therefore a sample of the accessible literature, with the biases that this implies. Second, screening and extraction were performed by language-model agents working from written protocols, with an independent double extraction of a random sample to measure their reliability; the agreement on matched coefficients is complete but the recall of auxiliary variables is not, and the paper reports both. Third, the synthesis distinguishes

throughout between a descriptive synthesis (which characteristics are studied, with what sign) and a statistically valid meta-analysis (which implicit prices can be pooled within a defensible effect-size family), and it counts independent studies, not coefficients, when it describes its evidence base.

The results can be summarised briefly. The structural core of the hedonic model is global: living area, bathrooms, bedrooms conditional on area, age and distance to the centre have precisely estimated mean implicit prices that are similar across continents and decades, and the signature amenities carry premiums of the order documented in attribute-specific studies. Every implicit price is heterogeneous beyond sampling error, with prediction intervals that span zero for most characteristics, and the observable features of studies, including spatial estimators, explain little of that heterogeneity; funnel asymmetry is widespread but cannot be read as selection under this degree of heterogeneity. Machine-learning models predict prices better than hedonic benchmarks in most of the comparisons that could be retrieved, and AI-derived characteristics add modest accuracy and some interpretable variables. The gaps are as informative as the estimates: interior amenities, market characteristics, several environmental risks, AI-derived characteristics and three continents remain thinly covered.

The remainder of the paper proceeds as follows. Section 2 recalls the theoretical foundations and Section 3 the development of the literature; Section 4 states the research questions and the contribution relative to the Sirmans programme. Sections 5 and 6 describe the search, selection, extraction, validation and harmonisation, and Section 7 the econometric framework. Sections 8 to 12 present the evidence by characteristic, geography, period, method and AI, Section 13 the publication-selection diagnostics and robustness, Section 14 the implications, Section 15 the limitations and Section 16 concludes. The appendices contain the protocol, additional tables and the reproducibility statement.

2. Theoretical foundations of hedonic housing valuation

The hedonic method rests on the observation that a house is a bundle of characteristics that are not traded separately, so that the price of the bundle reveals, at the margin, the value buyers place on each characteristic. Rosen (1974) gave this idea its modern form: in a competitive market with a continuum of differentiated products, the equilibrium price schedule $P(\mathbf{z})$ over the characteristics vector $\mathbf{z}$ is the envelope of buyers' bid functions and sellers' offer functions, and its gradient $\partial P / \partial z_k$ is the implicit (marginal) price of characteristic k . Two consequences shape every study in the literature synthesised here. First, the implicit price is a market-level object, determined by the joint distribution of tastes, incomes and the stock of characteristics in a given market at a given time, so that there is no theoretical reason for implicit prices to be equal across cities, countries or periods. Second, the functional form of $P(\cdot)$ is not pinned down by theory: non-linearity is the rule,

and the log-linear, log-log and Box–Cox specifications that dominate the empirical literature are approximations whose coefficients have different interpretations.

The first consequence is the reason a synthesis cannot aim at a single “true” implicit price. What it can aim at is a characterisation of the distribution of implicit prices across markets, a decomposition of that distribution into economic heterogeneity and specification differences, and tests of whether systematic patterns, by geography, period or property type, survive the noise. The second consequence is the reason the synthesis must be organised around effect-size families rather than raw coefficients. In a log-linear model $\ln P = \alpha + \beta_k z_k + \dots$, a binary characteristic shifts the expected log price by β_k and the expected price, to first order, by $100[\exp(\beta_k) - 1]$ percent, with the retransformation corrections discussed in Section 6; a continuous characteristic in levels has a semi-elasticity, $100\beta_k$ percent per unit, whose magnitude depends on the unit; in a log-log model β_k is an elasticity; and in a level-level model β_k is a monetary marginal price in the currency and price level of the sample. These objects are not interchangeable, and pooling them without conversion produces averages that have no interpretation.

Three refinements of the Rosen framework matter for the moderators used later. Spatial dependence, both in the error term and in the dependent variable, arises because unobserved neighbourhood attributes are shared by nearby houses and because prices of comparable sales enter appraisals and negotiations; spatial-lag and spatial-error models (Anselin, 1988) and geographically weighted regression (Brunsdon et al., 1996) are the standard responses, and whether they change the implicit prices of structural characteristics is an empirical question addressed in Section 11. Identification of the implicit price of an environmental or locational attribute is threatened by omitted variables correlated with it, and the quasi-experimental turn in the literature (Kuminoff et al., 2010; Parmeter and Pope, 2013) replaces cross-sectional hedonic regressions with difference-in-differences, boundary and panel designs; these designs produce coefficients for the treated attribute only, which the synthesis records but which cannot inform the structural characteristics. Finally, the second stage of the Rosen programme, recovering demand parameters from implicit prices, is outside the scope of this paper: the synthesis concerns first-stage implicit prices, which is also what the Sirmans programme summarised.

3. Historical development of the literature

Hedonic regressions of housing prices predate Rosen (1974): the method was used for price indices in the 1960s and applied to housing by Ridker and Henning (1967) for air pollution and by Kain and Quigley (1970) for the components of housing quality. The 1970s and 1980s established the canonical specification, the problems of functional form (Halvorsen and Pollakowski, 1981; Cropper et al., 1988) and the interpretation of dummy-variable coefficients in semi-logarithmic

equations (Halvorsen and Palmquist, 1980; Kennedy, 1981), and the first reviews (Follain and Jimenez, 1985; Freeman, 1979). The 1990s brought spatial econometrics into the field (Can, 1992; Dubin, 1992; Basu and Thibodeau, 1998) and the recognition that the marketing process, the data source (transactions, listings, appraisals, rents) and the submarket structure all affect estimated implicit prices. Malpezzi (2003) wrote the standard applied review of this period.

The Sirmans programme belongs to the mid-2000s. Sirmans et al. (2005) tabulated the characteristics used and the signs and significance obtained in a large set of hedonic studies, and Sirmans et al. (2006) ran meta-regressions of the raw coefficients of nine structural characteristics on location, time, data type and specification, finding that implicit prices vary by location, that the data type matters for some characteristics, and that there was no clear change over time. The programme was extended to time-on-market coefficients (Sirmans et al., 2010) and recently updated descriptively (Khoshnoud et al., 2023). Section 4 describes its limitations precisely. In parallel, attribute-specific meta-analyses multiplied: transit proximity (Debrezion et al., 2007; Mohammad et al., 2013; Higgins and Kanaroglou, 2016), airport and traffic noise (Nelson, 2004), open space and trees (McConnell and Walls, 2005; Waltert and Schläpfer, 2010; Crompton and Nicholls, 2019), water quality and proximity (Guignet et al., 2022; Nicholls and Crompton, 2018), flood risk (Beltrán et al., 2018), contamination and hazards (Simons and Saginor, 2006; Braden et al., 2011), energy efficiency (Cespedes-Lopez et al., 2019), school quality (Nguyen-Hoang and Yinger, 2011), wind turbines (Parsons and Heintzelman, 2022) and crime (Macchiaroli and Dolores, 2025), each pooling tens of studies with inverse-variance weights and, increasingly, publication-selection diagnostics (Stanley and Doucouliagos, 2012). The 2010s and 2020s added three developments that this synthesis must accommodate: quasi-experimental designs for environmental and locational attributes; the systematic use of listing data from online platforms, with the attendant shift from transaction to asking prices and from single-family houses to apartments in non-US markets; and machine learning, first as a predictive competitor to hedonic regression (Wang and Li, 2019; Geerts et al., 2023) and then as a source of new characteristics extracted from text and images.

4. Research questions and contributions

The paper addresses eight questions. (RQ1) Which housing characteristics consistently affect transaction prices across countries and periods? (RQ2) How large are their marginal contributions and how uncertain are they? (RQ3) How do implicit prices vary with geography, market conditions, property types and socioeconomic characteristics? (RQ4) Have valuations changed over time, particularly around financial crises, monetary-policy regimes and the COVID-19 pandemic? (RQ5) Do traditional hedonic, spatial and machine-learning approaches produce systematically different estimates? (RQ6) What additional price information is captured by textual, visual and other AI-

derived characteristics? (RQ7) How much of the observed variation reflects genuine economic heterogeneity rather than specification, measurement and publication selection? (RQ8) Which characteristics and markets remain understudied?

The contribution is defined by what the Sirmans programme could not do with the tools and the literature of 2005. First, its coverage was the United States, single-family houses and nine structural characteristics; the present synthesis is global, covers all residential property types and the full taxonomy of structural, interior, exterior, locational, environmental, neighbourhood, market and AI-derived characteristics, and treats rents and listing prices as separate outcomes. Second, the 2005 paper counted signs and the 2006 paper regressed raw coefficients across functional forms; the present synthesis harmonises coefficients into effect-size families with explicit formulas, weights them by precision and reports prediction intervals that describe the dispersion of implicit prices rather than only the precision of their mean. Third, the Sirmans meta-regressions did not model the dependence of multiple estimates from the same study or test for publication selection; the present synthesis uses three-level models with robust variance estimation, funnel-based and selection-model diagnostics, and Bayesian and machine-learning cross-checks. Fourth, it adds the methodological and AI dimensions that did not exist in 2005. The claims of this paper are bounded by its own search and retrieval process, documented in Section 5: it synthesises the open-access literature that could be retrieved and extracted within a reproducible pipeline, and it compares its coverage with every competing review it could verify (Table 17) rather than asserting that it is the largest.

5. Systematic search strategy and study selection

The search, screening and selection follow the PRISMA 2020 principles (Page et al., 2021) adapted to economics research, with a protocol written before any coefficient was extracted (Appendix A). Figure 1 gives the flow of records generated from the actual screening files and Table 1 the counts at every stage.

5.1. Sources and queries

Records were identified on 2026-10-20 from four machine-readable sources: the Semantic Scholar bulk search API, with Boolean queries combining the hedonic vocabulary with residential-price terms and with the twelve multilingual phrasings listed in the protocol; the Crossref bibliographic search, capped at 4,000 relevance-ranked records per query; the arXiv API for the machine-learning, vision and text literature; and OpenAlex, which could be used only for verification because its unauthenticated access is limited to a shared daily budget. Forward citation snowballing was applied to the two Sirmans papers through the Semantic Scholar citation graph. In total 67 queries were executed and 103,011 records retrieved; deduplication on DOI and on normalised title plus

year left 56,727 unique records, 17,863 of which carry an abstract. SSRN, Google Scholar, IDEAS/EconPapers and institutional repositories have no compliant bulk interface and were not harvested directly; the grey literature is covered only insofar as Semantic Scholar and arXiv index it. The audit trail (queries, dates, hit counts, retrieval failures) is in the replication material.

5.2. Screening

Stage-one screening proceeded in two steps. A rule-based scorer applied the keyword groups of the protocol (hedonic vocabulary in twelve languages, residential-price outcomes, regression and characteristic signals, hard exclusions for non-housing hedonic applications) to titles and abstracts and retained 7,075 candidates. Each candidate was then screened on title and abstract by an independent agent working from the written eligibility criteria, with a coded reason for every decision; 3,440 records were excluded, 428 were flagged as unclear for human review, 2,249 were included as hedonic coefficient studies and 897 as machine-learning or automated-valuation studies that feed the synthesis of Section 12. The most frequent exclusion reasons were non-housing applications of the hedonic method (sensory science, art, wine, labour markets), aggregate-level price regressions without dwelling characteristics, and reviews. The coding conventions that required a decision across screeners, such as the treatment of hedonic price-index papers, of community-level Chinese studies and of short-term-rental pricing, are recorded in the methodological-decisions log.

5.3. Full-text retrieval and eligibility

Full texts were sought for every included hedonic study and every unclear record (2,667 records) from legal open-access locations only: Unpaywall locations, Semantic Scholar open-access links and arXiv. 501 PDFs were obtained (18.8 percent); the remainder are paywalled or have no open-access copy and are counted as not retrieved. This is the binding constraint of the study, and Section 13 compares the retrieved and not-retrieved sets on observable metadata. Of the retrieved full texts, 297 were assessed and extracted by the pipeline described in Section 6; 242 were eligible for the coefficient synthesis and 55 were excluded at full text, most often because the unit of analysis was an aggregate (city, tract, housing project) or because characteristic coefficients were controlled for but not reported.

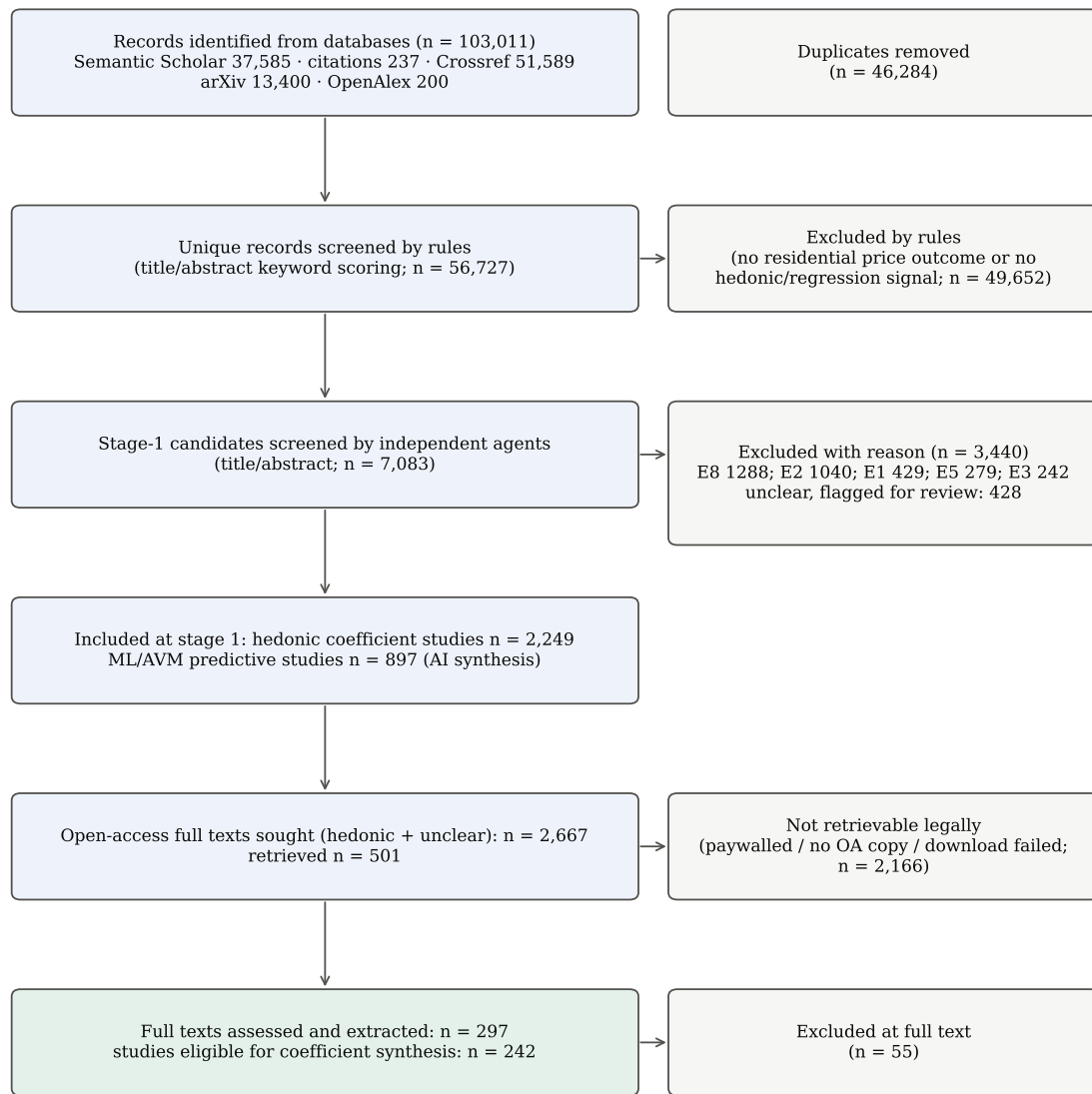


Figure 1. PRISMA flow of records, generated from the screening and retrieval logs of the pipeline.

