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Estimating View Premiums in High-Rise Residential Housing: Hedonic Evidence and Implications for Data-Driven Valuation

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Abstract

Residential valuation under the comparison principle requires systematic adjustment for material differences between comparable units. In high-density, high-rise housing markets, however, visual amenities such as harbour and skyline views are often treated qualitatively or implicitly embedded in comparable evidence, reducing transparency and auditability. This study examines whether view quality is systematically capitalized into transaction prices in Hong Kong and whether such premiums vary across market conditions. Using 352 secondary market transactions from six prime high-rise estates (2015–2024), we estimate hedonic models with the logarithm of price per saleable area as the dependent variable. View quality is specified as an ordered categorical variable (*nil*, *partial*, *full*), constructed from listing descriptions and cross-validated using map and street-view evidence. Controlling for floor level, estate age, monthly market movements proxied by the Centa-City Index (CCI), and estate fixed effects, the pooled estimates indicate that partial views command an approximate 11% premium and full views an approximate 22% premium relative to nil view, with a clear incremental premium for full over partial views. Split-sample estimation using GDP-defined regimes reveals partial state dependence: *full view* premiums remain economically meaningful across market conditions, whereas partial view effects become less precisely identified during weaker periods. The findings demonstrate that view quality is a material and systematically priced attribute in Hong Kong's vertically differentiated housing market. By providing transparent percentage-based adjustment benchmarks grounded in within-estate variation, the study enhances the consistency, transparency, and evidential rigor of comparable-based valuation practice.

Keywords: data-driven valuation; hedonic pricing; high-rise residential building; valuation; view premium; visual amenities

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1. Introduction

Visual amenities, especially views, are routinely invoked by buyers, developers, and valuers as key determinants of residential desirability in high-density cities. In cities such as Hong Kong, where vertical living is the dominant housing form and a large share of the stock is differentiated by elevation, orientation, and exposure to waterfronts and iconic skylines, "view quality" is not just an aesthetic preference; it is a plausible source of systematic price dispersion. If views are reflected in the transaction prices, they represent an economically meaningful component of housing wealth, a channel through which planning and redevelopment decisions redistribute value, and a potential source of valuation error when left unmeasured [1].

Despite this practical importance, conventional valuation workflows, particularly those grounded in the market/comparative approach, tend to prioritize observable structural and tenure characteristics (e.g., age, floor level, layout, building quality) alongside broad comparables, while the contribution of views is often handled qualitatively or implicitly absorbed by comparables. As emphasized in standard valuation texts (e.g., the principal methods and comparative factors in Modern Methods of Valuation), comparability typically turns on location, physical characteristics, tenure, purpose, and time; however, "location" is frequently operationalized in coarse spatial units, and the visual dimension of location is rarely measured explicitly [2]. The result is a practical tension: As other qualitative factors (like coastal amenities and flood hazards), practitioners acknowledge view effects, but valuation evidence is often not expressed in a transparent, replicable metric that can be audited, stress-tested, or transferred across submarkets and market cycles [3].

Recent research illustrates both the feasibility and the value of making views measurable. Jayasekare et al. [4] demonstrate that when view is quantified rather than treated as a narrative attribute, using spatial tools to construct view indicators, view variables explain meaningful variation in sale prices and help address omitted-variable bias in hedonic models. Their results show that specific view types (notably beach/sea) attract sizeable premiums and that the magnitude of the effect depends on how view is operationalized (e.g., distance thresholds for visibility). This methodological insight is particularly salient for cities: if view is systematically correlated with other routinely modelled attributes (floor level, building age, proximity to public transport, neighborhood fixed effects), then treating view only qualitatively risks misattributing premiums to the wrong covariates, biasing adjustment grids in the market approach, and weakening the evidential basis for valuation and policy decisions.

Against this backdrop, this paper examines whether view quality is priced in Hong Kong's residential market and whether the magnitude of view-related premiums varies across market conditions. The study makes three contributions with direct research and practice impact. First, it provides an explicit estimate of the price-per-area premium associated with ordered view quality categories (*nil view*, *partial view*, *full view*), offering a transparent adjustment metric that can complement comparable-based valuation. Second, it tests whether view-related price premium is state-dependent by comparing stronger versus weaker market conditions, thereby clarifying whether "view premiums" behave like a stable amenity value or a cyclical luxury attribute, an issue with implications for risk management, mortgage lending, and appraisal robustness through booms and downturns. Third, it discusses implications for valuation practice, focusing on the direction and magnitude of bias that may arise when view quality is omitted or only implicitly embedded in comparables.

While Jayasekare et al. [4] provide compelling evidence from a coastal, predominantly low-rise Australian housing market where views are derived from parcel-based visibility measures, this research differs in ways that may alter both the mechanism and magnitude of view-related price premiums. Our case study is an ultra-dense, high-rise, transit-oriented (TOD) city in which "view" is produced and constrained by vertical form, floor level, building spacing, and skyline/waterfront orientation, and in which households routinely trade off internal space against external visual amenities. These features imply that results from low-density, parcel-level settings may not transfer directly to Asian vertical cities, where view quality is tightly bundled with height, congestion, and micro-location within the same estate. By providing evidence from a dense TOD environment and testing whether view premiums vary across market states [4,5], this study extends the literature beyond predominantly low-rise contexts and supports fairer residential pricing by offering an explicit, auditable basis for separating view-related premiums from other correlated attributes (e.g., proximity to rail, floor level, and neighborhood effects). This improves transparency for buyers and lenders and reduces the risk that view benefits are over- or under-capitalized in comparable-based valuation, particularly in high-demand, high-density housing markets.

This study aims to quantify how view quality is assessed in residential transaction prices in dense cities' high-rise housing market, and to assess whether explicitly accounting for view improves the fairness and transparency of pricing and valuation. The study objectives are:

1. To estimate the marginal price premium (in percentage) associated with ordered view quality categories (*nil view*, *partial view*, *full view*) after controlling for structural, locational and neighborhood factors.
2. To test whether view-related price premiums vary across market conditions (e.g., stronger vs weaker periods), indicating state-dependent price effects.

Concomitantly, the research questions to be answered are:

1. RQ1. Do residential properties with higher view quality in Hong Kong (partial/full vs. *nil view*) sell for a statistically significant price premium after controlling for structural attributes?
2. RQ2. Does the magnitude of the view premium differ across market conditions (e.g., expansion vs. downturn), and what does this imply for fair pricing and appraisal practice in high-density housing markets?

A related methodological concern is the risk of double counting view-related value when visual amenities are not explicitly modelled. In high-rise environments, view quality is frequently correlated with floor level, orientation and building spacing—the horizontal separation between adjacent high-rise blocks, which directly affects visual openness and the extent of obstruction. If valuers adjust for floor level while implicitly assuming that view is "embedded" within that adjustment, part of the visual premium may be counted twice or misattributed to structural characteristics. From an econometric perspective, this raises the issue of multicollinearity: when view quality is strongly correlated with other covariates, its independent marginal effect may be obscured or imprecisely estimated. Explicitly modelling view as a separate attribute therefore improves transparency and reduces the risk that its economic contribution is either overstated or inadvertently absorbed by correlated proxies. The novelty of this study lies in three contributions. First, it provides, one of the first explicit estimates of ordered intra-building view premiums in a dense, high-rise Asian housing market. Second, it tests whether such premiums are state-dependent by comparing stronger and weaker macroeconomic regimes. Third, it offers transparent, percentage-based adjustment benchmarks grounded in within-estate variation, providing a structured empirical foundation for comparable-based valuation practice in vertically differentiated housing markets.

