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Four-Quarter Rolling Time-Dummy Hedonic Architecture for Uzbekistan's Residential Property Price Index

Togayeva Dildora Akramovna¹

1. Independent Researcher, Institute for Personnel Development and Statistical Research of the National Statistics Committee of the Republic of Uzbekistan, Tashkent, Uzbekistan

Abstract: The heterogeneity of residential properties and time-varying changes in the composition of listings complicate the interpretation of observed housing price movements as pure price change. This study empirically evaluates the operational stability, quality-adjustment performance and segment-specific diagnostic properties of the four-quarter rolling time-dummy (RTD) hedonic architecture used for quarterly residential property price measurement in Uzbekistan. The empirical audit covers 1,654,058 OLX and Telegram listings from 2024Q1 to 2026Q2, 28 market-location strata, seven overlapping four-quarter windows and 196 stratum-window regressions. The median adjusted R^2 across all models is 0.720; the mean is 0.753 for apartment models and 0.561 for individual-house models. Cook's Distance filtering removes 5.78 percent of observations on average. The median cross-window revision is 0.191 percentage points; 85.7 percent of apartment links and 72.9 percent of house links show revisions below 0.5 percentage points. In 2025Q1 the hedonic apartment index differs from the normalised raw median and geometric-mean series by 3.64 and 4.04 index points, respectively. The findings support the four-quarter RTD architecture as a coherent local estimation regime for Uzbekistan's quarterly RPPI production system, while not establishing it as empirically optimal relative to alternative rolling-window lengths.

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1. Introduction

A residential property price index (RPPI) measures the change over time in the price of housing assets. Housing, however, is not a standardised good: dwellings differ in floor area, number of rooms, storey, building height, construction material, location, market segment and other quality attributes. A simple difference in mean or median prices between two periods therefore reflects not only pure market price change but also shifts in the quality mix of the properties that happen to be observed. Conceptually, the observed price change can be decomposed as

$$\Delta P_{obs} = \Delta P_{pure} + \Delta P_{quality} + \Delta P_{composition},$$

and the task of RPPI methodology is to isolate constant-quality price dynamics from this observed change. International RPPI methodology treats hedonic regression as one of the principal tools for this purpose (Eurostat et al.; IMF) [1].

A time-dummy hedonic model relates the price of a dwelling to its observable quality and locational characteristics and to a set of time effects. Pooling all historical periods in a single, ever-expanding regression, however, allows new observations to revise previously published time coefficients and imposes the strong assumption that the implicit prices of

attributes remain constant over a long horizon. The rolling time-dummy (RTD) approach relaxes this constraint by re-estimating the regression within a bounded window that moves forward each period. The choice of window length, the linking of overlapping estimates and model stability in segments with few observations are the central methodological questions of RTD (Hill et al.) [2].

The theoretical foundation of hedonic pricing goes back to Rosen, who interprets the price of a differentiated good as a function of its bundle of characteristics; Silver systematically compares time-dummy, characteristics and imputation approaches for RPPIs. Hill et al. identify window length, linking and low transaction volume as the central design choices of RTD. A longer window brings more observations and more precise parameters but increases the risk that implicit prices become stale; a shorter window adapts faster to new market signals but raises variance in thin-market strata (Hill & Steurer). State-space hedonic approaches have also been proposed for higher-frequency indices (Hill, Rambaldi & Scholz), which underlines that RTD is one of several available options rather than a unique standard [3].

Official international practice confirms that no universal window exists: Ireland and Cyprus use four-quarter RTD models, whereas Portugal applies a two-adjacent-period RTD specification (Eurostat). The four-quarter choice for Uzbekistan is therefore consistent with international practice, but its scientific assessment has to be carried out through national sample density, quality mix, model diagnostics and revision stability (Table 1) [4].

Table 1. International comparison of official RTD practice: Ireland, Cyprus, Portugal and Uzbekistan.

Country	Hedonic method	Rolling window	Linking and main features
Ireland	Log-linear RTD	4 quarters	New q/q change applied to previous sub-index; dwelling type, location, BER, floor area, deprivation index.
Cyprus	Rolling-year time-dummy	4 quarters	Chain-linked; sub-indices for new and existing dwellings; annual weights based on transaction values.
Portugal	Semi-log RTD, OLS	2 adjacent quarters	Q/q change obtained by exponentiating the time-dummy coefficient; combined with stratification.
Uzbekistan	Log-linear RTD by stratum	4 quarters	28 strata; adjacent links chain-linked; annual weights = mean listing price × number of notarial transactions.