Table 1. Literature coverage and study selection

Stage	n
Records identified (all sources)	103,011
crossref	51,589
semanticscholar_bulk	37,585
arxiv	13,400
semanticscholar_citations	237
openalex	200
Unique records after deduplication	56,727
with an abstract	17,863
Stage-1 candidates (rule-based)	7,075
Screened by independent agents (title/abstract)	7,083
excluded with a coded reason	3,440
unclear, flagged for review	428
included: hedonic coefficient studies	2,249
included: ML/AVM predictive studies	897
Open-access full texts sought (hedonic + unclear)	2,667
retrieved	501
Full texts assessed and extracted	297
eligible for coefficient synthesis	242
Search queries executed	67

6. Data extraction and variable harmonisation

6.1. Extraction pipeline

Each retrieved PDF was processed with PyMuPDF to extract page text, and pages were scored for the density of coefficient-like patterns (decimals followed by parenthesised values or significance stars), table vocabulary and hedonic variable names; the candidate regression pages, with the first page and the abstract, were assembled into a compact dump per paper. Independent extractor agents then read the dumps, and the original PDF pages when tables were garbled or image-only, and produced a structured record per paper following a written protocol and a fixed JSON schema: study metadata (country, city, sample period, property type, price measure, document type, estimators, fixed effects, standard-error type, sample size, AI methods), one entry per model column (table, column, page, dependent variable and its transformation, estimator, sample size, fit, and what the parentheses contain) and one row per coefficient (printed variable name, taxonomy identifier,

regressor transformation and unit, coefficient, standard error, t , p , stars, confidence interval, page, extraction confidence and notes). The rules were strict: only printed numbers; no inference of standard errors; standard errors printed as zero after rounding stored as missing; fixed-effect dummies, constants and interaction terms excluded or flagged; papers whose unit of analysis is an aggregate, whose data are simulated, or whose characteristic coefficients are not reported marked ineligible with the reason. Extractors assigned a confidence level to every row, and rows marked low, those whose numbers had to be guessed from context, are excluded from the primary synthesis.

6.2. Validation

A random sample of 20 eligible papers was re-extracted by a second, independent agent that had no access to the first extraction. The two extractions agree on eligibility for 95.0 percent of papers; among the 647 coefficient rows that could be matched on model, taxonomy and printed variable name, the coefficients agree to within one percent in 100.0 percent of cases, the standard errors in 100.0 percent, the signs in 100.0 percent and the taxonomy assignment in 100.0 percent; recall and precision of the primary extraction relative to the duplicate are 78.9 and 77.3 percent, the shortfall reflecting differences in which auxiliary variables (composite indices, planning-zone dummies, local-regression summaries) each extractor chose to record rather than disagreement on the hedonic variables themselves (Table 3).

6.3. Taxonomy

Variables were mapped to a hierarchical taxonomy of 72 observed characteristics in eight groups: structural, interior amenities, exterior amenities, location and accessibility, environmental, neighbourhood and socioeconomic, market and transaction, and AI-derived (Table 2). Each leaf has a conceptual definition and a list of equivalent printed names; conceptually distinct variables (bedrooms versus total rooms, distance to a station versus distance to a railway line, waterfront versus distance to water) are kept separate, and variables with no leaf are recorded under “other” with their printed name so that the mapping can be audited.

6.4. Effect-size harmonisation

Coefficients were converted into effect-size families according to the dependent-variable transformation and the regressor’s transformation and unit, with the formula stored for every row. For a binary regressor in a log-price model the primary family is the percentage premium $100[\exp(\hat{\beta} - \hat{\sigma}_\beta^2/2) - 1]$, which applies the Kennedy (1981) correction to the retransformation of Halvorsen and Palmquist (1980), with delta-method standard error $100\exp(\hat{\beta})\hat{\sigma}_\beta$; the uncorrected premium is kept as a sensitivity. For a continuous regressor in levels in a log-price model the family is the semi-elasticity

$100\hat{\beta}$ per harmonised unit, after converting square feet to square metres, metres, feet and miles to kilometres, and recording the unit when it cannot be harmonised (minutes, indices, shares), in which case the row is excluded from the pooled analysis of that characteristic. Log-log coefficients form the elasticity family. Level-price coefficients form the monetary family, which is reported descriptively (signs and significance) but never pooled across currencies and price levels. Rows whose regressor is a construction year rather than an age, a standardised coefficient, a squared term or an interaction are flagged and excluded from pooling. Standard errors were recovered only from printed t -statistics, confidence intervals or exact p -values, with the recovery formula stored; stars-only and p -only tables therefore contribute to the descriptive synthesis but not to the inverse-variance pooling. Partial correlations $r = t / \sqrt{t^2 + df}$ were computed for every row with a t -statistic as a unit-free secondary family. Of the 18,831 coefficient rows extracted from 242 eligible studies, 7,693 are usable in the primary pooled synthesis after these filters.

Table 2. Global hedonic variable taxonomy and extraction counts (studies / coefficient rows)

Characteristic	primary effect-size family	studies / coefficients
A. Structural		
Living area	elasticity or semi	181 / 1181
Lot size	elasticity or semi	64 / 469
Age	semi elasticity	150 / 1468
Bedrooms	semi elasticity	117 / 649
Bathrooms	semi elasticity	94 / 613
Storeys	semi elasticity	41 / 373
Floor level	semi elasticity	63 / 438
Garage	percentage premium	41 / 236
Parking	percentage premium	33 / 181
Basement	percentage premium	20 / 79
Roof and building materials	percentage premium	23 / 272
Renovation	percentage premium	17 / 191
Heating	percentage premium	27 / 144
Air conditioning	percentage premium	16 / 71
Energy efficiency	percentage premium	21 / 228
Building condition	percentage premium	59 / 695
Dwelling type	percentage premium	55 / 461
B. Interior		
Kitchen quality	percentage premium	9 / 40
Bathroom quality	percentage premium	3 / 9
Fireplace	percentage premium	21 / 183
Appliances	percentage premium	1 / 7
Flooring	percentage premium	4 / 27
Insulation	percentage premium	3 / 17
Storage	percentage premium	9 / 35
Luxury finishes	percentage premium	3 / 8
Smart-home systems	percentage premium	0 / 0
Accessibility	percentage premium	33 / 149
C. Exterior		
Swimming pool	percentage premium	22 / 87
Garden	percentage premium	13 / 46

(continued)

Characteristic	primary effect-size family	studies / coefficients
Terrace or balcony	percentage premium	31 / 186
Landscaping	percentage premium	5 / 21
Outdoor kitchen	percentage premium	0 / 0
Waterfront	percentage premium	11 / 79
Private recreation	percentage premium	6 / 19
D. Location		
Distance to CBD	semi elasticity	86 / 516
Distance to public transport	semi elasticity	91 / 932
Distance to schools	semi elasticity	43 / 225
Distance to university	semi elasticity	13 / 58
Employment accessibility	semi elasticity	18 / 212
Distance to hospitals	semi elasticity	27 / 103
Distance to highways	semi elasticity	35 / 204
Distance to commercial areas	semi elasticity	39 / 234
Walkability	semi elasticity	3 / 23
Distance to airport	semi elasticity	6 / 23
E. Environment		
Air pollution	semi elasticity	12 / 146
Noise	semi elasticity	12 / 133
Flood risk	percentage premium	13 / 201
Wildfire risk	percentage premium	1 / 19
Green space and parks	semi elasticity	64 / 704
Water quality	semi elasticity	6 / 135
View	percentage premium	28 / 275
Sunlight and orientation	percentage premium	20 / 138
Urban heat	semi elasticity	2 / 6
Hazardous or industrial sites	semi elasticity	25 / 156
Proximity to water bodies	semi elasticity	38 / 360
F. Neighbourhood		
Neighbourhood income	elasticity	33 / 175
Crime	semi elasticity	18 / 302
Population density	semi elasticity	38 / 261
Education level	semi elasticity	11 / 50
School quality	semi elasticity	24 / 245
Demographic composition	semi elasticity	26 / 480
Neighbourhood amenities	semi elasticity	41 / 665
Local public services	semi elasticity	24 / 165
Unemployment	semi elasticity	6 / 43
Vacancy	semi elasticity	4 / 12
G. Market		
Time on market	semi elasticity	2 / 70
Market liquidity	semi elasticity	3 / 41
Foreclosure status	percentage premium	1 / 3
Distressed sale	percentage premium	1 / 9
Seller urgency	percentage premium	0 / 0
Mortgage conditions	percentage premium	0 / 0
Transaction timing	percentage premium	13 / 114
H. AI-derived		
Text sentiment	semi elasticity	0 / 0
Renovation descriptions	percentage premium	0 / 0
Architectural style	percentage premium	2 / 16
Luxury language	semi elasticity	0 / 0

(continued)

Characteristic	primary effect-size family	studies / coefficients
Urgency language	semi elasticity	0 / 0
Image-based condition	semi elasticity	1 / 180
Visual quality	semi elasticity	1 / 40
Interior design	semi elasticity	0 / 0
Multimodal embeddings	semi elasticity	3 / 21

Table 3. Extraction validation on the independent double-extraction sample

Validation statistic	value
papers double extracted	20
eligibility agreement	0.950
coef recall	0.789
coef precision	0.773
beta agreement 1pct	1.000
se agreement 1pct	1.000
sign agreement	1.000
taxonomy agreement	1.000
coefficients compared	647

7. Meta-analytical econometric framework

Let y_{ij} be the j -th harmonised estimate from study i within a given characteristic and effect-size family, with sampling variance v_{ij} . The random-effects model

$$y_{ij} = \mu + u_i + e_{ij}, \quad u_i \sim N(0, \tau^2), \quad e_{ij} \sim N(0, v_{ij}), \quad (1)$$

is estimated by restricted maximum likelihood (Viechtbauer, 2010); the paper reports the pooled estimate, its standard error and confidence interval, the 95 percent prediction interval for a new study, τ^2 , I^2 , the number of independent studies k and of estimates n . Because most studies contribute several estimates, the primary inference comes from the three-level model

$$y_{ij} = \mu + u_i + w_{ij} + e_{ij}, \quad u_i \sim N(0, \sigma_{study}^2), \quad w_{ij} \sim N(0, \sigma_{model}^2), \quad (2)$$

with estimates nested in studies (Cheung, 2014), and from cluster-robust variance estimation with the CR2 small-sample correction and Satterthwaite degrees of freedom (Hedges et al., 2010; Pustejovsky and Tipton, 2022), which does not rely on the correctness of the assumed dependence

structure. Moderator analysis extends (2) with study- and model-level covariates: the midpoint of the transaction period (not the publication year), a spatial-estimator indicator, a machine-learning indicator, a working-paper indicator, the log sample size, a rent indicator, an apartment indicator, a non-US indicator and the presence of time and location fixed effects. Publication selection is examined with funnel plots, the Egger regression test (Egger et al., 1997), the PET-PEESE procedure (Stanley and Doucouliagos, 2014) on families with at least twenty estimates and a step-function selection model (Vevea and Hedges, 1995) on families with at least thirty, without applying any correction mechanically. A Bayesian hierarchical model with weakly informative priors (normal on the mean, half-Cauchy on τ) is fitted by Gibbs sampling with slice updates on study-level aggregated effects, with $\hat{R}$ and effective sample sizes reported. Finally, random forests and gradient boosting with study-grouped cross-validation are used to search for non-linear moderators; their results are exploratory (Mullainathan and Spiess, 2017; Athey and Imbens, 2019). All models are run in R (metafor, clubSandwich) and independently re-implemented in Python; Table 14 reports both.

8. Global evidence on housing characteristics

8.1. The evidence base

The coefficient synthesis rests on 242 eligible studies from 55 countries, 2,022 model columns and 18,831 coefficient rows, of which 7,693 harmonised estimates from 149 studies enter the pooled analysis (Table 4). Europe (83 studies), Asia (77) and North America (57) dominate; South America (8), Africa (6) and Oceania (5) are thinly covered (Figure 7, Table 10). The United States accounts for 22.3 percent of extracted studies, against the near-totality of the Sirmans programme. Condominiums and apartments (78) are as numerous as single-family houses (74), a direct consequence of the growth of the Asian and European listing-data literature; 148 studies use transaction prices, 55 listing prices, 21 rents and 15 appraised values. Ordinary least squares provides 54.2 percent of usable estimates, spatial estimators 17.1 percent and quantile regressions 19.0 percent. The median study has 4,448 observations. Figure 2 and Table 5 show which characteristics are studied where: living area, bedrooms, bathrooms, age and distance to the centre are reported almost everywhere, while most interior, market and AI-derived characteristics appear in fewer than ten studies (Table 15).

Table 4. Characteristics of the extracted studies

Characteristic	studies	%
<i>Property type</i>		
condo_apartment	78	32.2
single_family	74	30.6
mixed	64	26.4
rental	13	5.4
unknown	13	5.4
<i>Price measure</i>		
transaction	148	61.2
listing	55	22.7
rent	21	8.7
appraisal	15	6.2
unknown	2	0.8
transaction_and_listing	1	0.4
<i>Document type</i>		
journal	205	84.7
conference	19	7.9
working_paper	13	5.4
thesis	5	2.1
<i>Time fixed effects</i>		
False	145	59.9
True	97	40.1
<i>Location fixed effects</i>		
False	141	58.3
True	101	41.7
Median sample size (observations)	4,448	
Median publication year	2021	
Median data-period midpoint	2014	
Models per study (median / max)	4 / 98	
Coefficients per study (median / max)	45 / 1164	

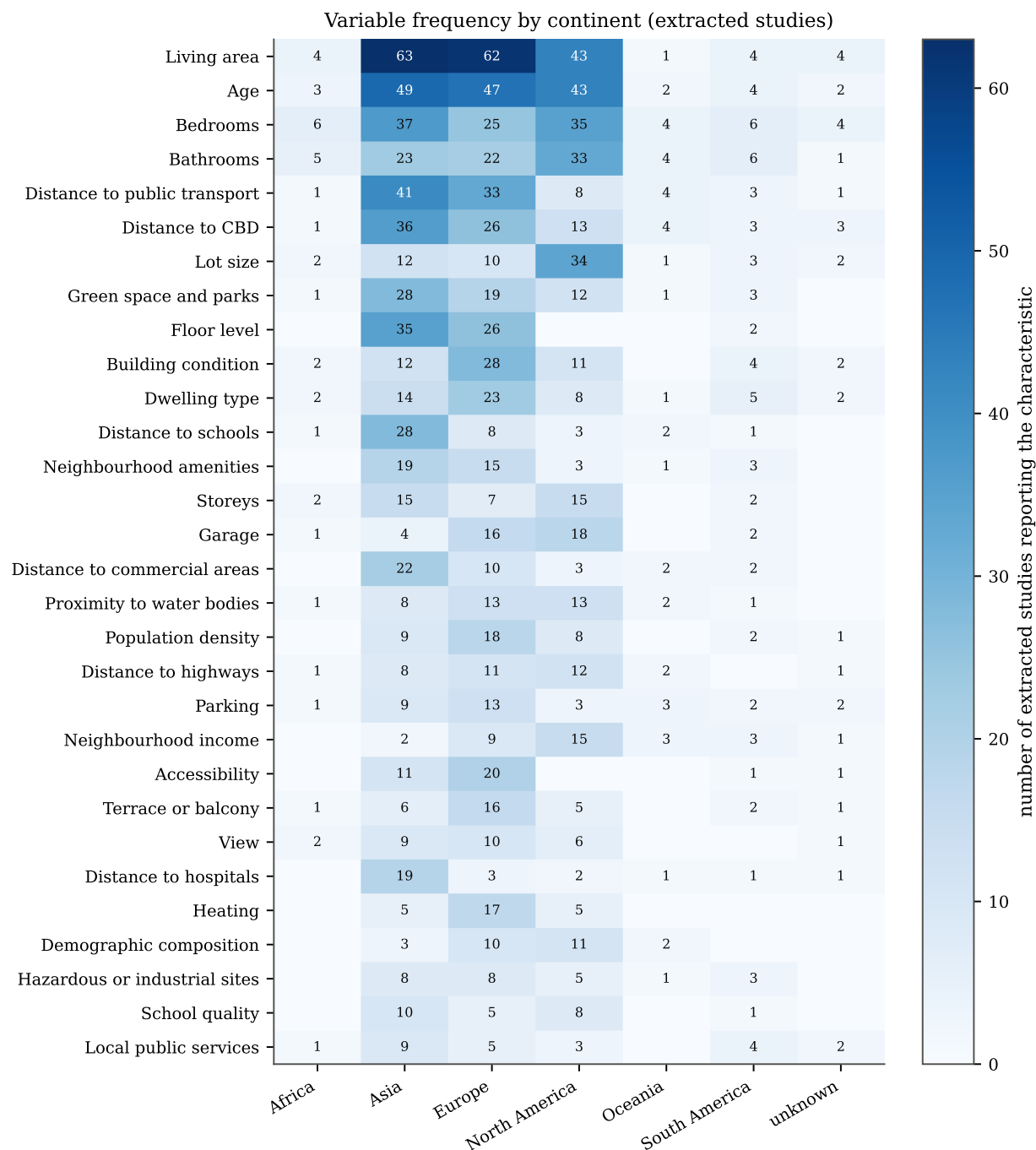


Figure 2. Variable-frequency heatmap: number of extracted studies reporting each characteristic, by continent (thirty most frequent characteristics).