The remainder of this paper is structured as follows. Section 2 synthesizes prior research on hedonic housing models, the implicit price effect of urban amenities, and empirical approaches to measuring and operationalizing "view" as a priced attribute, drawing on measurement-oriented strategies used in related built-environment research. Section 3 outlines the study context and data, defines the construction of view-quality variables and other covariates, and details the econometric identification strategy used to estimate view premiums and assess market-state dependence. Section 4 presents the main empirical results, including baseline estimates and comparisons between stronger and weaker market conditions. Section 5 interprets the findings for valuation practice, addresses limitations, and identifies avenues for extending view measurement in ultra-dense, high-rise settings, while also discussing implications for future AI-enabled valuation workflows. Section 6 concludes.

2. Literature Review

2.1. Hedonic Pricing and Residential Valuation in the Built Environment

Hedonic pricing models are widely applied in built-environment research to analyze how residential property values reflect the capitalization of heterogeneous attributes [6–8]. Within this framework, housing prices are decomposed into the implicit prices of structural characteristics, building attributes, locational factors, and environmental amenities [8,9]. While hedonic analysis has been extensively applied to evaluate how design- and context-related attributes are reflected in urban housing prices, it faces well-documented methodological limitations, particularly with respect to variable measurement and model specification [10].

In professional valuation practice, hedonic models are increasingly recognized as a quantitative complement to the market comparison approach. While comparable-based valuation relies on professional judgment to adjust for differences across properties, hedonic estimation provides an explicit and replicable basis for deriving adjustment factors. This is particularly important in high-density cities, where vertical form, building configuration, and micro-location can generate substantial price variation that is difficult to assess consistently using qualitative adjustments alone [9,10]. However, the effectiveness of hedonic valuation depends on whether relevant building and environmental attributes are explicitly measured. When important characteristics are omitted or only indirectly proxied, their effects may be absorbed by correlated variables, reducing interpretability and potentially biasing valuation outcomes. This limitation is especially salient for attributes that are widely acknowledged in practice but remain difficult to quantify, such as visual quality [11].

2.2. Visual Amenities and Conceptual Extensions Toward Data-Driven Measurement

A substantial empirical literature has examined the pricing of sea, lake, park, and skyline views in residential markets. Studies in coastal and low-density settings generally report statistically significant premiums for water and open views, often ranging between 5% and 25%, depending on measurement approach and market segment [12]. However, much of this evidence derives from parcel-level differentiation in low-rise environments, where view quality varies primarily across properties rather than within buildings [13]. In high-rise, high-density cities, view is an intra-building attribute shaped by floor level, orientation, and surrounding massing, and its view-related price premium mechanisms may differ [10,11,14]. Empirical evidence explicitly isolating ordered view categories within vertically differentiated Asian housing markets remains relatively limited.

Visual amenities, including open views, skyline exposure, and waterfront visibility, are commonly cited as value-enhancing features in residential buildings. From a built-environment perspective, view quality is shaped by building height, spacing, orientation, and surrounding urban form, making it an inherently design- and context-dependent attribute [14–16]. These characteristics suggest that views may be systematically capitalized into housing prices.

Despite their recognized importance, visual amenities are inherently difficult to quantify in a consistent and objective manner. Accordingly, this study operationalizes view quality using a relative, comparison-based classification. Residential units are categorized as having a *full view* or a *partial view* based on systematic comparison with nearby units within the same estate or immediate surroundings, capturing differences in openness and visual exposure under broadly comparable locational and building conditions. This comparative approach is commonly employed for benchmarking purposes and provides a practical means of translating qualitative assessments of visual amenities into consistent quantitative indicators suitable for empirical analysis [17].

Empirical studies that explicitly quantify views generally find positive and statistically significant price effects. For example, Jayasekare et al. [4] demonstrate that when views are measured using structured indicators, they explain a meaningful share of price variation and reduce omitted-variable bias in hedonic models. However, most existing studies focus on low-rise or low-density contexts, where view quality is largely determined at the parcel level.

Hedonic studies in Asian high-density contexts provide further evidence of view differentiation. Oh and Lee [18] report approximately 6% premiums for landscape visibility, with river views commanding higher premiums than mountain views or openness. In Hong Kong, Jim and Chen [19] found that only harbour views were positively capitalized (broad harbour views +2.97%; confined harbour views +2.18%), while mountain views reduced prices by 6.7% and street views by 3.7%. Hui et al. [20] further demonstrate that landscape effects vary across vertical submarkets, with garden views positively correlated with prices across all floor levels, but sea views not uniformly valued in high-storey units, highlighting vertical spatial differentiation in compact cities.

In high-rise, high-density cities, view quality varies substantially even within the same building and is closely intertwined with other attributes such as floor level and layout. As a result, conventional hedonic models and valuation practice often rely on indirect proxies or qualitative descriptors, which may confound view effects with other building characteristics. More broadly, urban economics emphasizes that a wide range of amenities, including built cultural heritage, location context, and the architectural distinctiveness of new development, can exert a direct influence on real estate prices [14].

While the present study employs a conventional hedonic regression framework, recent advances in AI and digital building analytics suggest a broader applicability of explicitly measured view attributes. Computer vision applied to listing photographs, street-level imagery, or BIM, combined with ML models using geospatial and three-dimensional urban data, offer potential for more granular and reproducible view classification [21–23]. ML methods, including supervised learning algorithms and text-based semantic representations, have demonstrated strong predictive performance in AVM applications [24–27]. Complementing these with XAI techniques can further ensure that feature contributions remain interpretable, auditable, and consistent with hedonic pricing principles [28–30], addressing the transparency requirements of professional valuation contexts [6,23]. These approaches represent promising directions for future integration rather than components of the current empirical analysis.

2.3. Market Conditions, State Dependence, and Valuation Robustness

A growing literature suggests that the capitalization of residential attributes may vary across market conditions. In stronger market periods, buyers may exhibit higher willingness to pay for discretionary or design-related amenities, whereas in weaker markets price sensitivity and affordability constraints may dominate. This implies that the implicit prices of amenities such as views may be state-dependent rather than constant over time [30,31].

Empirical evidence on this issue remains mixed. Some studies find relatively stable amenity premiums across market cycles, while others report attenuation or loss of statistical significance during downturns. These differences may reflect variation in market liquidity,

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transaction volume, and measurement precision, particularly for attributes that are difficult to observe directly [32,33].

For valuation and building-related decision-making, understanding whether view premiums are stable across market states is critical. If view-related price effects weaken during downturns, applying uniform adjustment factors may reduce appraisal robustness and increase valuation risk. Conversely, if view premiums persist, explicitly accounting for them can improve pricing transparency and fairness across cycles [34].

Against this background, the present study examines the implicit pricing of view quality in an Asian main city's high-rise residential market under different market conditions. By combining an ordered measure of view quality with market-state classification based on the CCI [35], the study contributes evidence relevant to both built-environment research and valuation practice. Prior studies suggest that the implicit prices of amenities may vary across market cycles, with coefficients becoming attenuated or less precisely estimated during downturns due to liquidity constraints and sample composition effects [36,37].

State dependence in amenity pricing may reflect buyer heterogeneity and financing constraints. In stronger markets, higher-income or liquidity-unconstrained buyers may exhibit greater willingness to pay for discretionary amenities such as premium views, whereas in weaker markets tighter credit conditions, interest-rate sensitivity, and heightened risk aversion may compress premiums for mid-tier amenities [38]. In high-rise markets such as Hong Kong, segmentation between luxury (e.g., upper-floor or penthouse) units and standard units may further amplify these effects.

From a behavioural and urban-economic perspective, certain housing attributes, particularly prestige-related amenities such as unobstructed skyline or harbour views, may exhibit characteristics of positional goods. Their value derives from both functional utility and relative standing within a neighbourhood, where scarcity and status signalling amplify demand [39]. When households can observe relative differences in property quality, positional incentives may induce stronger capitalization or even over-investment effects [40]. Accordingly, willingness to pay for such amenities may vary with market sentiment, liquidity conditions, and perceived wealth, implying that amenity premiums can expand during optimistic expansions and compress under tighter financial constraints [39].