Source: compiled by the author from Eurostat national HPI metadata and the Uzbekistan RPPI methodology.

Online listing data offer timeliness and granularity but do not replace transaction records. Lyons shows that a list-price index can track and anticipate transaction-price trends; Kolbe et al. find that composition and implicit prices differ between listing and transaction data while asking-price indices remain useful for nowcasting; Loberto et al. show that duplicates can distort the composition of supply. This literature justifies listing data in the Uzbek context while requiring control of duplicates, selection and the asking-transaction gap [5].

The research gap for Uzbekistan lies not in describing the four-quarter RTD but in evaluating how stably it performs in the real production pipeline together with sample coverage, model diagnostics, quality mix and cross-window revision. The central question is: to what extent does the four-quarter RTD architecture of Uzbekistan's quarterly RPPI provide a stable and methodologically coherent local estimation regime for constant-quality price change under real listing microdata? The aim is to assess empirically its operational stability, quality-mix control and segment-specific diagnostics and to substantiate its role in the RPPI production system. The contribution is not a new method

but a comprehensive empirical audit of the existing architecture. Three hypotheses are tested.

H1 (operational stability). Cross-window revisions arising from the re-estimation of the same stratum–q/q price link in overlapping four-quarter windows are limited in most cases. A revision below 0.5 percentage points is used as a practical monitoring criterion; because this is not a normative threshold, results are also reported for 0.25, 0.75 and 1.0 percentage points [6].

H2 (quality mix). Changes in the composition of listings by market type, region and floor area produce an economically meaningful gap between raw median or geometric-mean price series and the hedonic constant-quality index. A gap of two index points is used as a descriptive criterion, and the conclusion rests on the persistence of the gap across consecutive quarters rather than on a single quarter [7].

H3 (segment-specific diagnostics). RTD models for apartments are expected to show higher explanatory power and lower standard errors of time-dummy coefficients than models for individual houses. The richer set of observable attributes in the apartment model is one plausible explanation, but the study does not identify a causal effect of attribute count on model fit.

2. Materials And Methods

Hedonic time-dummy specification

The price of a dwelling is treated as a function of its characteristics, $P_{ist} = f(X_{1ist}, \dots, X_{kist})$. For RPPI compilation a semi-logarithmic specification is convenient:

$$\ln P_{ist} = \alpha_s + \sum_k \beta_{ks} X_{kist} + \sum_\gamma \delta_{\gamma s} D_{\gamma it} + \varepsilon_{ist}$$

where P_{ist} is the price of dwelling i in stratum s in period t ; X_{kist} are quality and locational characteristics; β_{ks} are the implicit prices of these characteristics; $D_{\gamma it}$ are time-dummy variables; $\delta_{\gamma s}$ is the time effect net of quality differences; and ε_{ist} is the random error. With the base period set to 100, the time-dummy hedonic index is $I_{s,t/0} = 100 \cdot \exp(\delta_{s,t})$. The index does not compare the composition of dwellings observed in two periods directly; it isolates the time effect while statistically controlling observable quality attributes [8].

Rolling time-dummy architecture

In a simple multi-period time-dummy regression all available periods enter one model, $W_T = \{1, 2, \dots, T\}$; when period $T+1$ is added the model expands to $W_{T+1} = \{1, \dots, T, T+1\}$, so that new observations can affect the previously estimated δ_i and β_k , raising the risk of revision in official series. A rolling window instead covers only the last L periods, $W_t^{(L)} = \{t-L+1, \dots, t\}$, and in the next period becomes $W_{t+1}^{(L)} = \{t-L+2, \dots, t+1\}$: the oldest period is dropped and the newest is added. The core trade-off is between sample stability and adaptability to market change (Table 2). Window length must be treated as a methodological choice rather than a mechanical technical parameter (Hill et al.; Hill & Steurer) [9].

Table 2. Methodological trade-off in the choice of rolling-window length.

Criterion	Short window	Long window	Objective of the 4-quarter approach
Adaptation to new market signal	High	Lower	Sufficiently fast
Number of observations	Fewer	More	Increased through one-year pooling
Coefficient variance	May be higher	May be lower	Preserve stability
Influence of past market regime	Low	High	Limited
Revision and linking control	Fragile	More stable but inert	Managed through local links

Source: author's elaboration based on Hill et al. (2022).