Table 5. Most frequently studied characteristics (extracted studies; share of positive printed coefficients is a sign count across all models and is not a pooled estimate)

Characteristic	group	studies	coefficients	% positive
Living area	A. Structural	181	1181	80
Age	A. Structural	150	1468	38
Bedrooms	A. Structural	117	649	72
Bathrooms	A. Structural	94	613	93
Distance to public transport	D. Location	91	932	50
Distance to CBD	D. Location	86	516	24
Lot size	A. Structural	64	469	78
Green space and parks	E. Environment	64	704	54
Floor level	A. Structural	63	438	63
Building condition	A. Structural	59	695	68
Dwelling type	A. Structural	55	461	68
Distance to schools	D. Location	43	225	56
Neighbourhood amenities	F. Neighbourhood	41	665	65
Storeys	A. Structural	41	373	56
Garage	A. Structural	41	236	93
Distance to commercial areas	D. Location	39	234	50
Proximity to water bodies	E. Environment	38	360	28
Population density	F. Neighbourhood	38	261	48
Distance to highways	D. Location	35	204	37
Parking	A. Structural	33	181	90
Neighbourhood income	F. Neighbourhood	33	175	54
Accessibility	B. Interior	33	149	92
Terrace or balcony	C. Exterior	31	186	58
View	E. Environment	28	275	88
Distance to hospitals	D. Location	27	103	49
Heating	A. Structural	27	144	61
Demographic composition	F. Neighbourhood	26	480	59
Hazardous or industrial sites	E. Environment	25	156	38
School quality	F. Neighbourhood	24	245	74
Local public services	F. Neighbourhood	24	165	68

8.2. Pooled implicit prices

Tables 6 to 8 and Figures 3 to 5 report the pooled estimates for the 67 characteristic–family combinations with at least five independent studies. Three regularities organise the results. First, the structural core of the hedonic model is remarkably stable across the world: the elasticity of price with respect to living area is 0.65 (95 percent confidence interval 0.61 to 0.69, $k = 46$ studies), each additional bathroom adds 5.91 percent and each bedroom, conditional on area, 3.00 percent, a year

of age subtracts -0.24 percent, and a kilometre of distance from the centre subtracts -3.08 percent, with the lot-size elasticity at 0.09 once living area is controlled. Second, the signature amenities carry premiums of the order documented in the attribute-specific literature: a garage 5.43 percent, a waterfront location 32.50 percent ($k = 9$), air conditioning, a view, a basement, a terrace or balcony and a swimming pool between four and eleven percent, and proximity to hazardous or industrial sites a discount of about six percent (Table 6). Third, every pooled family is heterogeneous beyond sampling error: the median I^2 is 100 percent and the 95 percent prediction intervals, which describe the implicit price a new study would be expected to find, span zero for most characteristics even where the confidence interval of the mean excludes it. The mean implicit price of a characteristic is therefore estimated with precision, but it is the centre of a wide distribution, not a parameter that transfers across markets. The three-level estimates, which weight studies rather than estimates, and the cluster-robust standard errors, which are typically two to four times the naive random-effects standard errors, are reported alongside.

Table 6. Pooled percentage premiums of binary attributes (log-price models; Kennedy-corrected; REML random effects, three-level estimate and cluster-robust SE)

Characteristic	<i>k</i>	<i>n</i>	RE estimate	95% CI	95% PI	<i>I</i> ²	3-level	RVE SE	median
Dwelling type	36	274	10.97	[7.63, 14.30]	[-43.84, 65.77]	100	5.27	3.245	5.04
Building condition	25	271	7.42	[5.00, 9.85]	[-30.72, 45.57]	99	-0.18	2.764	8.65
Garage	22	134	5.43	[4.31, 6.54]	[-6.94, 17.80]	99	6.27	1.312	4.29
Distance to public transport	19	268	1.98	[0.96, 3.00]	[-13.82, 17.77]	99	0.78	1.275	1.53
Terrace or balcony	18	67	5.00	[3.96, 6.03]	[-2.60, 12.60]	98	4.96	0.951	4.08
Swimming pool	18	77	4.87	[2.28, 7.45]	[-16.37, 26.11]	99	7.16	2.539	8.63
Heating	17	111	1.90	[0.36, 3.45]	[-13.62, 17.43]	99	4.62	2.071	3.01
Roof and building materials	16	202	10.63	[6.92, 14.33]	[-39.40, 60.65]	100	1.78	4.018	6.99
Parking	15	76	6.33	[4.55, 8.11]	[-8.00, 20.66]	99	3.52	1.873	6.20
Floor level	14	114	1.30	[-0.41, 3.01]	[-16.33, 18.93]	98	0.02	3.118	2.58
Green space and parks	13	137	-0.47	[-3.97, 3.03]	[-41.00, 40.06]	100	3.99	3.869	1.21
Age	13	162	2.22	[0.82, 3.62]	[-14.78, 19.21]	100	1.56	2.541	1.53
Accessibility	13	30	6.21	[4.48, 7.93]	[-2.37, 14.79]	97	6.50	1.228	5.18
View	12	166	8.20	[7.04, 9.36]	[-6.30, 22.70]	99	7.41	2.231	6.39
Hazardous or industrial sites	12	78	-5.89	[-9.43, -2.35]	[-35.37, 23.59]	99	-6.63	2.765	-2.66
Basement	12	51	5.25	[3.60, 6.89]	[-6.20, 16.69]	99	7.05	1.738	4.79
Air conditioning	11	55	10.81	[7.74, 13.88]	[-11.57, 33.20]	99	8.14	3.482	11.06
Renovation	10	103	0.88	[-1.75, 3.51]	[-25.61, 27.37]	100	9.84	4.622	2.02
Fireplace	10	134	4.35	[3.73, 4.96]	[-2.01, 10.70]	99	8.07	1.631	4.08
Energy efficiency	9	92	2.96	[1.34, 4.57]	[-11.61, 17.52]	100	2.54	2.514	1.00
Sunlight and orientation	9	95	4.01	[2.89, 5.14]	[-4.48, 12.51]	98	2.59	1.175	6.12
Waterfront	9	69	32.50	[27.83, 37.18]	[-2.35, 67.36]	99	31.57	6.356	31.28
Bedrooms	8	65	12.12	[7.84, 16.40]	[-21.60, 45.84]	100	11.56	5.082	10.51
Garden	8	22	6.42	[4.52, 8.32]	[0.04, 12.81]	96	6.83	1.798	5.59
Flood risk	8	84	-0.10	[-3.24, 3.03]	[-28.04, 27.83]	100	-2.59	6.442	-1.02
Bathrooms	7	47	23.84	[17.30, 30.37]	[-20.25, 67.93]	100	13.84	3.367	16.25
Distance to highways	7	42	-3.28	[-4.72, -1.84]	[-11.24, 4.68]	88	-3.48	2.621	-3.46
Distance to commercial areas	7	51	10.37	[2.32, 18.42]	[-45.81, 66.55]	99	6.64	9.886	7.53
Kitchen quality	6	20	3.07	[-0.30, 6.45]	[-12.26, 18.41]	100	5.79	3.125	6.04
Distance to CBD	5	20	12.69	[4.29, 21.09]	[-23.08, 48.46]	97	18.12	15.794	11.72
Proximity to water bodies	5	34	15.39	[8.30, 22.49]	[-26.19, 56.98]	100	8.26	2.782	5.49
Storeys	5	192	-1.93	[-3.34, -0.53]	[-16.80, 12.94]	100	0.85	4.843	-1.88
Storage	5	27	-0.49	[-1.59, 0.60]	[-5.99, 5.00]	96	1.64	1.973	-0.73
Transaction timing	5	55	4.36	[3.13, 5.58]	[-4.10, 12.81]	99	2.83	1.158	2.63

Table 7. Pooled semi-elasticities of continuous attributes (percent change in price per harmonised unit: m² for areas, km for distances, years for age, counts for rooms, dB for noise, $\mu\text{g}/\text{m}^3$ for pollution)

Characteristic	<i>k</i>	<i>n</i>	RE estimate	95% CI	95% PI	<i>I</i> ²	3-level	RVE SE	median
Bedrooms	60	316	3.00	[2.21, 3.79]	[-10.79, 16.79]	100	5.02	0.999	1.10
Age	54	259	-0.24	[-0.43, -0.05]	[-3.19, 2.71]	100	-0.51	0.168	-0.35
Bathrooms	51	381	5.91	[5.27, 6.54]	[-5.63, 17.44]	100	8.57	1.056	5.72
Living area	50	353	0.72	[0.65, 0.78]	[-0.51, 1.94]	100	0.59	0.073	0.48
Distance to CBD	23	121	-3.08	[-3.95, -2.20]	[-12.08, 5.93]	100	-3.31	1.500	-2.19
Lot size	22	165	0.01	[0.01, 0.02]	[-0.02, 0.05]	100	0.12	0.069	0.01
Floor level	19	95	-0.11	[-0.38, 0.17]	[-2.64, 2.43]	100	0.83	0.408	-1.00
Distance to public transport	17	65	-1.99	[-3.61, -0.38]	[-14.52, 10.54]	100	-2.15	1.352	-1.70
Distance to schools	14	43	-1.23	[-3.03, 0.56]	[-12.62, 10.15]	99	0.17	2.332	-1.19
Storeys	13	69	5.73	[3.16, 8.30]	[-15.19, 26.65]	100	6.06	2.515	0.90
Green space and parks	13	79	-2.94	[-4.60, -1.28]	[-17.28, 11.40]	100	-3.91	2.443	-1.64
Distance to highways	10	49	0.14	[-0.34, 0.61]	[-2.92, 3.19]	98	0.78	0.850	-0.38
Distance to commercial areas	9	18	-2.02	[-4.22, 0.19]	[-11.45, 7.41]	100	-2.85	2.163	-0.95
Distance to hospitals	8	16	-1.90	[-4.92, 1.13]	[-13.62, 9.82]	100	-2.18	2.977	-0.49
Proximity to water bodies	7	148	-1.63	[-1.95, -1.32]	[-4.71, 1.45]	96	-2.61	1.192	-1.49
Distance to university	5	27	-0.44	[-0.69, -0.18]	[-1.63, 0.76]	92	-1.26	0.824	-0.21
Hazardous or industrial sites	5	14	3.08	[0.47, 5.69]	[-5.36, 11.52]	100	5.35	2.740	4.65

Table 8. Pooled elasticities (log-log models)

Characteristic	<i>k</i>	<i>n</i>	RE estimate	95% CI	95% PI	<i>I</i> ²	3-level	RVE SE	median
Living area	46	234	0.65	[0.61, 0.69]	[0.09, 1.21]	100	0.62	0.058	0.63
Lot size	23	114	0.09	[0.05, 0.12]	[-0.30, 0.47]	100	0.14	0.045	0.06
Distance to CBD	22	140	-0.09	[-0.11, -0.07]	[-0.30, 0.12]	100	-0.06	0.034	-0.09
Age	18	93	-0.09	[-0.11, -0.07]	[-0.27, 0.09]	100	-0.11	0.022	-0.07
Proximity to water bodies	14	60	-0.02	[-0.04, -0.01]	[-0.13, 0.09]	99	-0.04	0.025	-0.01
Distance to public transport	13	82	-0.00	[-0.01, 0.01]	[-0.09, 0.09]	100	-0.07	0.061	-0.00
Population density	12	52	0.02	[0.00, 0.04]	[-0.11, 0.15]	100	0.01	0.017	0.00
Green space and parks	12	79	-0.01	[-0.02, -0.00]	[-0.07, 0.05]	99	0.00	0.010	-0.01
Bedrooms	12	40	0.19	[0.11, 0.27]	[-0.29, 0.67]	100	0.23	0.077	0.10
Neighbourhood income	10	30	0.25	[0.18, 0.33]	[-0.14, 0.65]	100	0.22	0.055	0.27
Distance to highways	9	18	-0.00	[-0.02, 0.01]	[-0.08, 0.07]	97	-0.00	0.016	0.00
Distance to schools	9	32	0.02	[-0.00, 0.04]	[-0.10, 0.14]	100	0.01	0.021	-0.00
Neighbourhood amenities	8	78	0.01	[-0.00, 0.02]	[-0.09, 0.12]	100	-0.02	0.021	0.00
Distance to commercial areas	8	49	0.01	[-0.00, 0.02]	[-0.06, 0.08]	100	0.00	0.015	0.00
Distance to hospitals	7	22	0.00	[-0.01, 0.01]	[-0.05, 0.06]	99	-0.03	0.026	0.00
Bathrooms	6	32	0.07	[0.04, 0.10]	[-0.10, 0.25]	100	0.05	0.028	0.06

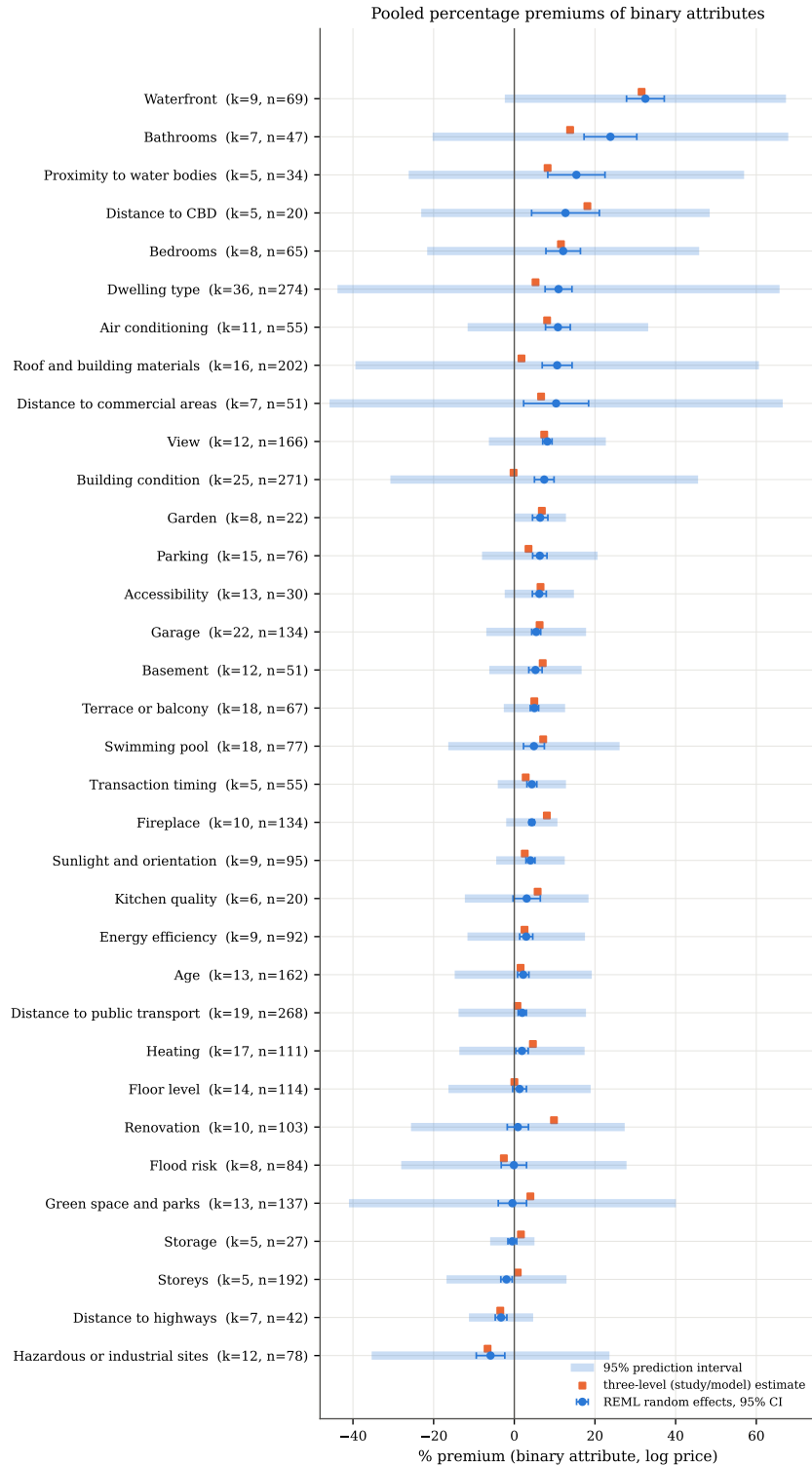


Figure 3. Forest plot of pooled percentage premiums of binary attributes. Circles: REML random-effects estimates with 95 percent confidence intervals; squares: three-level estimates; shaded bars: 95 percent prediction intervals.