2.4. Vertical Differentiation, Spatial Constraints, and Amenity Valuation in Dense Cities

Empirical evidence from globally connected high-demand metropolitan areas shows that supply constraints and concentrated demand can magnify price differentials associated with desirable housing attributes [38,41,42]. In such markets, environmental amenities, including visual openness and water views, may command stronger premiums because opportunities for substitution are limited and vertical development intensifies competition for scarce outlooks. View quality is inherently spatial, reflecting distance to waterfronts, skyline corridors, and surrounding building massing.

As discussed in Section 2.2, much of the established view-premium literature focuses on horizontally differentiated, low-rise settings. By contrast, research on high-rise and dense Asian housing markets indicates that environmental valuation operates along a vertical dimension, where elevation, building orientation, and surrounding massing shape exposure, privacy, and perceived environmental quality [43–45]. These vertically structured contexts introduce substantial intra-building heterogeneity, which differs fundamentally from parcel-level differentiation.

Section 2.3 highlighted the importance of transparent measurement and structured feature construction. In land-constrained cities characterized by intensive vertical development, explicitly categorizing view quality enables clearer identification of amenity effects and reduces reliance on coarse proxies such as floor level. Drawing on spatial equilibrium theory and empirical evidence from dense housing markets, the specification developed in Section 3 estimates ordered view premiums within a vertically differentiated urban environment. This framework links theoretical insights on constrained urban supply with an interpretable and replicable empirical strategy.

3. Study Context, Data, and Methodology

3.1. Study Context: The Hong Kong Residential Market as an International Reference Point

Hong Kong is widely recognized as one of the most densely urbanized territories in the world, with an overall population density of approximately 6800 persons per square kilometer and district-level densities in Kowloon and urban Hong Kong Island frequently exceeding 40,000 persons per square kilometer [46–48]. This extreme density reflects two fundamental geographical constraints: (1) predominantly mountainous terrain; and (2) the limited supply of developable flat land within a total territorial area of approximately 1115 km^2. As a result, the residential built environment is characterized almost entirely by multi-storey, high-rise apartment buildings, commonly organized into large-scale estate developments [49].

This vertically structured urban form generates systematic and measurable variation in housing attributes not only across estates and neighborhoods, but, critically, within individual buildings. Differences in floor level, building spacing and orientation, setbacks from surrounding structures, and proximity to open water, hillsides, and the urban skyline jointly shape the degree of visual exposure available to each unit [50,51]. Consequently, view quality in Hong Kong is best understood as an intra-building and intra-estate attribute, systematically differentiated by height and orientation, and representing a potentially material component of residential value.

Several features make Hong Kong a particularly suitable setting for identifying the implicit pricing of view quality. First, its extreme density and distinctive visual geography, shaped by Victoria Harbour, surrounding hillsides, and a concentrated high-rise skyline, generate systematic and observable variation in view quality within the same estates and even within individual buildings. Because this variation occurs under a single legal, institutional, and fiscal framework, hedonic estimation can isolate view premiums while holding broader regulatory conditions constant, thereby reducing cross-jurisdictional confounding.

Within the selected prime districts (Kowloon Station and adjacent waterfront corridors), private residential developments commonly exceed 30 storeys, creating pronounced vertical differentiation. The present study focuses on six estates selected through three purposive criteria: (i) substantial vertical height (typically 40+ floors), ensuring observable intra-building variation in view exposure; (ii) proximity to harbour or skyline corridors such that nil, partial, and full views coexist within the same development; and (iii) sustained secondary market transaction activity between 2015 and 2024, permitting reliable within-estate hedonic identification. Estates lacking meaningful view variation (e.g., uniformly obstructed inward-facing blocks) or exhibiting insufficient transaction depth were excluded. This focused sampling strategy strengthens internal validity by ensuring that estimated premiums arise from within-estate vertical differentiation rather than from broader cross-neighborhood price gradients.

Second, the Hong Kong residential market is consistently ranked highly in international transparency assessments, providing a substantial volume of arm's-length secondary market transactions with detailed and publicly accessible price records. The availability of the Centa-City Index (CCI) as a high-frequency market-wide indicator further strengthens identification by allowing transaction prices to be aligned with contemporaneous market conditions.

Third, housing prices in Hong Kong are among the highest globally relative to income [46–48]. In such a high-value environment, even moderate percentage differences associated with view quality translate into economically meaningful absolute price effects, increasing the practical relevance of accurate measurement for valuation and policy analysis.

Finally, a well-established body of hedonic research on the Hong Kong housing market provides methodological grounding and comparability benchmarks for the present analysis [52], supporting both internal validity and external interpretability.

Although Hong Kong is examined as a specific case, its structural characteristics are representative of a broader and rapidly growing class of cities worldwide, making its findings internationally generalizable. According to the United Nations World Urbanization Prospects, approximately 68% of the world's population is projected to reside in urban areas by 2050, with the fastest urbanization occurring in Asia [47]. Cities such as Singapore, Seoul, Taipei, Tokyo, Shanghai, Shenzhen, Kuala Lumpur, and Mumbai share with Hong Kong the defining urban morphological characteristics of high-rise residential density, within-building vertical differentiation of housing attributes, and transit-oriented development patterns [46–48]. Collectively, these cities accommodate hundreds of millions of urban residents, and the share of global housing wealth concentrated in such environments is substantial and growing. By contrast, the existing view-premium literature remains disproportionately concentrated in low-density, parcel-level contexts, primarily North American, Australian, and European coastal or suburban markets, where view quality is largely determined at the individual parcel level and varies little within a single building [5,52,53]. The view-related price premium mechanisms, measurement challenges, and valuation implications of view quality in high-rise vertically differentiated housing markets differ materially from those in low-density settings: premiums are distributed across floors rather than across parcels, intertwined with attributes such as floor level and building spacing, and concentrated across a relatively small share of total floor space. These structural differences mean that findings from parcel-level, low-rise settings cannot be straightforwardly transferred to Asian vertical cities.

3.2. Data Sources, Sample Selection, and Data Processing

This study employs transaction-level data for private, multi-storey residential units in Hong Kong covering the period from 2015 to 2024. The transactions were obtained from a commercial property database widely used in professional valuation practice, ensuring reliability and market relevance. The database provides detailed unit-level information, including transaction price, floor area, floor level, orientation, building age, and descriptive information regarding view conditions.

Each observation represents an arm's-length transaction in the secondary market. The dataset constitutes a repeated cross-section rather than a panel, as individual units are not tracked longitudinally. Standard data-cleaning procedures were applied, including the removal of non-arm's-length transactions, incomplete records, and statistical outliers. After screening and outlier treatment, the final analytical sample comprises 352 transactions.

To assess sensitivity, additional specifications were estimated using alternative trimming thresholds (0.5% and 2%). The estimated coefficients on view-quality variables remain quantitatively and statistically consistent across specifications, indicating that the main findings are not driven by extreme observations.

The transactions are drawn from six large residential developments comprising a total of 26 residential blocks. These developments were selected based on three criteria: (1) comparable high-rise typology and vertical structure; (2) strategic and representative urban locations; and (3) sustained and active transaction volumes during the study period. This sampling strategy ensures sufficient observations for econometric estimation while maintaining structural and locational comparability across projects. The selected developments are characterized by meaningful variation in elevation and view exposure, making them suitable for identifying implicit view premiums within a hedonic framework. Table 1 summarizes the projects included in the sample.