The 2026 national RPPI methodological regulation of Uzbekistan assumes that the implicit prices of quality characteristics are relatively stable over at least one year. The model therefore pools the current quarter with the three preceding quarters, $W_t = \{t-3, t-2, t-1, t\}$, and in the following quarter $W_{t+1} = \{t-2, t-1, t, t+1\}$ (National Statistics Committee of the Republic of Uzbekistan). The sequential shift of the window is shown in Figure 1. This architecture does not declare four quarters to be the absolutely optimal window; it is interpreted as a one-year local estimation regime in which the relative stability of attribute coefficients is assumed only within the relevant window, not over the whole history [10].

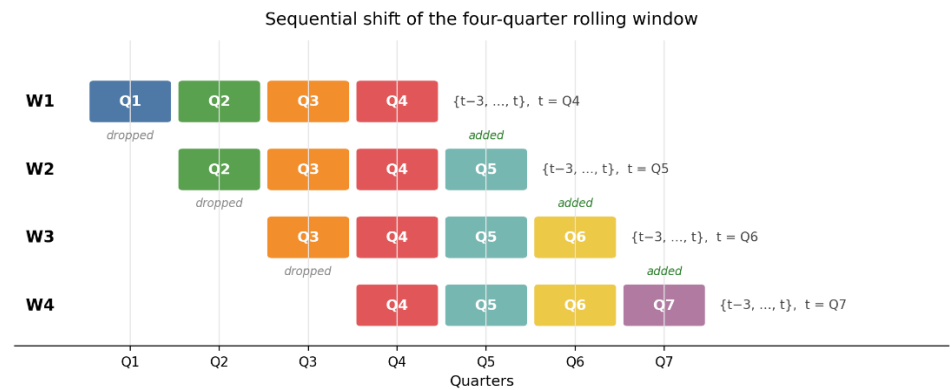


Figure 1. Sequential shift of the four-quarter rolling window. *Source: author's elaboration.*

Three properties of the window underpin its role. First, pooling raises the sample per stratum from $N_{s,t}^{(1)} = n_{s,t}$ to $N_{s,t}^{(4)} = \sum_{j=0..3} n_{s,t-j}$, which matters most in thin-market strata (Hill et al.). Second, implicit prices are assumed locally stable within the window, $\beta_{k,t-3} \approx \dots \approx \beta_{k,t}$, but are re-estimated in every subsequent window, so the model adapts to parameter evolution as old information leaves it. Third, a one-year horizon is an institutionally intelligible compromise between sample adequacy and adaptability, which does not by itself prove that four quarters are superior to three-, five- or six-quarter alternatives [11].

Linking and chain-linking

Overlapping windows produce repeated estimates for the same periods. If $\delta_{s,t-1}$ and $\delta_{s,t}$ are the time-dummy coefficients of the last two periods in window W_t , the quality-adjusted price relative for adjacent periods is

$$R_{s,t-1,t} = \exp(\delta_{s,t} - \delta_{s,t-1}),$$

and the long series is continued by chain-linking, $I_{s,t} = I_{s,t-1} \times R_{s,t-1,t}$. The 2026 national regulation stipulates that indices obtained from different rolling windows are chain-linked through the common overlap period (National Statistics Committee of the Republic of Uzbekistan) [12].

Stratification and model diagnostics

The market is first divided into relatively homogeneous strata and a separate hedonic model is estimated for each: the 2026 regulation defines nine strata for the primary apartment market, nine for the secondary apartment market and ten for individual houses (National Statistics Committee of the Republic of Uzbekistan). Stratification reduces structural heterogeneity between segments, hedonic regression controls quality differences within a stratum, the rolling window estimates parameters locally in time, and chain-linking builds a continuous index. Because the model is re-estimated in every window, diagnostics are performed for every stratum and window. The national methodology uses Cook's Distance to identify influential observations and adjusted R^2 , $R^2 = 1 - (1 - R^2)(n - 1)/(n - k - 1)$, to monitor explanatory power. The diagnostic ranges reported in that document (adjusted R^2 of roughly 0.57–0.84 for apartment models and

0.39–0.68 for house models) are indicators from the methodological document, not independent re-estimates of this study [13].