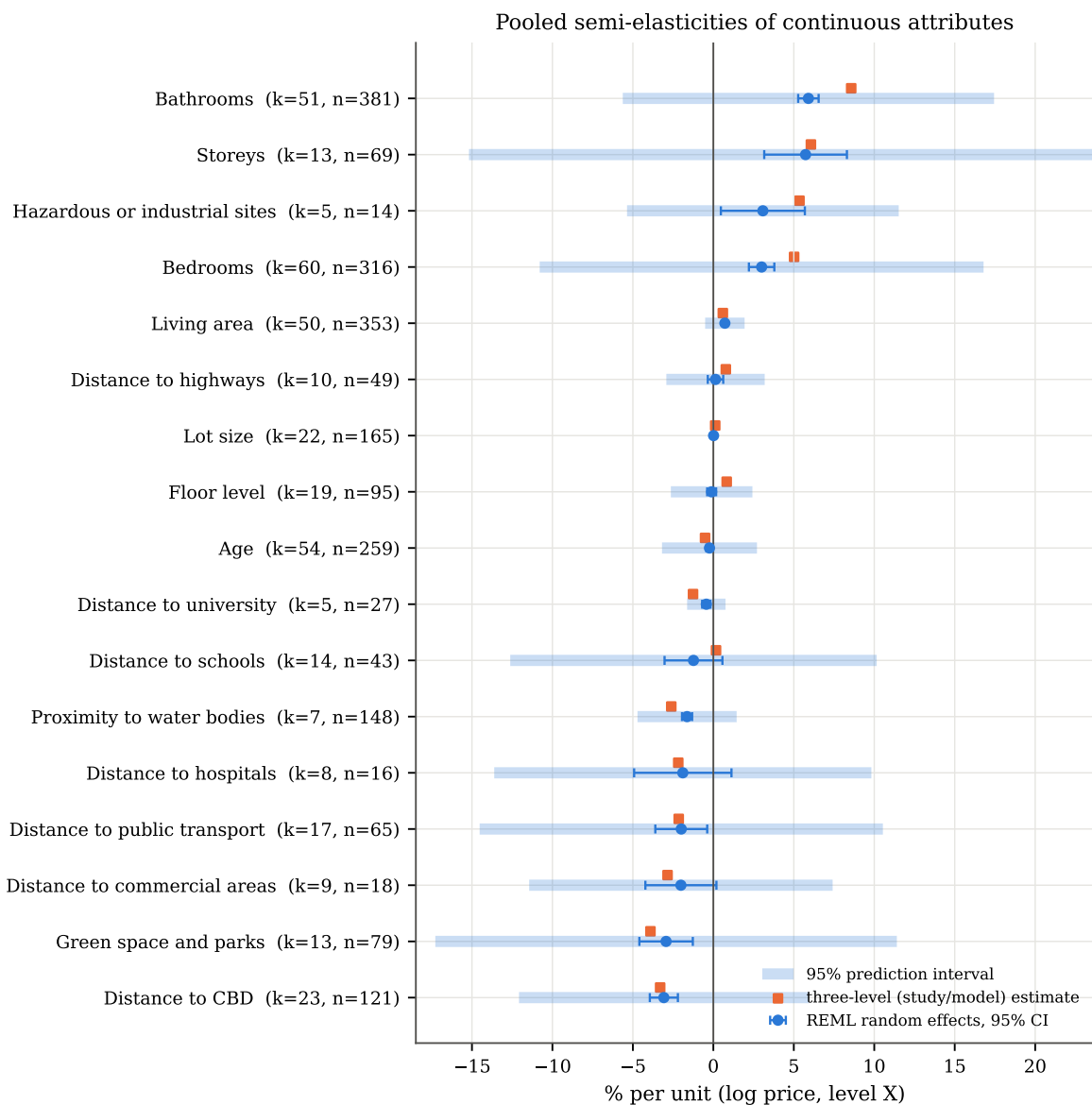


Figure 4. Forest plot of pooled semi-elasticities (percent per harmonised unit).

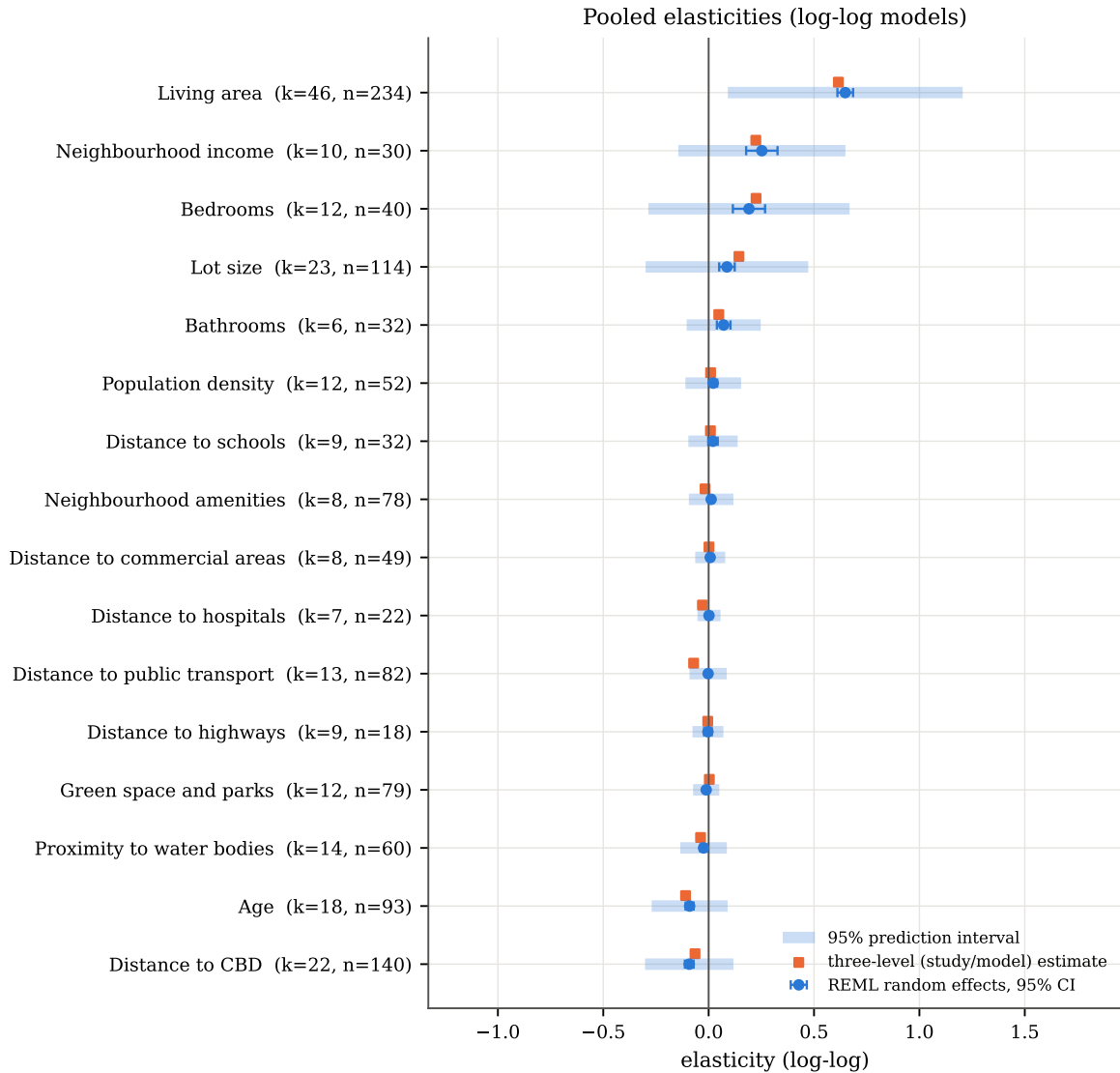


Figure 5. Forest plot of pooled elasticities from log-log models.

8.3. Comparison with the Sirmans programme

Table 9 places the pooled estimates for the nine characteristics of [Sirmans et al. \(2006\)](#) next to the qualitative findings that could be verified from that paper's abstract and references. The signs agree: living area, lot size, bathrooms, garage, pool, fireplace and air conditioning are positive and age is negative; bedrooms, which Sirmans et al. found of mixed sign, are positive on average here but with a prediction interval that includes large negative values, which is the expected consequence of conditioning on living area in most specifications. What the present synthesis adds is the magnitude with its uncertainty, the distinction between semi-elasticities and elasticities, and the global prediction interval; what it cannot do is reproduce the Sirmans meta-regressions on raw

coefficients, which are not comparable across functional forms.

Table 9. The nine Sirmans et al. (2006) characteristics: pooled estimates of this synthesis and the qualitative findings of the earlier meta-analysis (abstract-level; the full text was not accessible)

Characteristic	family	<i>k</i>	<i>n</i>	pooled	95% CI	95% PI	Sirmans et al. (2006) finding
square footage	% per unit	50	353	0.72	[0.65, 0.78]	[-0.51, 1.94]	positive; varies by location
square footage	elasticity	46	234	0.65	[0.61, 0.69]	[0.09, 1.21]	extquotedbl
lot size	% per unit	22	165	0.01	[0.01, 0.02]	[-0.02, 0.05]	positive; varies by location; smaller when sq ft controlled
lot size	elasticity	23	114	0.09	[0.05, 0.12]	[-0.30, 0.47]	extquotedbl
age	% premium	13	162	2.22	[0.82, 3.62]	[-14.78, 19.21]	negative; varies by location
age	% per unit	54	259	-0.24	[-0.43, -0.05]	[-3.19, 2.71]	extquotedbl
age	elasticity	18	93	-0.09	[-0.11, -0.07]	[-0.27, 0.09]	extquotedbl
bedrooms	% premium	8	65	12.12	[7.84, 16.40]	[-21.60, 45.84]	mixed sign
bedrooms	% per unit	60	316	3.00	[2.21, 3.79]	[-10.79, 16.79]	extquotedbl
bedrooms	elasticity	12	40	0.19	[0.11, 0.27]	[-0.29, 0.67]	extquotedbl
bathrooms	% premium	7	47	23.84	[17.30, 30.37]	[-20.25, 67.93]	positive; varies by location and data type
bathrooms	% per unit	51	381	5.91	[5.27, 6.54]	[-5.63, 17.44]	extquotedbl
bathrooms	elasticity	6	32	0.07	[0.04, 0.10]	[-0.10, 0.25]	extquotedbl
garage	% premium	22	134	5.43	[4.31, 6.54]	[-6.94, 17.80]	positive
pool	% premium	18	77	4.87	[2.28, 7.45]	[-16.37, 26.11]	positive; varies by location
fireplace	% premium	10	134	4.35	[3.73, 4.96]	[-2.01, 10.70]	positive
air conditioning	% premium	11	55	10.81	[7.74, 13.88]	[-11.57, 33.20]	positive; varies by location

8.4. Summary

Figure 6 assembles the pooled percentage premiums and semi-elasticities in one view, coloured by taxonomy group. Structural characteristics and signature exterior amenities have precisely estimated positive means; environmental disamenities (hazardous sites, highways, noise, pollution) have negative means that are less precisely estimated and rest on fewer studies; locational distances have negative semi-elasticities whose magnitudes depend heavily on the market's spatial structure. The prediction intervals are the message for applied work: an appraiser or a policy analyst transferring an implicit price from the literature to a particular market should expect the local value to lie anywhere within these intervals unless local evidence narrows them.



Figure 6. Summary of the pooled evidence: REML estimates with 95 percent confidence intervals for all pooled percentage premiums and semi-elasticities, coloured by taxonomy group.

9. Geographic heterogeneity

Figure 7 maps the coverage of the stage-one included records and of the extracted studies, and Table 10 lists the countries contributing the most records and estimates. Coverage is broad in records (103 countries at stage one) and narrower in extracted full texts (55 countries), because open-access availability is itself unequal across publication venues and regions. Figure 8 shows the distribution of harmonised estimates by continent for the six most-studied characteristic–family combinations. The living-area elasticity is centred between 0.5 and 0.8 on every continent with at least five studies; the bedroom semi-elasticity is close to zero in North America, where living area is almost always controlled, and larger in Asia and Europe, where room counts more often proxy for size; the age semi-elasticity is negative everywhere with a wider dispersion in Asia, where samples mix new-build and resale apartments; and the premium of a detached dwelling type varies from negative to large positive values within Europe, which reflects the diversity of reference categories rather than a geographic law. The moderator analysis of Section 11 tests the non-US indicator formally: it is significant in 1 of 19 models, raising the living-area semi-elasticity outside the United States, and insignificant elsewhere. The honest summary of RQ3 is that geography matters through the composition of studies (property types, specifications, units) more than through a detectable continental shift in implicit prices once those are controlled, with the important caveat that Africa, South America and Oceania contribute too few studies for any contrast to be powered.

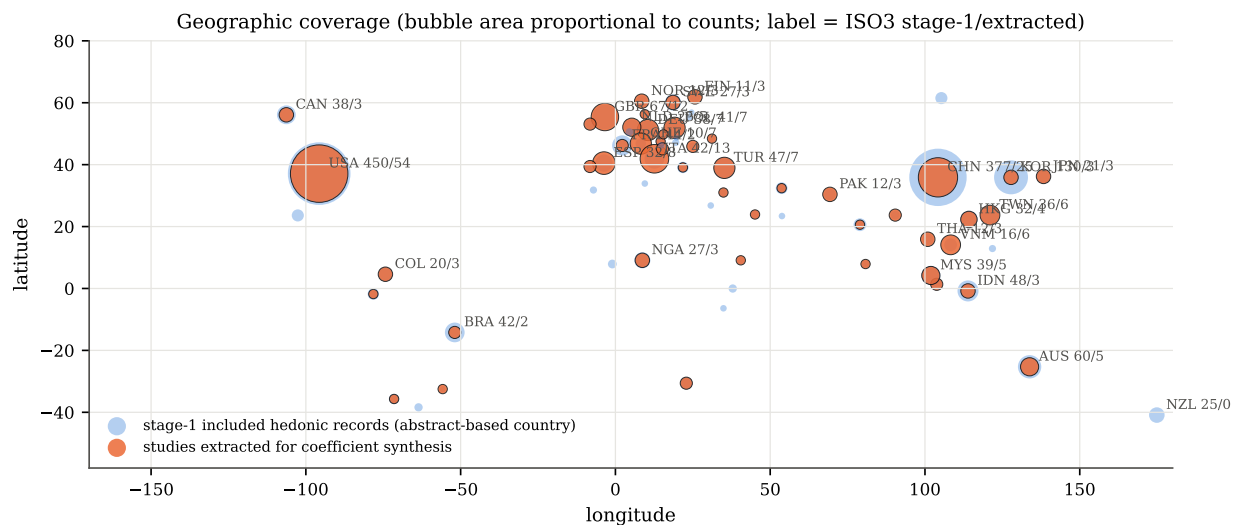


Figure 7. Geographic coverage: stage-one included hedonic records (country from title and abstract) and extracted studies.