While the selected developments are representative of vertically differentiated, high-density residential markets in Hong Kong, the findings should be interpreted within this context. The results may not directly generalize to low-rise or suburban housing markets where amenity gradients operate primarily along horizontal dimensions.

Table 1. Overview of the six sampled residential developments.

Number	Residential Project	Number of Blocks	Number of Units
1	The Arch (Phase I)	4	1051
2	Sorrento	5	2126
3	The Cullinan	7	825
4	The Harbourside	3	1122
5	The Masterpiece	1	345
6	The Waterfront	6	1288
	Total	26	6757

The six developments were selected purposively based on their prime high-rise typology, sustained and active secondary market transactions between 2015 and 2024, data completeness, meaningful intra-estate variation in view exposure, and geographic concentration within prime urban districts. This focused sampling strategy enhances structural comparability and strengthens identification of view premiums by exploiting within-estate variation. However, the findings are most directly applicable to comparable prime high-rise estates rather than to the broader Hong Kong housing market.

Within the selected districts, 25 high-rise estates exceeding 30 storeys are present. The six estates were chosen because they (i) exhibit observable variation in waterfront or skyline exposure, (ii) maintain sufficient transaction depth for reliable estimation, and (iii) share a broadly comparable vertical and architectural typology. To align transaction records with market-wide conditions, each transaction month is matched to the CCI at the monthly frequency. CCI data were downloaded in January 2025 [35]. Observations with missing values in any of the core variables (transaction price, saleable area, floor level, estate age, view classification, and matched CCI) are excluded.

Inclusion criteria. The analytical sample includes transactions satisfying all of the following conditions: (i) private residential apartments in purpose-built multi-storey high-rise buildings; (ii) completed secondary market transactions, defined as resales of previously occupied units rather than first assignments from the developer; (iii) market-based transactions concluded between unrelated parties under normal market conditions, as verified against transaction records; (iv) observations with complete information needed to construct the dependent variable and all covariates, including transaction price, saleable area, floor level, building age, view classification, and matched CCI value.

Exclusion criteria. The sample excludes the following categories on professional and econometric grounds: (i) Public and subsidized housing. (ii) Non-standard residential property types. (iii) Transactions estimated as intra-family transfers, gift conveyances, mortgagee sales, court-ordered disposals, or related-party dealings are excluded, as these do not reflect open-market conditions. This is consistent with the definition of market value under HKIS Valuation Standards and RICS Red Book Global Standards, which require that a transaction reflects a market-based exchange between a willing buyer and a willing seller, neither under compulsion [52,53]. (iv) Extreme outliers in unit price intensity. Consistent with common practice in hedonic applications, observations in the top and bottom 1%

of price per saleable area are removed to mitigate the influence of atypical transactions, recording errors, or transactions involving bundled non-residential components [54,55]. The 1% threshold is a conventional and conservative trimming rule in applied micro econometric research: it is sufficiently narrow to preserve nearly all valid market variation, retaining 98% of the sample, while reducing the disproportionate leverage that extreme values can exert in log-linear regressions [55,56].

3.3. Variable Definition and Construction

Dependent variable

The dependent variable is the logarithm of transaction unit price:

$$\ln(PPA_i) = \ln\left(\frac{Price_i}{SaleableArea_i}\right) \quad (1)$$

where $Price_i$ is the transaction price and $SaleableArea_i$ is saleable area (square feet). Using price per area rather than total price is standard in high-density apartment markets because it normalizes for scale and aligns with valuation practice and market reporting conventions [44]. However, Li et al. [54] document that larger residential units in Hong Kong command relatively higher per-unit prices, suggesting potential non-linear scale effects in size-price relationships. Equation (1) adopts the standard semi-log hedonic specification, in which the logarithm of price per saleable area is modeled as a function of differentiated housing attributes. All unit-price values reported in the analysis are expressed in Hong Kong dollars (HKD) per square foot of saleable area, consistent with standard Hong Kong market practice.

Definition of saleable area.

In Hong Kong, "saleable area" refers to the internal floor area of a residential unit measured to the external face of enclosing walls (or the centerline of party walls), and excludes common areas such as lift lobbies, staircases, clubhouse facilities, and external common corridors. It differs from Gross Floor Area (GFA), which may include common areas and shared facilities apportioned to individual units, and from broader marketing measures historically used in some jurisdictions.

In international terms, Hong Kong saleable area is broadly comparable to IPMS Residential 1 (Internal Area), as defined under the International Property Measurement Standards (IPMS), although minor technical differences in wall treatment and balcony inclusion may arise. Because price per area is computed using saleable area, cross-jurisdictional comparisons should take measurement conventions into account. Within Hong Kong, however, saleable area is the standard and legally regulated basis for residential price reporting and valuation.

Key explanatory variable: View quality

View quality is captured using an ordered categorical indicator View_Type with three levels:

- 0 = *Nil view* (blocked or facing adjacent buildings or a slope, as shown in Figure 1a)
- 1 = *Partial view* (some openness or limited skyline/landmark/water exposure, as shown in Figure 1b)
- 2 = *Full view* (substantially unobstructed skyline/harbour/landmark exposure, as shown in Figure 1c)

(**a**)

(**b**)

(**c**)

Figure 1. (**a**) *Nil View*: Blocked Outlook Facing Adjacent Buildings or Slope (an illustrative example); (**b**) *Partial View*: Limited Skyline, Landmark, or Water Exposure, or Facing Adjacent Buildings at a distance of 50 m or more (an illustrative example); (**c**) *Full View*: Substantially Unobstructed Skyline, Harbour, or Landmark exposure (an illustrative example).

The three-level ordered classification (*nil*/*partial*/*full*) reflects a balance between conceptual precision and empirical reliability. While view quality may vary along a continuous spectrum (e.g., angular breadth, distance to obstruction, compositional quality), transaction-scale data derived from listing descriptions and imagery do not consistently permit finer geometric measurement. A coarser but clearly defined categorical framework enhances coding consistency and reduces subjective ambiguity. Given the moderate sample size

(N = 352), introducing additional subcategories could reduce statistical power and increase classification error.

As a robustness check, we also estimated an ordered specification treating view as a ranked categorical variable; the results preserve the monotonic ordering (*full* > *partial* > *nil*) and yield qualitatively similar economic magnitudes. Accordingly, the three-level specification captures economically meaningful differentiation while maintaining interpretability and empirical stability.

For estimation, the baseline category is *nil view*. Two dummy variables are created:

- $PartialView_i$ equals 1 if the unit has a *partial view* and 0 otherwise.
- $FullView_i$ equals 1 if the unit has a *full view* and 0 otherwise.

The view category is coded from a main property agent's online listing description [35] and is cross-validated using Google Maps (version 25.24.x(Android)) (e.g., map and street-view imagery) to ensure consistent classification. While this approach does not directly measure view geometry (e.g., angle, distance, composition), it provides an operational and replicable proxy widely used in practice and suited to transaction-scale modelling.

View classification protocol

View categories were assigned using an AI-assisted image screening process applied to listing photographs, combined with a structured rule-based coding guide defining *nil*, *partial*, and *full view*. The AI system was used to flag visual openness, skyline/water presence, and obstruction cues. Subsequently, two trained researchers independently reviewed the AI-preclassified cases using standardized criteria. Inter-rater reliability was evaluated using Cohen's kappa, indicating substantial agreement prior to reconciliation. Discrepancies were resolved through joint adjudication. Google Maps and street-view imagery were used to validate surrounding building massing, obstruction distance, and visibility conditions. This multi-stage protocol reduces subjective bias and enhances replicability [55].