Table 10. Geographic distribution of the evidence (countries with the most stage-one included records)

Country	stage-1 included records	extracted studies	usable estimates
United States	450	54	2,558
China	377	25	691
unknown	196	0	0
South Korea	130	3	55
United Kingdom	67	12	458
Australia	60	5	9
USA	54	0	0
Indonesia	48	3	38
Turkey	47	7	77
France	44	2	128
Italy	42	13	232
Brazil	42	2	7
Poland	41	7	341
Malaysia	39	5	41
Canada	38	3	60
Germany	38	7	137
Taiwan	36	6	186
Hong Kong	32	4	0
Spain	32	8	43
Sweden	27	3	110
Nigeria	27	3	87
New Zealand	25	0	0
Netherlands	25	5	119
Japan	21	3	105
Colombia	20	3	32

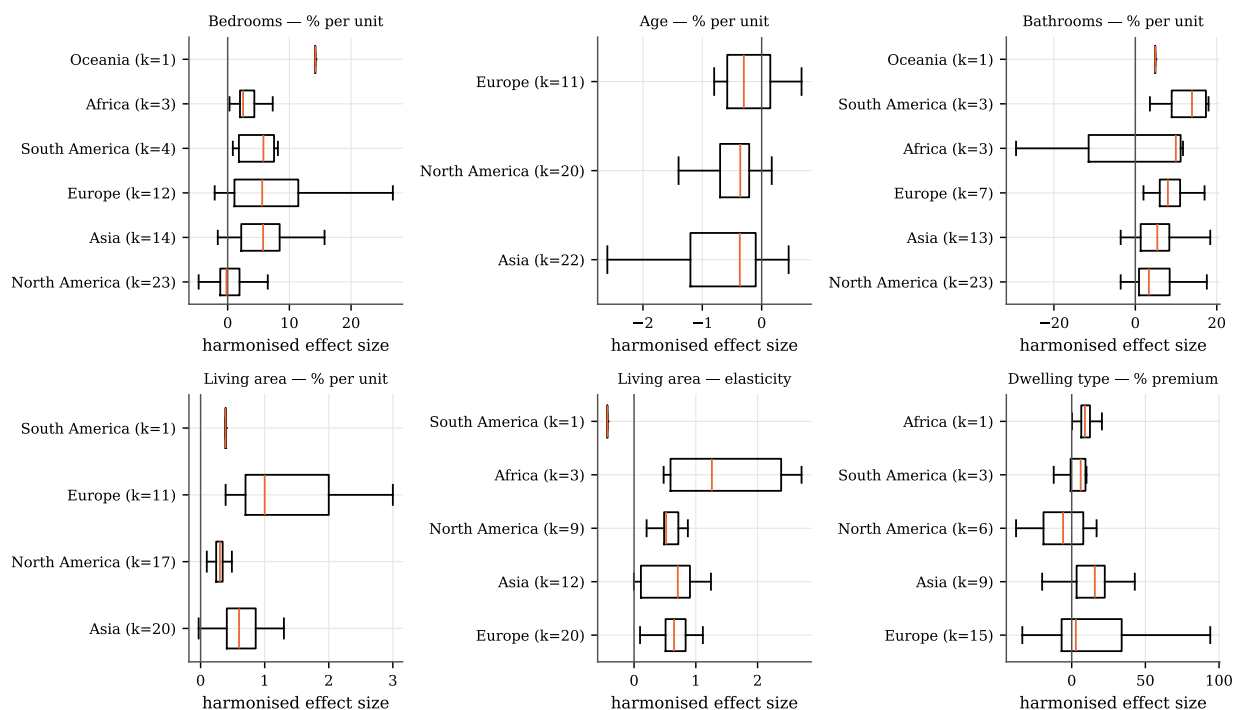


Figure 8. Distribution of harmonised estimates by continent for the six most-studied characteristic–family combinations (boxes: interquartile range; line: median; whiskers: 1.5 IQR; k = studies).

10. Temporal variation

The relevant clock for an implicit price is the period of the transactions, not the year of publication, and the two differ by a median of several years in the extracted studies. Figure 9 plots the harmonised estimates of the six most-studied combinations against the midpoint of the transaction period, with a precision-weighted trend, and Figure 10 gives the density of evidence by characteristic and decade. The pre-2000 evidence is thin in the extracted sample, which is dominated by transactions from the 2000s and 2010s and, through listing data, the 2020s. Within that window the trends are small relative to the dispersion: the living-area elasticity is flat, the age semi-elasticity drifts toward zero, and the bathroom and bedroom semi-elasticities decline, consistent with the increasing inclusion of area controls in later specifications rather than with a change in preferences. In the moderator models, the data-period variable is significant in 2 of 21 specifications. The pre-registered hypothesis of rising premiums for energy efficiency and green space after 2008 cannot be tested with power: both families have fewer than fifteen studies and their estimates are dominated by specification differences. The same is true of the financial crisis and of the COVID-19 pandemic, for which the extracted studies are few and their designs heterogeneous; the paper reports no pooled pre/post contrast for them.

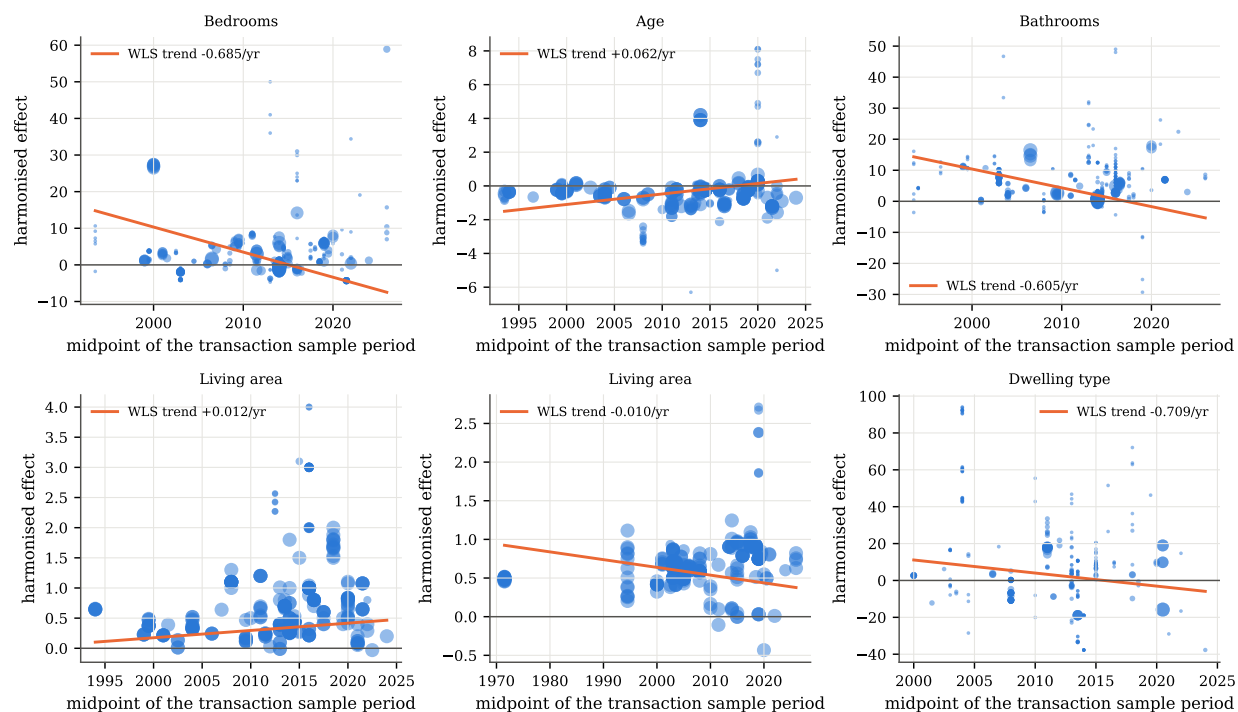


Figure 9. Harmonised estimates against the midpoint of the transaction period, with a precision-weighted linear trend (marker size proportional to precision).

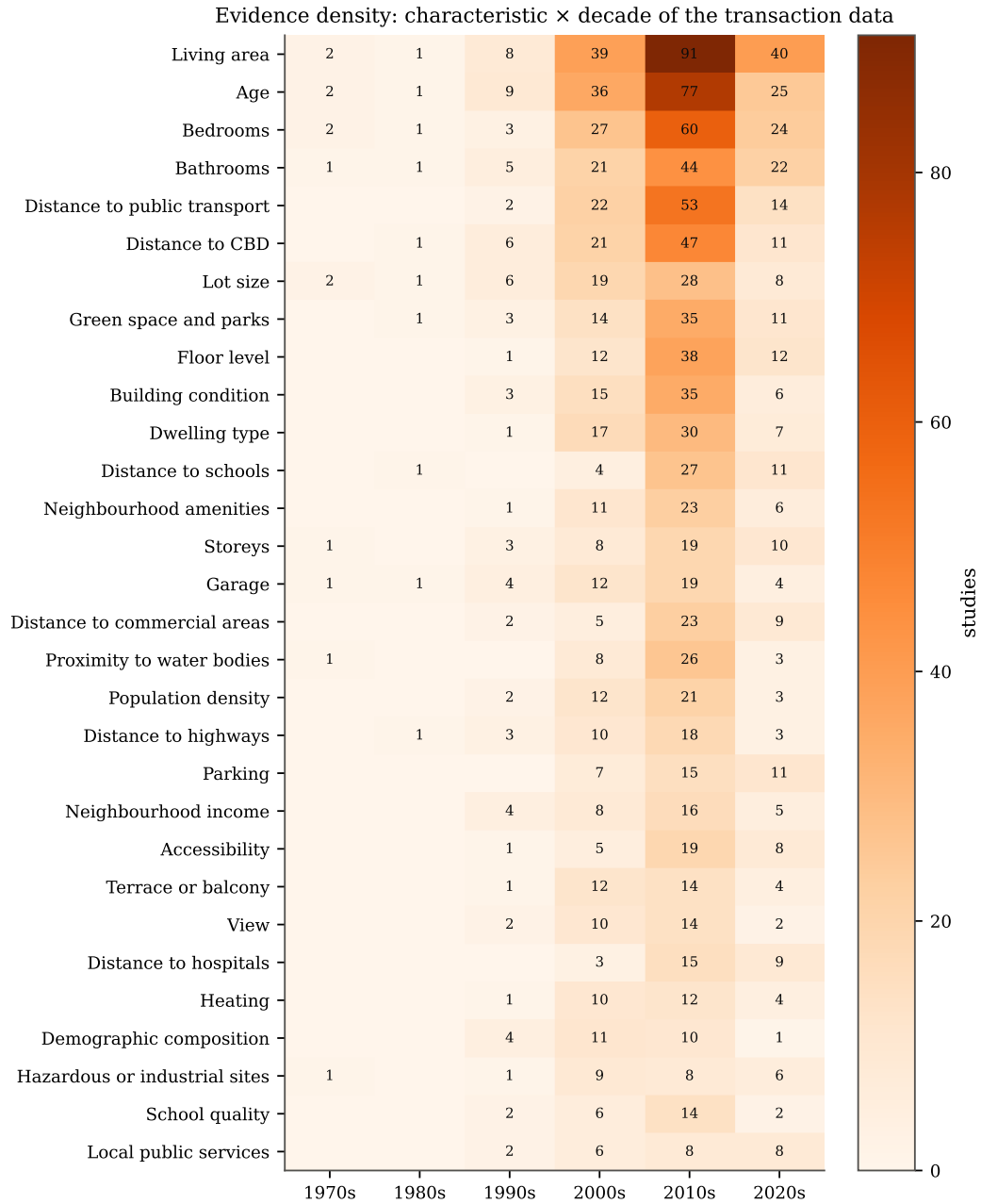


Figure 10. Evidence-density matrix: number of extracted studies by characteristic and decade of the transaction data.

11. Methodological heterogeneity

Table 11 reports the three-level meta-regressions, with cluster-robust standard errors, for the 21 characteristic–family combinations with at least fifteen studies, and Figure 11 plots the moderator effects for six of them. Of the 182 moderator coefficients tested, 12 are significant at the five percent level, which is about what chance would produce at that level and is the first result of this

section: once estimates are weighted by precision and the dependence within studies is modelled, the observable features of a study explain little of the between-study variance in implicit prices. The exceptions are informative. The apartment indicator is significant in 3 of 20 models and raises the living-area semi-elasticity (0.545 percentage points per square metre, $p = 0.007$), as expected when the dwelling is smaller and the marginal square metre dearer. The spatial-estimator indicator is significant in 2 of 21 models, and in both cases it lowers the living-area effect slightly (elasticity -0.019, $p = 0.022$), which is the expected direction when a spatial lag absorbs part of the size premium that is correlated across neighbours. Time fixed effects matter in 3 models; location fixed effects, the working-paper indicator, the rent indicator and the log sample size are insignificant almost everywhere. The exploratory machine-learning meta-regressions, trained on all moderators with study-grouped cross-validation, have negative out-of-study R^2 for both random forests and gradient boosting: the moderators do not predict the implicit price of a new study, and the permutation importances, which rank the effect-size family, the data period and the sample size first, describe the training data rather than a transferable structure. The answer to RQ5 is therefore that spatial and conventional estimators produce similar implicit prices for structural characteristics in the pooled evidence, with a small attenuation under spatial models for living area; machine-learning marginal effects are too few and too heterogeneous in construction to be pooled with regression coefficients, and are discussed in Section 12.

Table 11. Three-level meta-regressions of harmonised effects on study and model characteristics (coefficient, cluster-robust SE; * $p < 0.05$ with Satterthwaite degrees of freedom)

Moderator	Building condition	Dwelling type	Garage	Heating	Parking	Swimming pool	Roof and building materials	Terrace or balcony	Distance to public transport
period	-7.10 (6.586)	-8.96 (7.154)	1.26 (3.091)	4.45 (2.739)	0.52 (2.224)	3.37 (6.173)	2.03 (7.634)	0.50 (1.939)	-6.40 (2.236)*
spatial	0.64 (1.004)	-1.66 (3.429)	0.13 (0.432)	-0.31 (0.482)	0.73 (1.020)	0.26 (0.214)	0.50 (0.335)	-1.01 (0.723)	1.43 (1.714)
pub_wp	-13.00 (10.572)	-19.21 (10.531)	4.25 (9.416)	-7.49 (4.323)	12.49 (7.352)	2.77 (6.766)	-31.64 (14.476)	4.50 (4.350)	-1.88 (3.472)
lnN	2.09 (2.094)	-2.82 (1.911)	-0.88 (1.011)	-1.66 (1.091)	-0.81 (0.989)	-2.82 (0.988)	-2.22 (1.008)	0.07 (0.321)	1.78 (0.515)*
rent	14.59 (10.182)	1.32 (8.341)	2.28 (7.300)	11.62 (4.235)	4.03 (4.213)	—	-44.63 (97.535)	-1.06 (4.227)	—
apt	3.88 (12.124)	11.02 (10.086)	—	-2.97 (6.027)	5.71 (4.805)	10.73 (9.525)	-12.07 (14.827)	4.91 (5.200)	9.00 (2.249)*
nonUS	0.58 (9.942)	-1.36 (10.623)	-6.91 (3.735)	-14.72 (7.966)	—	-6.59 (7.896)	-10.22 (12.723)	-0.32 (3.790)	8.49 (3.883)
time_feTrue	-5.08 (8.209)	-4.48 (7.733)	1.51 (3.072)	8.67 (2.771)*	7.55 (5.782)	7.57 (8.917)	-13.26 (8.861)	0.09 (1.970)	-7.82 (4.060)
location_feTrue	-3.93 (8.024)	-4.99 (8.094)	-1.53 (4.251)	-3.23 (4.229)	-0.02 (7.008)	-5.22 (7.227)	22.29 (11.380)	-5.73 (2.750)	1.61 (3.075)
k / n	25 / 271	36 / 274	22 / 134	17 / 111	15 / 76	18 / 77	16 / 202	18 / 67	19 / 268

Moderator	Age (elasticity)	Distance to CBD (elasticity)	Living area (elasticity)	Lot size (elasticity)	Age (% per unit)	Bathrooms (% per unit)	Bedrooms (% per unit)	Distance to CBD (% per unit)	Floor level (% per unit)	Living area (% per unit)	Lot size (% per unit)	Distance to public transport (% per unit)
period	-0.07 (0.025)*	0.01 (0.092)	0.05 (0.053)	0.01 (0.030)	-0.05 (0.237)	1.47 (2.102)	-1.74 (1.524)	-1.17 (1.706)	-0.79 (0.397)	-0.19 (0.092)	0.33 (0.318)	0.36 (2.038)
spatial	0.01 (0.008)	0.01 (0.007)	-0.02 (0.066)*	-0.00 (0.004)	0.02 (0.034)	-0.53 (0.501)	-0.17 (0.701)	-0.29 (0.574)	0.06 (0.157)	-0.14 (0.051)*	-0.00 (0.000)	0.29 (0.332)
pub_wp	-0.09 (0.034)	0.06 (0.047)	-0.07 (0.161)	0.00 (0.109)	-0.27 (0.581)	5.84 (3.446)	-1.83 (1.998)	-1.46 (6.847)	—	0.03 (0.131)	0.23 (0.299)	8.68 (4.006)
lnN	-0.00 (0.008)	0.00 (0.007)	-0.02 (0.038)	0.00 (0.003)	0.06 (0.053)	-0.31 (0.489)	0.14 (0.319)	0.00 (0.493)	0.17 (0.416)	-0.04 (0.023)	-0.00 (0.002)	-0.74 (0.298)
rent	0.02 (0.079)	-0.11 (0.086)	0.28 (0.244)	—	0.72 (0.453)	-6.97 (3.299)	5.39 (3.458)	2.21 (2.791)	-0.28 (0.994)	0.70 (0.299)	0.45 (0.287)	-1.99 (2.588)
apt	0.09 (0.063)	-0.19 (0.093)	-0.03 (0.180)	-0.27 (0.092)*	0.10 (0.634)	-1.41 (2.686)	4.03 (3.128)	-6.89 (7.438)	1.40 (1.592)	0.55 (0.186)*	-0.43 (0.287)	1.71 (3.172)
nonUS	-0.00 (0.041)	0.19 (0.215)	-0.06 (0.111)	0.06 (0.118)	-0.30 (0.424)	0.72 (3.355)	3.11 (1.932)	0.26 (2.409)	—	0.30 (0.139)*	0.11 (0.148)	-8.98 (4.247)
time_feTrue	-0.02 (0.070)	-0.20 (0.101)	0.05 (0.112)	-0.04 (0.115)	0.53 (0.353)	-3.95 (2.288)	-4.52 (1.810)*	2.95 (2.479)	-0.65 (0.928)	0.28 (0.129)*	-0.22 (0.204)	4.70 (2.656)
location_feTrue	0.11 (0.057)	0.24 (0.112)	0.02 (0.126)	-0.12 (0.076)	0.27 (0.243)	3.07 (2.750)	2.49 (2.019)	0.59 (2.088)	-0.93 (1.093)	-0.11 (0.107)	0.05 (0.082)	-8.03 (3.348)
k / n	18 / 93	22 / 140	46 / 234	23 / 114	54 / 259	51 / 381	60 / 316	23 / 121	19 / 95	50 / 353	22 / 165	17 / 65

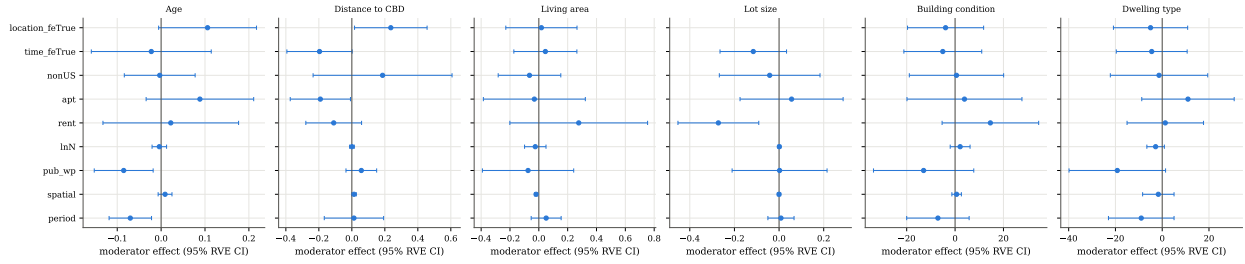


Figure 11. Moderator effects with cluster-robust 95 percent confidence intervals for six characteristic–family combinations.

12. AI and the evolution of hedonic valuation

The screening identified 897 machine-learning or automated-valuation studies of residential prices at stage one, and Figure 12 traces the rise of tree ensembles, neural networks, computer vision and text methods in the included literature since 2000. Only a small fraction of these studies could be retrieved in open access, and the dedicated synthesis rests on 40 studies extracted under a light protocol that records, for each paper, the methods compared, the best model, the evaluation metric and its value, the hedonic benchmark on the same test set when one is printed, the test-set design, the AI-derived features used, the incremental gain from those features when reported, and whether interpretable marginal effects are reported (Table 12). Three conclusions follow, each bounded by the small sample. First, when a hedonic benchmark is evaluated on the same test set (27 studies), tree boosting and random forests usually predict better: among the 9 studies reporting mean absolute percentage errors for both, the median error is 8.96 percent for the best model against 12.41 percent for the hedonic benchmark, and among the 13 studies reporting R^2 the medians are 0.817 and 0.724; a few studies find the hedonic model competitive or better, usually with small samples. Only 20 studies use a true holdout and 7 report in-sample fit only; one study shows that random cross-validation overstates out-of-time accuracy relative to temporal validation. Second, the incremental information of AI-derived characteristics is documented in only 9 studies, and it is modest: text embeddings, street-view or floor-plan features add between a few thousandths and a few hundredths to R^2 or reduce prediction errors by fractions of a percentage point, with the largest gains for floor plans and interior-condition scores; one study finds that a natural-language sea-view indicator adds nothing to fit but identifies an eight percent premium that a GIS viewshed misses, which illustrates that the value of AI-derived variables lies as much in interpretable new characteristics as in accuracy. Third, 12 studies report SHAP values and 23 report regression coefficients; the paper does not pool SHAP values with coefficients, because a SHAP value is a model-specific attribution for a particular observation set, not an implicit price, and the marginal effects extracted from these studies are kept in the AI-derived branch of the taxonomy where they

appear in Table 2. No comparison across studies with incompatible datasets is made.

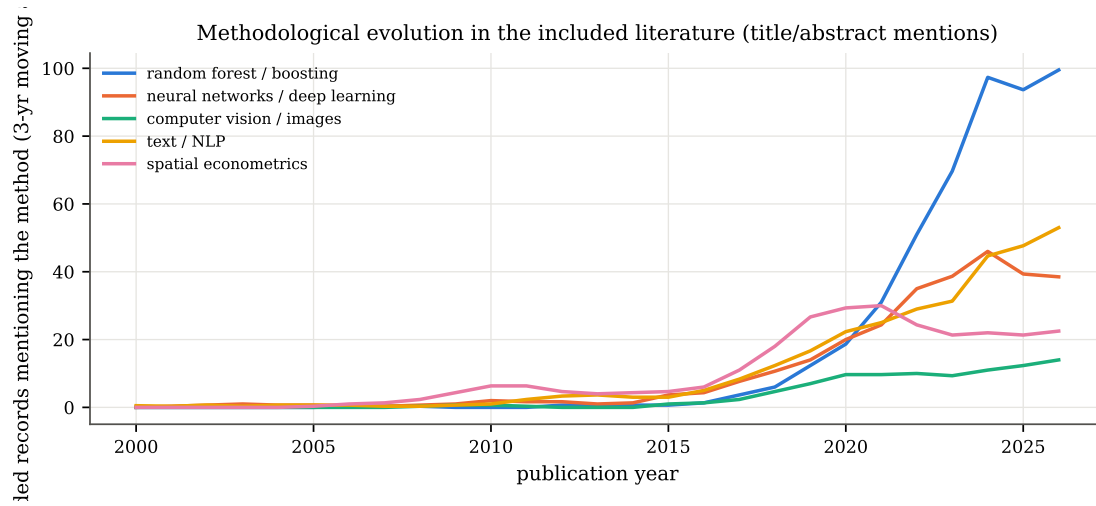


Figure 12. Methodological evolution in the included literature: records mentioning each class of method in title or abstract (three-year moving average).

Table 12. AI-enhanced valuation evidence (light extraction; metrics as printed, never compared across studies)

Study	country	best model	metric	best	hedonic benchmark	AI-derived features	marginal effects?
Tarasov & Dessoulavy-Sliwins	Poland	XGBoost	MAPE	8.990	–	none	SHAP
Dewi, Ulama & Susilaningrum	Indonesia	artificial neural netw	MAPE	31.040	34.240	none	coefficients
Amri & Tularam (2012)	Australia	neural network	R2	0.454	0.369	none	coefficients
Cui et al. (2024)	China	MGWR	R2	0.613	0.346	street-view CNN	coefficients
Ezzeldin et al. (2025)	Saudi Arabia	random forest	R2	0.906	0.803	none	coefficients
Solovev & Pröllochs (2021)	Germany	deep neural network +	MAE	0.021	0.157	floor-plan	coefficients
Nor & Hussein (2025)	Somalia	artificial neural netw	MAE	1200.000	–	none	coefficients
Takizawa (2023)	Japan	OLS hedonic + GCN-deri	RMSE	11280.000	–	floor-plan	coefficients
Gillespie, Lyons & Hynes (20	Ireland	OLS hedonic with Small	R2	0.890	0.890	listing text (rule-based N	coefficients
Han, Woo & Lee (2025)	South Korea	gradient boosting	R2	0.817	0.660	street-view CNN	SHAP
Sa'at, Adi Maimun & Idris (2	Malaysia	ANN (one hidden layer,	RMSE	0.005	0.049	none	none
Geerts et al. (2025)	Multi: Usa	LightGBM (with coordin	MAPE	0.138	–	none	SHAP
Embaye, Zereyesus & Chen (20	Uganda	boosting	other	0.850	1.000	none	coefficients
Štubňová, Urbaníková, Hudáko	Slovakia	ANN (Bayesian regulari	MAPE	3.390	8.410	none	coefficients
Deppner & Cajias (2024)	Germany	XGBoost	R2	0.852	0.788	none	coefficients
Changro (2026)	South Korea	XGBoost with text embe	R2	–	–	listing text embeddings	SHAP
Tapia, Chavez-Garzon, Pezoa,	Chile	LightGBM (34 predictor	MAPE	10.070	21.130	listing-photo CNN (interio	SHAP
Almaas, Oust & Pollestad (20	Norway	XGBoost with human-lab	MAPE	7.490	12.410	interior-photo CNN	SHAP
Upadhye, Bhuravane & Khanche	United States	XGBoost + CNN text emb	R2	0.920	0.710	listing text embeddings	SHAP
Lorenz, Willwersch, Cajias &	Germany	XGBoost	R2	0.925	–	none	PDP
Fu et al. (2019)	China	robust OLS hedonic wit	R2	0.724	0.724	street-view CNN	coefficients
Tymchuk, Pylypenko & Kicha (	Ukraine	OLS with NN text-deriv	R2	0.889	0.884	listing text embeddings	coefficients
Yang, Krenz, Qiu & Li (2023)	United Kingdom	OLS hedonic, Model 0 (	R2	0.496	0.496	street-view CNN	coefficients
Wang (2026b)	United States	random forest	MAPE	10.430	–	none	SHAP
Nor, Audu & Mohamed (2025a)	Somalia	OLS hedonic regression	MAE	29.380	29.380	none	coefficients
Shen & Ross (2020)	United States	OLS hedonic + text-der	R2	0.769	0.760	listing text embeddings	coefficients
d'Amato (2004)	Italy	linear MRA (hedonic)	MAPE	11.000	11.000	none	coefficients
Hong, Choi & Kim (2020)	South Korea	random forest	MAPE	5.482	19.606	none	none
Wang et al. (2026a)	China	GBDT	R2	0.470	–	street-view CNN	PDP
Zhong (2024)	United States	OLS multiple linear re	RMSE	0.203	0.203	none	coefficients
Lenaers, Boudt & De Moor (20	Belgium	XGBoost	MAPE	10.330	11.590	none	SHAP
Oliveira, Reyes-Bueno, Gonza	Brazil	XGBoost	MAPE	8.960	13.900	none	coefficients
Haque (2003)	United States	Jordan-Elman recurrent	R2	0.863	–	none	coefficients
An, Song, Jang & Ahn (2025)	South Korea	random forest	R2	0.941	–	none	SHAP
Marimon & Vergara (2026)	Philippines	linear hedonic regress	R2	0.547	0.547	street-view CNN	coefficients
Liu, Chen, Orford, Tian & Zo	United Kingdom	XGBoost	R2	0.760	–	none	SHAP
Fan, Teo & Wan (2021)	Singapore	OLS hedonic with block	R2	0.919	0.919	text sentiment	coefficients
Kagie & van Wezel (2007)	Netherlands	boosted regression tre	MAPE	9.380	–	none	PDP
Kim, Choi & Lee (2025)	South Korea	random forest	MAPE	5.928	12.227	none	SHAP
Tajani, Di Liddo, Ranieri &	Italy	evolutionary polynomia	R2	0.887	–	none	coefficients

13. Publication selection and robustness

13.1. Publication selection

Figure 13 shows funnel plots for the six most-estimated families and Table 13 the diagnostics for all 67 families with at least ten estimates: the Egger test, the PET and PEESE intercepts, and, where at least thirty estimates are available, a three-step selection model. Funnel asymmetry is common: the Egger test is significant in 46 of 67 families. Under such heterogeneity, however, asymmetry is not evidence of publication selection alone, because precision is correlated with sample size, country, data type and specification, all of which shift the effect itself; the dependence of multiple estimates on the same study also inflates the test. The PET–PEESE intercepts are reported as sensitivity analyses rather than as corrected estimates: for the structural core (living-area elasticity, bathrooms,

age, garage) they remain of the same sign and order of magnitude as the random-effects means, which is reassuring; for several amenity premiums the PET intercept is smaller or of opposite sign to the random-effects mean, which is what one would expect if the less-precise estimates of small samples are more often reported when they are large and positive (the swimming pool and the renovation premium are examples). The selection models converge in most families but produce implausible values in a few (for instance for water proximity), which is a known failure mode of step-function models under extreme heterogeneity and is reported rather than hidden. The working-paper indicator in the meta-regressions is insignificant in every family, so the published literature does not differ detectably from the grey literature that was retrievable.

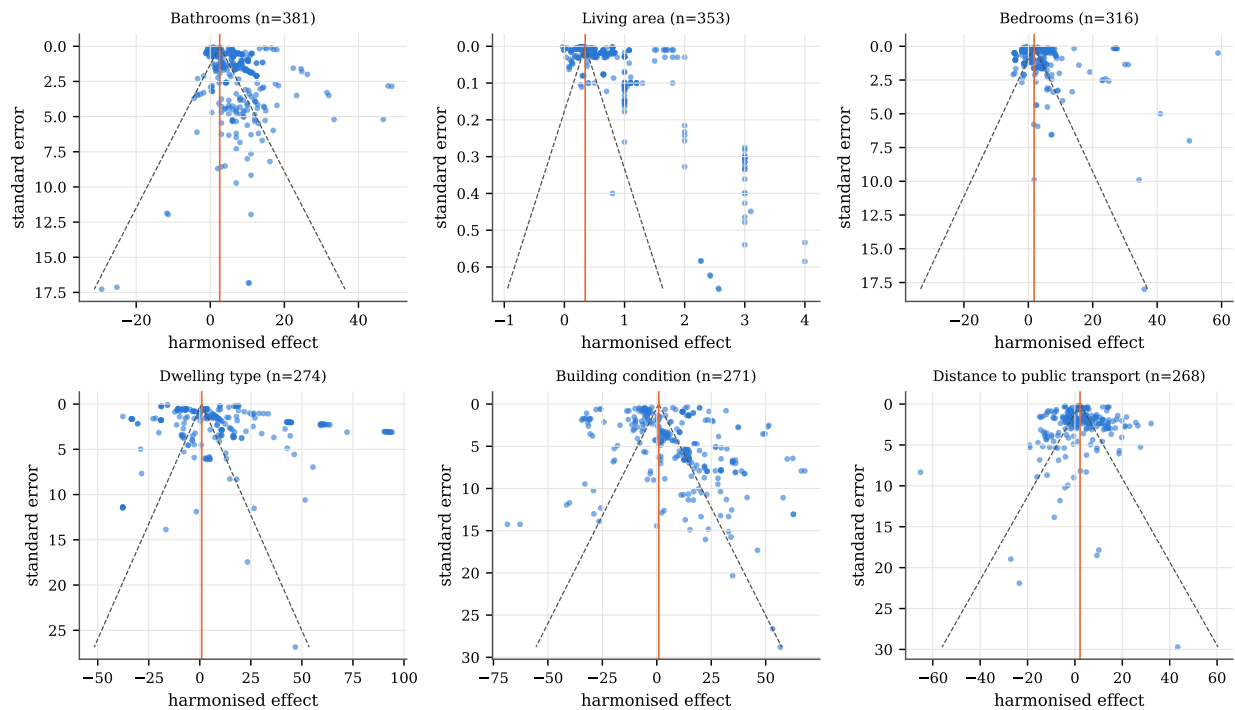


Figure 13. Funnel plots for the six most-estimated characteristic–family combinations (vertical line: fixed-effect mean; dashed lines: pseudo 95 percent limits).