Control variables

To isolate the marginal effect of view quality, the model controls for key structural and temporal determinants of price:

- *Floorno*: floor level of the unit. In high-rise housing, floor level captures vertical differentiation and is associated with openness, privacy, and reduced street-level disamenities. Controlling for floor level helps distinguish height effects from view effects.
- *Age*: age of the housing estate at the time of transaction (years). This variable proxies for depreciation, building obsolescence, and vintage-related differences in design and quality.
- *CCI*: Centa-City Index level in the transaction month. This controls for market-wide price movements and aligns each transaction with prevailing market conditions.

Because the dependent variable is specified as price per saleable area, unit size is controlled for by construction. Detailed information on interior finishes, renovation condition, layout efficiency, and bundled amenities is not consistently available in the transaction database. To mitigate potential omitted-variable bias, the model includes estate fixed effects and relies on within-estate variation. The estimated view premiums should therefore be interpreted as conditional on observable structural and market characteristics.

Market condition classification

To examine state dependence, market conditions are classified using an objective rule based on quarterly real GDP data published by the Census and Statistics Department of the Hong Kong SAR Government [46]. A quarter is defined as a recession (weaker-market period) if year-on-year real GDP growth is negative, and as an expansion (stronger-market period) if growth is positive.

Applying this rule to the sample period (2015Q1–2024Q4) identifies two recessionary episodes: 2019Q3–2020Q4 and 2022Q1–2022Q4. All remaining quarters (2015Q1–2019Q2, 2021Q1–2021Q4, and 2023Q1–2024Q4) are classified as expansion periods. Each transaction month inherits the classification of its corresponding quarter. A summary table of quarterly GDP growth rates and regime classification is provided for transparency and replicability.

Additional unit characteristics.

The transaction database does not consistently report detailed unit-level attributes such as interior renovation quality, layout efficiency, maintenance condition, parking or storage inclusion, or bundled amenities. These characteristics may influence price and could, in principle, be correlated with view quality. To mitigate potential omitted-variable bias, the specification includes estate fixed effects, floor level, estate age, and monthly market controls (*CCI*), which absorb persistent development-level quality differences and time-varying market conditions. Because the sample is restricted to relatively homogeneous high-rise estates, cross-sectional heterogeneity in shared amenities is further reduced.

3.4. Econometric Specification

The baseline hedonic model is estimated using a log-linear specification:

$$\ln(PPA_i) = \alpha + \beta_1 ViewType_i + \beta_2 Floorno_i + \beta_3 Age_i + \beta_4 CCI_t + \theta e + \varepsilon_i \quad (2)$$

where i indexes transactions, t indexes transaction month, θ_e denotes estate fixed effects, and ε_i is an idiosyncratic error term [55]. Equation (2) represents the baseline hedonic capitalization model. Within the hedonic framework, the coefficients on the view-category indicators capture the implicit marginal prices of visual amenities, conditional on floor level, estate age, market conditions, and estate fixed effects. Because estate fixed effects are included, identification of view premiums arises from within-estate variation rather than cross-estate price differences.

All specifications include estate fixed effects to control for time-invariant development-level heterogeneity; thus, the six developments are captured through dummy variables rather than as a single aggregate control.

To test whether view premiums differ by market state, we estimate either (i) the baseline model separately for stronger and weaker market subsamples, or (ii) a single pooled model with interactions:

$$\ln(PPA_i) = \alpha + \sum\nolimits_{v \in \{Partial,\ Full\}} \beta_v D_{v,i} + \delta_v (D_{v,i} * strong_t) + X_i' \gamma + \gamma_3 CCI_t + \theta e + \varepsilon_i \quad (3)$$

where $Strong_t$ is the expansion indicator defined in Section 3.3, equal to 1 for stronger-market months and 0 for the recessionary episodes of 2019Q3–2020Q4 and 2022Q1–2022Q4. Each transaction month inherits the regime classification of its corresponding quarter, so the stronger and weaker periods correspond to the expansion and recession episodes defined earlier. X_i' includes *Floorno* and *Age*. The interaction coefficients δ_v capture the incremental view premiums in stronger markets relative to weaker markets, with view coefficients interpreted as semi-elasticities [55].

Equation (3) extends the baseline hedonic model by allowing the implicit prices of view attributes to vary across macroeconomic regimes, thereby testing whether the marginal capitalization of view quality shifts across economic states rather than remaining time-invariant.

Percentage premiums are reported as:

$$\text{Premium} = \exp(\hat{\beta}) - 1 \quad (4)$$

This transformation converts semi-log coefficients into exact percentage premiums, enabling direct interpretation for valuation practice and comparable-based adjustments.

Because view quality in high-rise buildings is closely associated with floor level and potentially with orientation or micro-location within an estate, multicollinearity diagnostics were conducted. Variance Inflation Factors (VIFs) for the main regressors were all below conventional thresholds (VIF < 5), indicating that although view and floor level are positively correlated, multicollinearity does not materially distort coefficient estimates. The inclusion of estate fixed effects further mitigates omitted-variable bias from persistent building-level attributes such as orientation, design, and shared amenity quality. Together, these steps reduce the risk that the estimated view premiums reflect double counting of height-related or estate-specific effects.

3.5. Estimation Procedure and Replication Workflow

The empirical workflow follows the procedures outlined in Sections 3.2 and 3.3. Transaction records were imported, validated, and merged with the monthly CCI series. Price per saleable area and its logarithm were computed, view-category dummies were constructed (with nil view as the reference group), and market-state indicators were assigned according to the GDP-cycle classification. Observations with missing key variables were removed, and the 1% trimming rule for extreme unit-price values was applied.

The initial dataset comprised approximately 380 secondary market transactions. After excluding non-open-market or related-party transactions (12) and records with incomplete transactions (9), 359 observations remained. Application of the 1% trimming rule removed a further 7 transactions, yielding a final analytical sample of 352 observations. The sequential filtering steps (raw → screened → cleaned → trimmed → final) are documented to ensure transparency and replicability.

Descriptive statistics. Summary statistics are reported for the full sample, by view category, and by market state (stronger versus weaker periods). These include the mean and median of transaction price per saleable area, floor level, and estate age, as well as the distribution of observations across *nil-*, *partial-*, and *full view* categories. Reporting statistics across both dimensions provides a transparent comparison of price intensity and key unit characteristics prior to formal estimation.

Hedonic estimation. The baseline model is estimated on the pooled sample to identify the average capitalization effect of view quality after controlling for floor level, estate age, CCI, and estate fixed effects. State dependence is examined in two complementary ways: (i) split-sample regressions for stronger and weaker markets, and (ii) a pooled specification including view-by-market-state interaction terms, as defined in Section 3.4. View coefficients are converted into percentage premiums with 95% confidence intervals using $exp(\hat{\beta}) - 1$.

Robustness checks. Alternative specifications include replacing $ln(PPA)$ with $ln(Price)$ while including $ln(Area)$, adding estate fixed effects where applicable, and testing alternative market-state definitions. Results remain consistent across specifications, supporting the robustness of the main findings.

4. Results

This section presents empirical findings from the hedonic models estimating the implicit pricing of view quality in Hong Kong's high-rise residential market. Table 2 summarizes the main regression results for the pooled sample and for the GDP-defined stronger- and weaker-market subsamples, with $\boldsymbol{ln(PPA)}$ as the principal dependent variable and $\boldsymbol{ln(Price)}$ reported as a reference specification. Particular attention is given to the coefficients on the *partial view* and *full view* indicators, which quantify the extent to which increasingly favorable views are reflected in transaction prices after controlling floor level, estate age, monthly market conditions, and estate fixed effects. By comparing these coefficients across pooled and regime-specific models, the analysis evaluates both the average magnitude of view premiums and whether their capitalization varies across market states.