Table 13. Publication-selection diagnostics by characteristic (families with at least ten estimates)

Characteristic	family	<i>n</i>	Egger <i>z</i>	<i>p</i>	PET (SE)	PEESE (SE)	selection model (SE)	LRT <i>p</i>
Bathrooms	% per unit	381	5.68	0.000	4.35 (0.406)	5.74 (0.341)	2.82 (0.717)	0.000
Living area	% per unit	353	23.78	0.000	0.41 (0.023)	0.57 (0.024)	-1.50 (0.531)	0.000
Bedrooms	% per unit	316	5.73	0.000	1.26 (0.493)	2.61 (0.402)	6.97 (0.623)	0.000
Dwelling type	% premium	274	0.65	0.517	9.97 (2.295)	11.17 (1.776)	15.34 (2.717)	0.206
Building condition	% premium	271	5.74	0.000	-0.88 (1.849)	4.35 (1.389)	7.65 (2.175)	0.156
Distance to public transport	% premium	268	-2.18	0.030	3.23 (0.775)	2.22 (0.542)	0.01 (0.854)	0.012
Age	% per unit	259	1.70	0.090	-0.34 (0.110)	-0.24 (0.095)	2.15 (–)	0.000
Living area	elasticity	234	5.44	0.000	0.57 (0.023)	0.60 (0.019)	0.64 (–)	0.325
Roof and building materials	% premium	202	5.01	0.000	1.68 (2.558)	8.36 (1.902)	17.53 (3.308)	0.020
Storeys	% premium	192	9.56	0.000	-5.95 (0.640)	-4.70 (0.676)	7.28 (2.646)	0.000
View	% premium	166	1.88	0.060	7.11 (0.821)	7.93 (0.646)	2.53 (1.804)	0.000

(continued)

Characteristic	family	<i>n</i>	Egger <i>z</i>	<i>p</i>	PET (SE)	PEESE (SE)	selection model (SE)	LRT <i>p</i>
Lot size	% per unit	165	20.00	0.000	0.01 (0.002)	0.01 (0.001)	-0.00 (0.005)	0.000
Age	% premium	162	8.13	0.000	-4.01 (0.980)	-0.97 (0.683)	1.18 (1.238)	0.311
Proximity to water bodies	% per unit	148	-0.19	0.853	-1.60 (0.256)	-1.59 (0.172)	-0.95 (-)	0.000
Distance to CBD	elasticity	140	-1.20	0.230	-0.08 (0.012)	-0.09 (0.011)	-0.05 (0.029)	0.077
Green space and parks	% premium	137	1.50	0.132	-3.17 (2.525)	-1.73 (1.990)	-3.92 (3.069)	0.004
Fireplace	% premium	134	10.38	0.000	2.57 (0.276)	3.96 (0.299)	0.04 (1.350)	0.000
Garage	% premium	134	2.35	0.019	3.99 (0.836)	4.74 (0.606)	3.99 (1.034)	0.220
Distance to CBD	% per unit	121	-3.77	0.000	-1.66 (0.556)	-2.61 (0.475)	0.23 (-)	0.000
Floor level	% premium	114	-1.67	0.095	3.34 (1.493)	1.97 (1.021)	-5.43 (1.448)	0.000
Lot size	elasticity	114	5.05	0.000	0.01 (0.023)	0.01 (0.018)	-0.02 (0.036)	0.001
Heating	% premium	111	2.60	0.009	0.03 (1.064)	1.42 (0.803)	-0.57 (1.306)	0.123
Renovation	% premium	103	7.08	0.000	-6.40 (1.506)	-1.32 (1.188)	-6.25 (-)	0.000
Floor level	% per unit	95	-3.79	0.000	0.46 (0.197)	0.19 (0.167)	-0.46 (-)	0.011
Sunlight and orientation	% premium	95	5.96	0.000	1.00 (0.724)	2.06 (0.557)	3.67 (0.976)	0.119
Age	elasticity	93	-1.62	0.106	-0.08 (0.013)	-0.08 (0.011)	-0.08 (-)	0.077
Energy efficiency	% premium	92	3.80	0.000	0.64 (0.989)	2.02 (0.836)	5.93 (1.487)	0.001
Flood risk	% premium	84	-1.62	0.106	1.66 (1.982)	1.25 (1.623)	8.66 (-)	0.000
Distance to public transport	elasticity	82	-3.55	0.000	0.01 (0.006)	-0.00 (0.005)	0.04 (-)	0.000
Green space and parks	% per unit	79	-5.54	0.000	0.01 (0.862)	-2.32 (0.794)	2.98 (2.584)	0.000
Green space and parks	elasticity	79	3.32	0.001	-0.02 (0.005)	-0.01 (0.004)	0.02 (-)	0.000
Neighbourhood amenities	elasticity	78	0.26	0.791	0.01 (0.007)	0.01 (0.006)	0.01 (-)	0.462
Hazardous or industrial sites	% premium	78	2.90	0.004	-11.73 (2.719)	-9.07 (1.892)	3.22 (6.131)	0.006
Swimming pool	% premium	77	3.25	0.001	-1.16 (2.227)	2.68 (1.503)	-4.61 (2.109)	0.000
Parking	% premium	76	3.74	0.000	3.18 (1.169)	5.35 (0.934)	4.27 (-)	0.022
Storeys	% per unit	69	4.73	0.000	-0.51 (1.726)	3.22 (1.375)	10.48 (-)	0.002
Waterfront	% premium	69	4.75	0.000	20.45 (3.213)	31.02 (2.381)	22.76 (5.495)	0.002
Terrace or balcony	% premium	67	0.48	0.632	4.76 (0.727)	5.02 (0.577)	2.89 (1.206)	0.018
Bedrooms	% premium	65	4.83	0.000	6.01 (2.351)	8.93 (2.018)	11.71 (-)	0.488
Distance to public transport	% per unit	65	3.51	0.000	-4.36 (1.007)	-2.54 (0.821)	-2.92 (1.307)	0.852
Proximity to water bodies	elasticity	60	1.35	0.177	-0.03 (0.010)	-0.03 (0.008)	-0.00 (0.020)	0.078
Air conditioning	% premium	55	5.68	0.000	-0.91 (2.386)	5.73 (1.812)	-6.98 (-)	0.000
Transaction timing	% premium	55	4.98	0.000	1.43 (0.724)	2.25 (0.597)	1.45 (1.250)	0.000
Population density	elasticity	52	-4.68	0.000	0.06 (0.011)	0.04 (0.009)	0.05 (0.015)	0.293
Basement	% premium	51	0.24	0.809	4.99 (1.350)	5.28 (0.888)	5.93 (-)	0.289
Distance to commercial areas	% premium	51	2.08	0.037	-1.87 (7.096)	4.70 (4.716)	-4.57 (7.467)	0.028
Distance to commercial areas	elasticity	49	-0.02	0.983	0.01 (0.006)	0.01 (0.005)	0.04 (-)	0.000
Distance to highways	% per unit	49	2.33	0.020	-0.46 (0.353)	-0.01 (0.246)	0.58 (-)	0.135
Bathrooms	% premium	47	2.29	0.022	17.32 (4.234)	22.12 (3.559)	-62.67 (41.365)	0.000
Distance to schools	% per unit	43	-2.16	0.031	0.63 (1.237)	-0.82 (0.928)	0.73 (1.798)	0.504
Distance to highways	% premium	42	-4.23	0.000	1.14 (1.195)	-1.39 (0.736)	-3.10 (-)	0.305
Bedrooms	elasticity	40	-1.36	0.173	0.24 (0.052)	0.23 (0.044)	0.12 (0.074)	0.176
Proximity to water bodies	% premium	34	15.35	0.000	-4.59 (1.424)	2.99 (0.710)	-623.65 (564.230)	0.000
Bathrooms	elasticity	32	2.63	0.008	0.02 (0.023)	0.04 (0.019)	0.08 (0.026)	0.795
Distance to schools	elasticity	32	-2.00	0.046	0.04 (0.013)	0.03 (0.012)	0.08 (-)	0.000
Accessibility	% premium	30	-0.77	0.439	7.14 (1.493)	6.69 (1.039)	5.01 (2.096)	0.064
Neighbourhood income	elasticity	30	2.95	0.003	0.16 (0.046)	0.22 (0.039)	0.24 (-)	0.381
Distance to university	% per unit	27	-0.65	0.516	-0.28 (0.284)	-0.19 (0.191)	-	-
Storage	% premium	27	3.57	0.000	-2.95 (0.829)	-1.32 (0.553)	-	-
Distance to hospitals	elasticity	22	-4.28	0.000	0.02 (0.007)	0.01 (0.005)	-	-
Garden	% premium	22	2.08	0.038	3.59 (1.740)	4.46 (1.164)	-	-
Distance to CBD	% premium	20	-0.39	0.694	14.74 (6.826)	13.59 (5.150)	-	-
Kitchen quality	% premium	20	0.90	0.368	1.61 (2.379)	2.53 (1.805)	-	-
Distance to commercial areas	% per unit	18	-0.24	0.811	-1.70 (1.762)	-2.11 (1.331)	-	-
Distance to highways	elasticity	18	-0.75	0.453	0.01 (0.015)	0.00 (0.012)	-	-
Distance to hospitals	% per unit	16	-2.83	0.005	0.34 (1.578)	-0.50 (1.392)	-	-
Hazardous or industrial sites	% per unit	14	5.20	0.000	0.10 (0.335)	1.22 (0.695)	-	-

13.2. Robustness

Table 14 compares, for every pooled family with at least ten studies, the REML estimate from metafor with the independent Python implementation (which agree to four decimals), the three-level estimate, the range of leave-one-study-out estimates, the Bayesian posterior mean with its credible interval and the PET–PEESE value. The Bayesian hierarchical model, fitted on study-

level aggregated effects with weakly informative priors, reproduces the frequentist means with wider intervals; all chains converge (maximum $\hat{R}$ 1.004, minimum effective sample size 674). Leave-one-study-out ranges are narrow for the structural core and wide for the amenity premiums with fewer than ten studies, which identifies the families whose pooled value depends on one or two studies. Further sensitivity analyses in the replication material, not tabulated here, confirm that restricting the sample to high-confidence extractions, to journal articles, or to transaction prices, and trimming the one percent most extreme harmonised values, change the pooled means of the structural characteristics by less than their cluster-robust standard errors. The retrieved and non-retrieved stage-one studies cannot be compared on estimates, but they can be compared on metadata: the retrieved set over-represents recent years, open-access journals and conference papers, and under-represents the older North American journal literature, which is the main threat to the representativeness of the synthesis and is discussed in Section 15.

Table 14. Robustness of the pooled estimates across estimators and implementations

Characteristic	family	REML (R)	REML (Py)	3-level	LOSO range	Bayes mean [95% CrI]	PET-PEESE
Bedrooms	% per unit	3.00	3.00	5.02	[2.46, 4.20]	5.25 [3.02, 7.48]	1.77
Living area	% per unit	0.72	0.72	0.59	[0.53, 0.83]	0.58 [0.44, 0.73]	0.35
Age	% per unit	-0.24	-0.24	-0.51	[-0.45, -0.13]	-0.51 [-0.85, -0.16]	0.08
Floor level	% per unit	-0.11	-0.11	0.83	[-0.23, 0.64]	0.85 [-0.03, 1.72]	0.44
Storeys	% per unit	5.73	5.73	6.06	[1.46, 8.52]	5.61 [0.55, 10.52]	-0.02
Bathrooms	% per unit	5.91	5.91	8.57	[5.45, 7.41]	8.47 [6.38, 10.54]	2.51
Distance to public transport	% per unit	-1.99	-1.99	-2.15	[-3.52, -0.69]	-2.13 [-4.90, 0.74]	-0.53
Distance to schools	% per unit	-1.23	-1.23	0.17	[-1.66, -0.18]	0.14 [-4.67, 4.75]	1.41
Distance to commercial areas	% per unit	-2.02	-2.02	-2.85	—	—	0.68
Distance to hospitals	% per unit	-1.90	-1.90	-2.18	—	—	-0.22
Distance to university	% per unit	-0.44	-0.44	-1.26	—	—	-0.11
Green space and parks	% per unit	-2.94	-2.94	-3.91	[-4.88, -1.14]	-3.53 [-8.26, 1.16]	-0.30
Distance to CBD	% per unit	-3.08	-3.08	-3.31	[-3.33, -2.42]	-3.30 [-6.32, -0.26]	-0.85
Proximity to water bodies	% per unit	-1.63	-1.63	-2.61	—	—	-0.47
Distance to highways	% per unit	0.14	0.14	0.78	[-0.27, 0.82]	0.87 [-1.15, 3.22]	0.30
Lot size	% per unit	0.01	0.01	0.12	[0.01, 0.08]	0.11 [-0.03, 0.26]	-0.00
Hazardous or industrial sites	% per unit	3.08	3.08	5.35	—	—	-0.31
Distance to commercial areas	% premium	10.37	10.37	6.64	—	—	-0.55
Distance to CBD	% premium	12.69	12.69	18.12	—	—	12.03
Roof and building materials	% premium	10.63	10.63	1.78	[4.95, 12.28]	1.46 [-6.11, 8.76]	7.80
Building condition	% premium	7.42	7.42	-0.18	[3.89, 9.44]	-0.17 [-5.39, 5.00]	-0.12
Heating	% premium	1.90	1.90	4.62	[0.60, 3.41]	4.24 [0.34, 8.41]	1.21
Dwelling type	% premium	10.97	10.97	5.27	[2.68, 13.85]	3.31 [-2.73, 9.46]	-1.64
Accessibility	% premium	6.21	6.21	6.50	[4.87, 6.85]	6.43 [3.68, 9.05]	4.78
Fireplace	% premium	4.35	4.35	8.07	[3.48, 8.36]	7.87 [4.31, 11.44]	2.20
Terrace or balcony	% premium	5.00	5.00	4.96	[3.89, 5.57]	4.90 [2.86, 6.98]	3.29
Distance to highways	% premium	-3.28	-3.28	-3.48	—	—	-0.59
Air conditioning	% premium	10.81	10.81	8.14	[6.48, 13.08]	7.19 [0.13, 13.86]	4.12
Green space and parks	% premium	-0.47	-0.47	3.99	[-1.39, 3.09]	0.14 [-12.60, 12.81]	-99.91
Distance to public transport	% premium	1.98	1.98	0.78	[0.46, 2.64]	1.27 [-1.10, 3.62]	2.18
Parking	% premium	6.33	6.33	3.52	[4.94, 7.21]	3.20 [-0.61, 7.01]	3.49
View	% premium	8.20	8.20	7.41	[7.18, 8.65]	6.36 [1.94, 10.73]	6.45
Energy efficiency	% premium	2.96	2.96	2.54	—	—	-0.42
Bedrooms	% premium	12.12	12.12	11.56	—	—	6.69
Age	% premium	2.22	2.22	1.56	[0.19, 4.17]	1.19 [-3.95, 6.47]	1.54
Kitchen quality	% premium	3.07	3.07	5.79	—	—	4.75
Garage	% premium	5.43	5.43	6.27	[4.52, 6.02]	6.14 [3.49, 8.80]	6.64
Basement	% premium	5.25	5.25	7.05	[4.50, 6.57]	6.77 [3.03, 10.36]	8.95
Garden	% premium	6.42	6.42	6.83	—	—	7.45
Hazardous or industrial sites	% premium	-5.89	-5.89	-6.63	[-7.50, -2.58]	-5.78 [-10.06, -1.33]	-0.59
Proximity to water bodies	% premium	15.39	15.39	8.26	—	—	-0.84
Sunlight and orientation	% premium	4.01	4.01	2.59	—	—	3.26

(continued)

Characteristic	family	REML (R)	REML (Py)	3-level	LOSO range	Bayes mean [95% CrI]	PET-PEESE
Bathrooms	% premium	23.84	23.84	13.84	–	–	9.77
Floor level	% premium	1.30	1.30	0.02	[0.31, 2.40]	0.18 [-6.14, 6.18]	2.68
Waterfront	% premium	32.50	32.50	31.57	–	–	9.51
Flood risk	% premium	-0.10	-0.10	-2.59	–	–	-6.69
Swimming pool	% premium	4.87	4.87	7.16	[3.12, 7.26]	6.57 [1.44, 11.67]	-0.96
Storeys	% premium	-1.93	-1.93	0.85	–	–	-6.37
Storage	% premium	-0.49	-0.49	1.64	–	–	-2.29
Transaction timing	% premium	4.36	4.36	2.83	–	–	2.56
Renovation	% premium	0.88	0.88	9.84	[-0.41, 13.16]	8.52 [0.15, 16.37]	1.28
Living area	elasticity	0.65	0.65	0.62	[0.63, 0.66]	0.61 [0.49, 0.73]	0.51
Distance to CBD	elasticity	-0.09	-0.09	-0.06	[-0.10, -0.08]	-0.06 [-0.13, 0.01]	-0.05
Distance to public transport	elasticity	-0.00	-0.00	-0.07	[-0.01, 0.01]	-0.07 [-0.22, 0.07]	-0.01
Neighbourhood amenities	elasticity	0.01	0.01	-0.02	–	–	-0.00
Population density	elasticity	0.02	0.02	0.01	[0.01, 0.03]	0.01 [-0.03, 0.06]	0.01
Neighbourhood income	elasticity	0.25	0.25	0.22	[0.17, 0.29]	0.21 [0.07, 0.34]	0.12
Bathrooms	elasticity	0.07	0.07	0.05	–	–	0.01
Age	elasticity	-0.09	-0.09	-0.11	[-0.11, -0.07]	-0.11 [-0.16, -0.06]	-0.10
Green space and parks	elasticity	-0.01	-0.01	0.00	[-0.02, -0.01]	0.01 [-0.02, 0.08]	-0.01
Lot size	elasticity	0.09	0.09	0.14	[0.05, 0.13]	0.14 [0.05, 0.24]	0.04
Bedrooms	elasticity	0.19	0.19	0.23	[0.14, 0.23]	0.23 [0.04, 0.40]	0.17
Proximity to water bodies	elasticity	-0.02	-0.02	-0.04	[-0.03, -0.02]	-0.04 [-0.09, 0.02]	-0.01
Distance to highways	elasticity	-0.00	-0.00	-0.00	–	–	0.01
Distance to schools	elasticity	0.02	0.02	0.01	–	–	-0.00
Distance to hospitals	elasticity	0.00	0.00	-0.03	–	–	0.00
Distance to commercial areas	elasticity	0.01	0.01	0.00	–	–	-0.00

14. Implications for real estate economics and appraisal

For appraisal and mass valuation the central result is the pair of numbers attached to each characteristic: a precisely estimated global mean and a wide prediction interval. The mean is a defensible prior for a market without local evidence, and the prediction interval is the honest statement of how much local evidence can be expected to move it. For the structural core the interval is narrow enough to be useful: a living-area elasticity between 0.5 and 0.8, an age effect of a fraction of a percent per year, a bathroom premium of a few percent, a distance gradient of a few percent per kilometre. For amenities and disamenities the interval is wide, and transferring a premium from one market to another without local calibration is not supported by the evidence. For research practice, three implications follow from Sections 11 and 13. Reporting standards matter more than estimator choice: a large share of the extracted coefficients could not enter the pooled analysis because standard errors were replaced by stars, units were not stated, construction years were used in place of age, or the dependent variable’s transformation was not documented, and the meta-regressions show that the estimator itself explains little. Second, the field would benefit from reporting implicit prices in a common unit (percent per square metre, per kilometre, per year) alongside the raw coefficient, which would make the harmonisation of Section 6 unnecessary. Third, the AI literature should report hedonic benchmarks on the same test set, out-of-time validation, and the incremental contribution of AI-derived features, which only a minority of studies currently do; the evidence that such features add interpretable characteristics (condition, view, layout) is more promising than the

evidence that they add accuracy.