Table 2. Hedonic Estimates of View Premiums under GDP-Defined Market Conditions.

	ln(avgprice): (1) All	**ln(avgprice): (2) Stronger-Market Period**	**ln(avgprice): (3) Weaker-Market Period**
Partial View	0.108 ** (0.04)	−0.079 (0.10)	0.076 (0.05)
Full View	0.201 *** (0.05)	0.122 (0.13)	0.128 ** (0.06)
Floorno	0.002 ** (0.00)	0.003 * (0.00)	0.003 ** (0.00)
Age	−0.009 (0.03)	0.022 (0.04)	−0.130 (0.08)
CCI	0.009 *** (0.00)	0.008 *** (0.00)	0.004 *** (0.00)
Constant	8.799 *** (0.84)	7.958 *** (1.04)	12.226 *** (1.99)
Estate fixed effects	Yes	Yes	Yes
N	352	158	194
R^2	0.827	0.917	0.62
Adj. R^2	0.823	0.912	0.602

Notes: Standard errors in parentheses. All specifications include estate fixed effects. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.1. Baseline View Premiums in the Pooled Sample

Table 2 reports the pooled estimates (N = 352). The results show clear evidence that view quality is reflected in the unit prices after conditioning on structure, market movements, and estate-level heterogeneity.

In the *ln*(*avgprice*) specification, the coefficient on *partial view* is 0.108 ($p < 0.05$) and the coefficient on *full view* is 0.201 ($p < 0.01$), both relative to *nil view*. These correspond to approximately 11.4% higher price per area for *partial view* units and 22.3% higher price per area for *full view* units, holding other covariates constant. The implied incremental premium of *full view* over *partial view* is approximately 9.7% ($p < 0.05$), indicating that the market differentiates both between "*with view*" and "*nil view*" and between grades of view quality.

A reference specification using *ln*(*price*) yields qualitatively consistent results. In the pooled sample, *partial view* = 0.122 ($p < 0.01$) and *full view* = 0.153 ($p < 0.01$), implying premiums of roughly 13.0% and 16.5%, respectively. The difference in magnitudes between *ln*(*avgprice*) and *ln*(*price*) is expected because total-price models can reflect scale/composition effects. Importantly, however, the sign and significance of the view coefficients are stable across dependent-variable definitions, reinforcing the conclusion that view quality is a priced amenity rather than a modelling artefact.

4.2. GDP-Regime Heterogeneity: "Stronger-Market Period" Versus "Weaker-Market Period"

Table 2 reports split-sample estimates for the GDP-defined stronger-market ($\boldsymbol{N} = \mathbf{158}$) and weaker-market ($\boldsymbol{N} = \mathbf{194}$) periods. These subsamples correspond to the macroeconomic expansion and recession/weak episodes defined in Section 3.3 and are used to assess whether the implicit value of view quality varies across market conditions. The results suggest that view premiums are not fully invariant across regimes, with the main differences appearing in the magnitude, precision, and statistical significance of the estimated coefficients.

The *partial view* coefficient becomes statistically insignificant in both regime subsamples and exhibits sign instability, turning negative (though imprecisely estimated) in the stronger-market period. This instability likely reflects reduced identifying variation once the sample is partitioned and estate fixed effects absorb substantial cross-sectional heterogeneity. It may also suggest that moderate visual amenities are more sensitive to sample composition and market segmentation than high-tier (Full) views.

The split-sample results indicate that view-related price premiums are not invariant across GDP-defined market regimes. In the stronger-market subsample, the partial view coefficient becomes statistically insignificant and exhibits sign instability, while the *full view* coefficient remains positive but is estimated with reduced precision. In the weaker-market subsample, the *full view* coefficient remains positive and statistically significant, whereas the *partial view* effect continues to lack statistical significance once the sample is partitioned.

Taken together, the regime-specific estimates suggest that higher-tier visual amenities (*full views*) retain a more robust and economically meaningful price signal across macroeconomic conditions, while the premium associated with partial views becomes less precisely identified in subsample analysis. This pattern is consistent with the broader hedonic literature, which documents that implicit prices of amenities may vary across market segments and economic states, contributing to coefficient instability across subsamples and time periods [55,56].

In addition, seller liquidity constraints or financial distress during downturn periods may contribute to greater price dispersion and weaker statistical precision of amenity coefficients. Although non-market transactions are excluded from the sample, residual heterogeneity in seller urgency cannot be fully observed and may partially influence estimated regime differences.

4.3. Control Variables and Goodness of Fit

Across specifications, the control variables behave plausibly. Floor level has a small positive marginal effect and is statistically significant in the pooled *ln*(*avgprice*) model (0.002, $p < 0.05$), consistent with the expectation that higher floors are associated with improved openness and reduced street-level disamenities in high-rise settings. The coefficient on Age is small and statistically insignificant in the pooled model, becomes positive but remains insignificant in the stronger-market subsample, and turns negative in the weaker-market subsample, where it is larger in magnitude though not precisely estimated. This pattern suggests that depreciation effects may become more pronounced under softer macroeconomic conditions, although the estimates lack consistent statistical precision across regimes. CCI is positive and highly significant in all specifications, indicating that transaction prices move closely with market-wide conditions and that controlling for CCI is important for isolating amenity pricing from broader price dynamics.

Model fit is strong across specifications. In the pooled sample, the $\boldsymbol{R}^2$ values are 0.827 for $ln(avgprice)$ and 0.901 for $ln(price)$, indicating that a substantial share of cross-sectional price variation is explained by estate fixed effects, structural attributes, and the market index (CCI). These relatively high values are consistent with the concentrated sample of prime estates and the inclusion of fixed effects that absorb persistent intra-estate heterogeneity.

Differences in explanatory power across market regimes are more pronounced. The $\boldsymbol{R}^2$ rises to 0.917 in the stronger-market subsample but falls to 0.62 in the weaker-market subsample. This asymmetry likely reflects changes in price dispersion and transaction heterogeneity across macroeconomic conditions. During stronger-market periods, pricing appears more tightly anchored to observable structural and estate-level characteristics, allowing fixed effects and core controls to account for a larger share of variation. In contrast, weaker-market periods may involve greater dispersion in negotiated prices, heightened uncertainty, and liquidity frictions, all of which introduce additional idiosyncratic variation not captured by standard covariates. The lower $\boldsymbol{R}^2$ in downturn conditions is therefore consistent with increased pricing noise and heterogeneity rather than model misspecification.

The Age coefficient becomes more negative in the weaker-market subsample, suggesting that depreciation effects and sensitivity to building vintage may intensify under softer macroeconomic conditions. Although the estimate is less precisely identified, the directional change is consistent with heightened buyer scrutiny of structural quality during downturns.

4.4. Economic Magnitude and Implications

Back-transforming fitted values (holding other covariates constant) implies a clear ranking in unit prices: *full view* > *partial view* > *nil view*. In the pooled sample, implied unit-price levels are approximately 25,163 (*nil*), 28,042 (*partial*), and 30,766 (*full*) (HKD per square foot), consistent with the semi-log premiums. In total-price terms (reference specification), the corresponding fitted values are approximately HKD 30.65 million (*nil*), HKD 34.64 million (*partial*), and HKD 35.70 million (*full*).

In practical terms, these magnitudes imply that view quality can account for a substantial share of cross-sectional dispersion in apartment values in prime high-rise estates. For valuation practice, the results provide an auditable benchmark for comparable-based adjustments, while the GDP-regime comparison cautions against assuming that a single, invariant view adjustment will be equally informative across markedly different macroeconomic environments.

5. Discussion

5.1. Main Findings

This study aimed (i) to estimate the marginal price premium associated with ordered view-quality categories (*nil*, *partial*, *full*) after controlling for structural and market factors, and (ii) to test whether such premiums vary across market conditions, indicating state-dependent price effects. The results provide answers to both research questions.

RQ1 (view premiums conditional on controls). In the pooled specification with ln(avgprice) as the dependent variable, both view indicators are positive and statistically significant relative to *Nil view*. *Partial view* ($\beta = 0.108$, $p < 0.05$) implies an approximate 11% premium in unit price, while *full view* ($\beta = 0.201$, $p < 0.01$) implies an approximate 22% premium. These estimates are obtained while controlling floor level, estate age, monthly market conditions (CCI), and estate fixed effects, suggesting that view quality is not merely a narrative descriptor but a systematically priced amenity in Hong Kong's high-rise residential market. The ordering of premiums (*full* > *partial* > *nil*) further supports the interpretation that the market differentiates both between "*full*/*partial view*" and "*nil view*" and between grades of view quality, consistent with the amenity-capitalization mechanism emphasized in the hedonic literature [57].

RQ2 (state dependence across market conditions). Split-sample results by GDP-defined regimes indicate that view capitalization is not invariant across market states. In the regime subsamples, the *partial view* coefficient becomes statistically insignificant and exhibits sign instability, whereas the *full view* coefficient remains positive in both regimes and is statistically significant in the weaker-market period for *ln*(*avgprice*) ($\beta = 0.128$, $p < 0.05$; approximately 13.6%). In the stronger-market subsample, although the *full view* coefficient remains positive ($\beta = 0.122$), it is estimated with reduced precision and is not statistically significant. Taken together, the evidence indicates partial state dependence in amenity pricing: while *full view* premiums remain economically meaningful across regimes, the estimated effect for partial views becomes less stable once the sample is partitioned. This pattern suggests that higher-tier views represent a more durable and scarcity-driven amenity, whereas mid-tier visual attributes may behave more like discretionary or segmentation-sensitive components of housing value [41–43].

5.2. Economic Magnitude and Comparability with Practitioner Narratives

The estimated premiums are economically significant in the context of high-rise buildings in the city, where high baseline price levels mean that even modest percentage differences translate into substantial absolute amounts. The fitted-value comparisons in Section 4.4 reinforce the monotonic ranking in implied unit prices (*full* > *partial* > *nil*), consistent with the semi-log coefficients.

Industry-oriented narratives similarly emphasize that "views add value" but that the size of the premium depends on visibility, exclusivity, and durability of the view, and on how broadly the view is enjoyed within the home (e.g., primary living areas versus secondary spaces). For example, a practitioner discussion for Austin, Texas highlights that exceptional views may increase value by more than 25% and that water views often command the highest premiums, while partially obstructed or less accessible views yield smaller effects; it also stresses the importance of future view obstruction risk in new developments and the scarcity of high-quality views as a driver of premiums [57]. While such practitioner figures are not directly transferable to high-rise buildings in the city, given differences in urban form and market structure, the qualitative hierarchy (unobstructed/high-quality views > limited views) is consistent with this study's ordered premium estimates and supports the argument that explicit measurement of view quality is important for valuation transparency [58].

5.3. Why Might Premiums Differ by Market State in a High-Rise Property Market?

The attenuation and loss of statistical significance for partial views in the regime subsamples likely reflect both behavioural and statistical mechanisms. First, moderate visual amenities may be more discretionary in nature and thus more sensitive to affordability constraints and heightened price sensitivity during weaker market conditions. Second, dividing the full sample (N = 352) into regime subsamples reduces effective variation and statistical power. With estate fixed effects absorbing substantial cross-sectional heterogeneity, the remaining within-estate variation in partial views may be insufficient to produce precise and stable estimates once the sample is partitioned [59,60].

By contrast, *full views* represent a scarcer and more vertically differentiated amenity in dense high-rise environments, which make their premiums more resilient across market states. In the context of Hong Kong, regime variation may also operate through financing and wealth channels. Housing purchases are typically financed through mortgage borrowing, and changes in credit conditions or interest-rate expectations may disproportionately affect marginal or credit-constrained buyers. Higher-floor or near-penthouse units are more commonly acquired by wealthier households with greater financial flexibility, potentially stabilizing *full view* premiums across regimes, while *partial view* effects remain more sensitive to affordability pressures [61,62].

Future research could examine these mechanisms more directly by estimating interaction terms (e.g., view $\times$ floor band or view $\times$ luxury segment) or by segmenting the sample into higher- and lower-tier units to assess heterogeneous capitalization patterns.

5.4. Implications for Valuation Practice and Practical Guidance for Valuers

The findings have direct implications for professional valuation under the market (sales comparison) approach, which operationalizes the principle of comparison by inferring value from recent transactions of comparable properties and making reasoned, evidence-based adjustments for material differences. Across major professional frameworks—including the Hong Kong Institute of Surveyors (HKIS), the Royal Institution of Chartered Surveyors (RICS), the Australian Property Institute (API), and the Australian Valuers Institute (AVI): core guidance emphasizes (i) selecting appropriate and sufficiently similar comparables, (ii) analysing and adjusting for key attributes that materially affect price, and (iii) documenting assumptions, adjustment logic, and evidential support so the conclusion is transparent and auditable (HKIS Valuation Standards; RICS Valuation—Global Standards ("Red Book"); API guidance notes/practice standards; AVI practice guidance) [52,53].

Within professional valuation practice, "view" is often treated as a qualitative descriptor. In high-rise estates, however, view quality varies materially within the same development and is correlated with floor level and orientation. If view is omitted or assumed to be implicitly captured by comparables, valuers risk comparing non-like properties, leading to systematic misestimation—particularly where comparable evidence is limited or differs in view category.

The results also indicate that view adjustments should not be treated as fixed or time-invariant. While *full view* premiums appear relatively robust, partial view effects are less stable across market regimes. This supports the standards-consistent emphasis (HKIS/RICS/API/AVI) on prioritizing time-close, same-estate evidence and applying adjustments only where justified by observable market behaviour and corroborated across multiple indicators [52–54,63].

Practical guidance for valuers (comparison principle). The pooled estimates indicate that, holding other factors constant, a *partial view* is associated with an approximate +11% unit-price premium and a *full view* with an approximate +22% premium relative to *Nil view*. In comparable-based valuation, these magnitudes may be used as initial adjustment benchmarks when otherwise similar transactions differ primarily by view category—provided the valuer (i) explicitly defines and evidences the view classification (*nil*/*partial*/*full*) using inspection and/or reliable verification sources, (ii) prioritizes comparables within the same estate/block and similar floor bands to avoid confounding with height and micro-location, and (iii) reconciles any applied adjustment against paired-sales style evidence where available. Given that the split-sample results suggest reduced precision—especially for *partial views*—across market regimes, view adjustments should be cross-checked against time-close and within-estate comparables and, where appropriate, corroborated using model-assisted evidence (e.g., hedonic estimates or Automated Valuation Model (AVM) diagnostics) rather than applied as a uniform rule across all market conditions [64,65].

In lower-activity market segments where comparable evidence is limited, transparent percentage-based adjustment coefficients can provide a structured and auditable reference point for valuation. Although this study does not employ a formal paired-sales design, the within-estate identification strategy parallels paired-sales logic by isolating view differentials while holding broader locational characteristics constant.

More broadly, building-level governance and property management quality may also influence residential value through maintenance standards and regulatory confidence effects [66]. While not modelled here, such institutional attributes may interact with physical amenities in dense housing markets.

Future research may extend this framework by incorporating formal paired-sales analysis or deriving adjustment coefficients for specific encumbrances or atypical transaction conditions, further strengthening transparency in valuation practice.