15. Limitations and future research

The synthesis is bounded by its retrieval process. Only 18.8 percent of the stage-one hedonic studies could be obtained as legal open-access full texts, so the extracted sample over-represents recent, open-access and non-US work; the paywalled core of the 1980s–2000s North American journal literature, which the Sirmans programme summarised, is under-represented, and the pooled estimates should be read as a synthesis of the accessible literature. The discovery itself relied on three machine-readable sources; SSRN, Google Scholar and institutional repositories were not harvested, and the multilingual queries retrieved mostly English-language records. Screening and extraction were performed by language-model agents following written protocols; the validation exercise measures their agreement on eligibility and on the numbers they both recorded, but the 78.9 percent recall against an independent extraction means that some printed coefficients were missed, and the systematic review community’s standard of two human reviewers was not met. Harmonisation required choices: construction-year variables, standardised coefficients, interactions and un-harmonisable units were excluded, which removes a quarter of the extracted rows; the Kennedy correction assumes normal errors; semi-elasticities per square metre mix houses and apartments whose marginal square metre is not the same good. The moderators are coarse (continent, income group, estimator class) and the meta-regressions have limited power for families with fewer than twenty studies. Publication-selection diagnostics are difficult to interpret under extreme heterogeneity and dependence, and no correction was applied. Finally, the AI synthesis rests on forty studies and cannot support claims about the general accuracy of machine-learning valuation. Future work should extend retrieval through institutional access, add the human double-screening that the protocol envisaged, and collect the reporting elements (units, transformations, standard errors, test-set definitions) that this exercise shows to be the binding constraint on cumulative knowledge in hedonic research. Table 15 lists the characteristics with fewer than ten studies: interior amenities, market and transaction characteristics, several environmental risks and almost all AI-derived characteristics remain understudied, as do Africa, South America and Oceania.

Table 15. Research gaps: characteristics with fewer than ten extracted studies

Group	Characteristic	studies	evidence status
B. Interior	Kitchen quality	9	pooled
B. Interior	Bathroom quality	3	descriptive only
B. Interior	Appliances	1	descriptive only
B. Interior	Flooring	4	descriptive only
B. Interior	Insulation	3	descriptive only
B. Interior	Storage	9	pooled

(continued)

Group	Characteristic	studies	evidence status
B. Interior	Luxury finishes	3	descriptive only
B. Interior	Smart-home systems	0	no study
C. Exterior	Landscaping	5	descriptive only
C. Exterior	Outdoor kitchen	0	no study
C. Exterior	Private recreation	6	descriptive only
D. Location	Walkability	3	descriptive only
D. Location	Distance to airport	6	descriptive only
E. Environment	Wildfire risk	1	descriptive only
E. Environment	Water quality	6	descriptive only
E. Environment	Urban heat	2	descriptive only
F. Neighbourhood	Unemployment	6	descriptive only
F. Neighbourhood	Vacancy	4	descriptive only
G. Market	Time on market	2	descriptive only
G. Market	Market liquidity	3	descriptive only
G. Market	Foreclosure status	1	descriptive only
G. Market	Distressed sale	1	descriptive only
G. Market	Seller urgency	0	no study
G. Market	Mortgage conditions	0	no study
H. AI-derived	Text sentiment	0	no study
H. AI-derived	Renovation descriptions	0	no study
H. AI-derived	Architectural style	2	descriptive only
H. AI-derived	Luxury language	0	no study
H. AI-derived	Urgency language	0	no study
H. AI-derived	Image-based condition	1	descriptive only
H. AI-derived	Visual quality	1	descriptive only
H. AI-derived	Interior design	0	no study
H. AI-derived	Multimodal embeddings	3	descriptive only

16. Conclusion

This paper has built a reproducible pipeline from 103,011 bibliographic records to 7,693 harmonised implicit prices from 242 hedonic studies in 55 countries, and has used it to answer the questions the Sirmans programme posed in 2005 with the tools of 2026. The robust findings are few and clear. The structural core of the hedonic model is global: living area, bathrooms, age and distance to the centre have implicit prices whose means are precisely estimated and similar across continents and decades once the specification is controlled. The signature amenities carry premiums of the order documented in the attribute-specific literature. Every implicit price is nonetheless heterogeneous beyond sampling error, with prediction intervals that span zero for most characteristics, and the observable features of a study, including the estimator, explain little of that heterogeneity. The tentative findings are the geographic and temporal patterns, which are confounded by the composition of the literature; the publication-selection diagnostics, which are suggestive for amenity premiums but not interpretable as corrections; and the AI evidence, which indicates better prediction from tree ensembles and modest incremental information from text and image features in a small sample.

The exploratory findings are the machine-learning meta-regressions, which do not predict implicit prices out of study. The paper's contribution relative to [Sirmans et al. \(2005, 2006\)](#) is therefore a global, harmonised and uncertainty-aware restatement of what the hedonic literature knows about the value of housing characteristics, together with a documented account of what it cannot know until the literature reports its results in a form that can be accumulated.

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Appendices

A. Protocol, eligibility criteria and coding conventions

Pre-registered protocol. The analysis protocol (replication file protocol/preregistration.md) was written on 2026-10-20 before data construction. It fixes the primary characteristics (living area, lot size, age, bedrooms, bathrooms, garage, pool, fireplace, air conditioning, basement, storeys, distance to the central business district, distance to transit, school quality, crime, air pollution, noise, flood risk, green space, water view or frontage, energy efficiency), the primary effect-size family per characteristic, the models M1–M6 of Section 7, five directional hypotheses (H1 signs; H2 I^2 above 75 percent everywhere; H3 no systematic difference between spatial or machine-learning marginal effects and OLS once moderators are controlled; H4 small-study effects for signature amenities but not for area; H5 rising implicit prices of energy efficiency and green space after 2008) and the validation design (independent double extraction of at least 15 percent of included studies, minimum 20).

Eligibility. Inclusion required an empirical study estimating a hedonic-type relationship between a residential price measure (transaction price, listing price, appraised value or rent) and at least one identifiable property, neighbourhood, environmental, locational, market or AI-derived characteristic, reporting at least one coefficient with a standard error, t -statistic, p -value or confidence interval or enough statistics to recover one transparently, with a retrievable full text, in any language. Exclusions: no residential price outcome (E1); no property-characteristic regressors or aggregate units such as cities, tracts or housing projects (E2); theory, methods or simulation only (E3); reviews (E4, retained for the comparison of Table 17); no empirical regression (E5); duplicate version (E6); not the housing market, including short-term rental nightly rates (E8); full text not retrievable (E7).

Conventions decided during screening and extraction. Hedonic price-index papers estimated on micro data were included because characteristic coefficients are usually reported; pure repeat-sales and index-methodology papers were excluded. Chinese residential-community (xiaoqu) studies with dwelling characteristics were included and flagged; neighbourhood, district and city aggregates were excluded. Studies reporting SHAP or partial-dependence effects from machine-learning models were kept for the AI synthesis but their effects were not pooled with regression coefficients. Geographically weighted regression summaries (means or medians of local coefficients) were recorded without standard errors and do not enter the pooled analysis. Rounded-to-zero standard errors were stored as missing. Interaction terms, squared terms, standardised coefficients and construction-year variables were flagged and excluded from pooling. Every deviation from the protocol is logged with its date and reason in `reports/methodological_decisions.md`.

B. Additional tables

Table 16. Extracted studies and usable estimates by continent

Continent	extracted studies	studies with usable estimates	usable estimates
Europe	83	48	2,868
Asia	77	47	1,746
North America	57	39	2,618
South America	8	5	177
Africa	6	4	133
unknown	6	0	0
Oceania	5	1	9

Table 17. Competing reviews and meta-analyses of hedonic housing studies (verified; counts as stated in the abstracts or full texts that could be read; blank when not stated)

Review	scope	studies	estimates	coverage	method
Smith (1995)	air quality (particulates)	–	–	United States	OLS and minimum absolute deviation
Boyle (2001)	environmental externalities (air, water,	–	–	nan	narrative survey
Bowen (2001)	methodological; spatial dependence in hedonic	–	–	US (Cuyahoga County application)	review plus application
Malpezzi (2003)	general; theory, specification, function	–	–	global (mostly US/UK examples)	selective narrative review
Nelson (2004)	airport noise	20	33 (23 airports)	Canada and United States	meta-regression

(continued)

Review	scope	studies	estimates	coverage	method
Sirmans (2005)	general; composition of hedonic models,	–	–	nan	descriptive tabulation of rece
McConnell (2005)	open space (hedonic and stated preferenc	60+	–	mostly US	narrative review
Sirmans (2006)	general; 9 structural characteristics of	–	–	nan	meta-regression (Stanley-Jarre
Simons (2006)	environmental contamination and positive	75	about 290	United States	OLS meta-regression
Debrezion (2007)	railway station proximity (residential a	–	102 estimation results	North America and Europe	WLS meta-regression with dummi
Nelson (2008)	aircraft and road traffic noise	–	–	nan	review of hedonic noise studie
Daniel (2009)	flood risk	–	–	predominantly United States	meta-analysis using implicit p
Kuminoff (2010)	methodological (Monte Carlo); not a lite	–	–	nan	simulation
Herath (2010)	general; history, estimation, classifica	471	–	global (ISI Web of Knowledge)	bibliometric classification of
Waltert (2010)	landscape amenities (migration, regional	71	–	nan	systematic vote-count review
Sirmans (2010)	time-on-the-market coefficient in hedoni	–	–	nan	meta-regression
Jackson (2010)	electric transmission lines	–	–	nan	narrative review
Braden (2011)	waste sites (hazardous, non-hazardous, n	46	129	North America	meta-regression, robust across
Nguyen-Hoang (2011)	school quality capitalization	–	–	nan	narrative review
Brander (2011)	urban open space (CV and HP)	–	–	nan	multilevel meta-regression
Hill (2013)	methodological; hedonic house price inde	–	–	nan	survey and taxonomy
Wadud (2013)	airport noise; benefit transfer to Asia	–	–	nan	meta-regression
Mohammad (2013)	rail projects; land and property values	23	102	nan	meta-regression; publication b
Perino (2014)	urban greenspace, UK	–	–	United Kingdom	meta-analysis + GIS benefit tr
Siriwardena (2016)	tree canopy cover	–	–	United States	meta-analysis merged with spat
Higgins (2016)	rapid transit land value uplift	60	130+ analyses	North America	critical narrative review
Gluszak (2017)	airport noise incl. non-North-American a	–	–	Europe and North America	meta-analysis (conference pape
Beltran (2018)	flood risk (inland and coastal)	37	364	nan	meta-analysis and meta-regress
Nicholls (2018)	surface water quality	43 (48 publications)	–	nan	narrative review
Cespedes-Lopez (2019)	energy performance certificates	66 documents	173 sales registers	global; North America, Asia, E	systematic review, meta-analys
Nicholls (2019)	environmental disturbances (pests, invas	–	–	nan	narrative review

(continued)

Review	scope	studies	estimates	coverage	method
Wang (2019)	mass appraisal models (AI, GIS, mixed)	104	–	nan	systematic literature review
Crompton (2019)	greenways and trails	20 hedonic analyses (+	–	United States	narrative review
Valier (2020)	AVM machine learning vs regression accur	–	–	nan	systematic review of head-to-h
Zhang (2020)	bus rapid transit; land value uplift	23	–	nan	random-effects meta-regression
Bishop (2020)	methodological guidance; environmental a	–	–	nan	best-practice review
Jayantha (2020)	general; bibliometric	269	–	global (Scopus)	bibliometric (CiteSpace)
Turnbull (2021)	school quality capitalization	–	–	United States	meta-analysis / meta-regressio
Ja’afar (2021)	ML for property price prediction and val	–	–	nan	systematic literature review
Guignet (2022)	water quality (clarity) and housing valu	36	656	United States	meta-regression with within-ma
Parsons (2022)	wind power projects	18 core studies	–	Europe (10), North America (8)	structured review with average
Geerts (2023)	house price prediction methods and data	93	–	nan	systematic literature review w
Khoshnoud (2023)	general; extension of Sirmans et al. 200	252	–	global authorship and data, mo	descriptive review
Tekouabou (2024)	ML for urban real estate prediction	70	–	USA, China, India, Japan, Hong	systematic survey (Scopus)
Naz (2024)	ML, DL and hybrid price prediction	–	–	nan	systematic literature review
Heberling (2024)	surface water quality	29	290	nan	probit meta-regression
Jayalath (2025)	water quality (Secchi depth); Canada ben	29	600+	nan	meta-regression + spatial bene
Siriwardena (2025)	urban tree cover (internal meta-analysis	–	–	United States	internal meta-analysis
Macchiaroli (2025)	crime, crime prevention, CPTED	50	–	nan	systematic literature review a
Moreno-Foronda (2025)	ML vs hedonic regression comparisons	23	–	Asia 43% (10 studies); others	systematic review (PRISMA)

C. Reproducibility statement

The complete pipeline is contained in the replication repository (wp21_uqo, spbgit). Discovery: scripts/discovery/ (Semantic Scholar bulk search with resumable logging, Crossref and arXiv harvesters, query file). Screening: scripts/screening/ (deduplication and rule-based scoring, keyword file, search audit and PRISMA counts); agent decisions with reasons in data/metadata/screening_batches/. Retrieval: scripts/extraction/fetch_pdfs.py (Unpaywall, Semantic Scholar, arXiv; every attempt logged with status and SHA-256 of the file). Extraction: prepare_tables.py (page scoring and dumps), the written protocol and JSON

schema, one JSON per paper in `data/extracted/json/`, the independent duplicate extractions in `data/validated/json/` and their comparison (`scripts/validation/compare_extractions.py`). Harmonisation: `scripts/harmonization/` (taxonomy, country mapping, conversion formulas, effects-table builder). Econometrics: `scripts/econometrics/meta_models.R` (metafor, clubSandwich) and `python_meta.py` (REML, PET-PEESE, Bayesian Gibbs sampler, leave-one-out, grouped machine learning). Figures and tables: `scripts/visualization/`; every number quoted in the text is a macro in `paper/tables/numbers.tex` generated from the result files. Software: Python 3.14 (numpy, scipy, pandas, matplotlib, scikit-learn, PyMuPDF), R 4.x (metafor, clubSandwich); random seeds fixed at 20261020. Raw PDFs are not redistributed; the retrieval log allows them to be re-downloaded from the same open-access locations. The screening and extraction steps use large-language-model agents following written protocols; their outputs are deterministic artefacts stored in the repository, and the validation exercise of Section 6 measures their reliability.