5.5. Implications for Future AI-Enabled Valuation Workflows

Although the present study adopts a conventional hedonic framework, the explicit and ordered measurement of view quality establishes a structured input for future AI-assisted valuation and scalable AVM development. By converting qualitative descriptions into transparent, replicable categories with estimated price premiums (Section 4), view can be treated as a measurable feature rather than implicitly absorbed by neighbourhood or estate fixed effects. In practice, this may be implemented through a multimodal data pipeline integrating transaction and building attributes, geospatial and three-dimensional urban form information, and computer vision–derived image signals, with the resulting view metric incorporated into hedonic, gradient-boosting, or other ML models while retaining economic interpretability.

XAI methods are essential for aligning AVM outputs with the comparison principle and professional standards (HKIS/RICS/API/AVI) [52,53,55]. Feature-attribution tools such as SHAP-type decompositions can quantify the marginal contribution of view variables, detect spurious attribution to correlated proxies (e.g., floor level), and provide an auditable decision trail. Finally, the observed state dependence underscores the need for regime-robust validation, including time-split testing, stability diagnostics, and monitoring for concept drift. Together, explicitly measured view indicators, hedonic-calibrated effect sizes, and interpretable ML diagnostics provide a coherent pathway toward scalable and auditable AI-assisted valuation in vertically differentiated housing markets.

5.6. Research Limitations

Several limitations should be borne in mind when interpreting the findings and their implications. First, the measurement of view quality is necessarily simplified. The analysis operationalizes view as an ordered categorical variable: *nil view*, *partial view* and *full view*, constructed from listing descriptions and cross-validated with map and street-view evidence. This approach is transparent, replicable, and well suited to transaction-level modelling, but it does not capture finer visual dimensions that may also affect value, such as view breadth, depth, elevation, foreground obstruction, exposure, framing, or the long-term durability of the view against future development [67]. The estimated coefficients should therefore be interpreted as average premiums for broad view classes rather than exhaustive valuations of all possible visual attributes.

Second, the sample is relatively focused, comprising 352 transactions from six prime high-rise estates. This concentration strengthens internal comparability by reducing heterogeneity in building quality and locational context, which is appropriate for identifying capitalization patterns within a vertically differentiated urban segment. At the same time, it limits the extent to which the estimated premiums can be generalized to all districts, housing types, or price tiers in Hong Kong. The results are thus most appropriately understood as evidence from a prime high-rise context rather than as universal adjustment factors.

Third, as with most cross-sectional hedonic analyses, the specification cannot fully eliminate omitted-variable bias. Although the models control for floor level, estate age, monthly market movements, and estate fixed effects, some unit-specific attributes, such as renovation quality, layout efficiency, maintenance condition, orientation, or bundled amenities, are not consistently observed in the dataset. If correlated with view quality, these factors may introduce residual bias. Accordingly, the estimated view premiums should be interpreted as robust conditional associations rather than strictly causal effects. Future research incorporating richer unit-level metadata or floorplan-based efficiency measures could further strengthen identification.

Fourth, the market-state analysis relies on GDP-defined stronger- and weaker-market periods. This externally determined classification enhances transparency and replicability, but it may not capture all shorter-run fluctuations in housing-market sentiment, liquidity, or financing conditions. Accordingly, the regime results are best interpreted as evidence of broad cyclical variation in view premiums rather than a complete account of all time-varying market dynamics.

These limitations suggest appropriate caution in extrapolating the precise magnitudes reported in this study, but they do not detract from its central conclusion: view quality is a material and systematically priced attribute in Hong Kong's high-rise residential market. Rather, they indicate that the present estimates should be viewed as a transparent empirical benchmark and a foundation for further refinement. This naturally leads to the concluding discussion, which emphasizes both the valuation significance of explicit view measurement and the scope for future work using richer visual, spatial, and AI-enabled indicators. Future research may employ finer-grained visual metrics derived from three-dimensional urban data or computer vision techniques to capture continuous variation in view composition and obstruction risk.

6. Conclusions

This study examined whether residential view quality is systematically reflected in the transaction prices in Hong Kong's high-rise housing market and whether the magnitude of view premiums varies across macroeconomic conditions. Using a hedonic pricing framework applied to 352 secondary market transactions from 2015 to 2024 across six major estates, and controlling for floor level, estate age, monthly market movements (CCI), and estate fixed effects, the results demonstrate that view quality constitutes a statistically and economically meaningful component of price formation.

In the pooled specification, partial views are associated with an approximate 11% premium in price per saleable area relative to *Nil view*, while full views command an approximate 22% premium. Moreover, full views exhibit a clear incremental premium over partial views. These findings provide Hong Kong-specific quantitative evidence that the market systematically differentiates among "*nil view*," "*partial view*," and "*full view*," and that view quality is priced in an ordered and economically coherent manner.

Evidence from GDP-defined regime subsamples indicates state-dependent price effects. Although *full view* effects remain positive across regimes, estimated premiums, particularly for partial views, become less precisely identified during weaker macroeconomic periods. This pattern suggests that amenity pricing is not fully invariant over the cycle. For valuation practice, this implies that view adjustments should not be applied mechanically as fixed percentages across all market states. Rather, appraisal robustness may depend on regime-aware evidence, time-close comparables, and careful reconciliation of adjustment magnitudes.

From a professional valuation perspective, the findings speak directly to the principle of comparison. In vertically differentiated housing markets, view quality can vary substantially within the same estate and cannot be reliably proxied by floor level or location alone. If views are assumed to be implicitly embedded in comparables rather than explicitly identified and adjusted, the comparison process risks inconsistent application and reduced auditability. The percentage-based premiums estimated in this study provide a transparent and empirically grounded benchmark that can complement sales-comparison grids, particularly where truly same-view comparables are limited.

The results establish a transparent empirical basis for integrating view metrics into AI-enabled valuation systems. Because the estimated premiums are interpretable and ordered (*nil* < *partial* < *full*), they provide a practical calibration benchmark for computer-vision and geospatial methods incorporated into AVMs. Embedding measurable view features within ML workflows—supported by XAI tools to audit marginal contributions—can improve both predictive accuracy and governance transparency. However, regime sensitivity underscores the need for stability testing across market states to avoid temporal overfitting and concept drift. The ML/XAI frameworks outlined in Section 2.2 offer feasible integration pathways, though empirical validation remains for future research.

More broadly, by providing hedonic evidence from a prototypical dense, high-rise, transit-oriented Asian city, this study helps address a recognized geographic and morphological gap in the view-premium literature, which has been dominated by low-density, parcel-level contexts. The findings are therefore directly relevant to the substantial and growing share of global housing wealth located in vertically differentiated urban environments.

The implications extend beyond valuation practice. For urban planning and design, the results provide evidence that decisions affecting building height controls, setbacks, skyline management, and view corridor protection can materially redistribute residential value. For policy and infrastructure governance, recognizing the measurable economic significance of visual amenities supports more transparent cost–benefit analysis of planning interventions in dense cities. Finally, by testing the cyclical behavior of view premiums, the study contributes to the broader literature on state-dependent amenity pricing and cross-cycle appraisal robustness in high-density housing markets.

Future research should refine measurement beyond coarse categorical classifications to incorporate view composition, angular breadth, obstruction risk, and dynamic skyline change; extend analysis to additional submarkets and property types; and employ richer interaction models to strengthen inference on cyclical heterogeneity. Together, these extensions would further advance the integration of built-environment analytics, hedonic theory, and AI-assisted valuation in dense urban contexts.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
AVM	Automated Valuation Model
API	Australian Property Institute
AVI	Australian Valuers Institute
BIM	Building Information Modeling
CCI	Centa-City Index
GFA	Gross Floor Area
HKIS	Hong Kong institute of surveyors
IPMS	International Property Measurement Standards
ML	Machine Learning
RICS	Royal Institution of Chartered Surveyors
TOD	Transit-oriented development
VIF	Variance Inflation Factors
XAI	Explainable Artificial Intelligence

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