Data and sample design

The empirical base comprises 1,654,058 housing advertisements collected from OLX and Telegram between 2024Q1 and 2026Q2: 1,358,499 OLX apartment listings, 219,031 OLX individual-house listings, 47,398 Telegram apartment listings and 29,130 Telegram house listings. The estimation architecture consists of 28 strata, seven overlapping four-quarter windows and 196 regressions in total; the seventh window covers 2025Q3–2026Q2. The sample is not uniform over time: 204,576 observations in 2024Q1 fall to 120,981 in 2026Q2, a decline of 40.9 percent relative to the initial quarter (Figure 2). Nevertheless, the smallest stratum–quarter cell contains 610 observations; of 280 stratum–quarter cells, only nine contain fewer than 1,000 observations, all of them individual-house strata in Tashkent city. This strengthens the role of four-quarter pooling in preserving parameter precision precisely in thin-market segments [14].

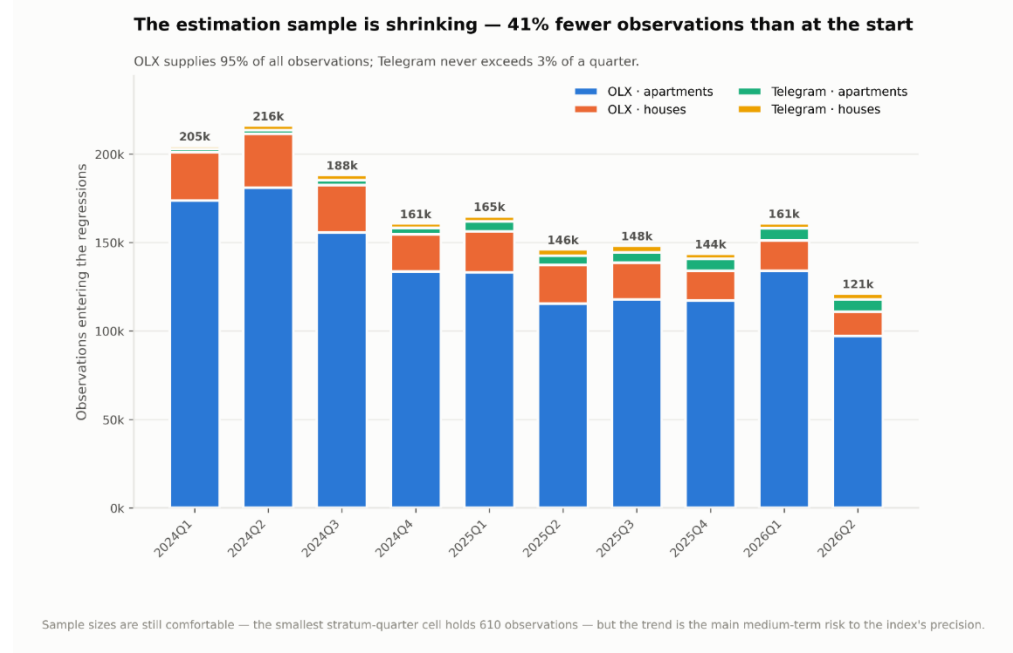


Figure 2. Size of the estimation sample by quarter, 2024Q1–2026Q2.

Source: author's calculations, RPPI audit workbook.

The composition of listings also shifted markedly. The share of primary-market apartments rose from 34.8 to 52.6 percent, the mean floor area of apartments offered increased from 66.7 to 69.9 m², and the share of Tashkent city in total listings fell from 88.5 to 81.3 percent (Figure 3). Such quality-mix shifts are exactly why simple mean or median price dynamics cannot be interpreted as pure price change.

In preprocessing the sample was filtered by plausibility and regional price ranges: apartment floor area 20–500 m², price per square metre 1–300 million UZS (upper bound 30 million UZS for Telegram), storey not exceeding building height for OLX records; house asking price 50 million–30 billion UZS and plot area 50–3,200 m² (50–1,200 m² in Tashkent city). Region-specific price ranges were applied to both segments, and observations that could not be assigned to a geographic unit or stratum were excluded.

Regression specification and influential-observation control

In the operational specification of the audit workbook the dependent variable is $\ln(\text{price_UZS})$, the logarithm of the total asking price converted to UZS at the monthly average exchange rate. Apartment models include total area, number of rooms, storey, building height and quarter dummies; district fixed effects are added in the relevant

Tashkent strata and region fixed effects in multi-region strata. House models include plot area, number of rooms and quarter dummies, with geographic fixed effects where necessary. The first quarter of each rolling window is the omitted reference category ($\delta = 0$). For every stratum–window combination an initial OLS is estimated, Cook's Distance is computed, influential observations with $D_i \geq 4/n$ are removed, and the model is re-estimated to obtain the final index coefficients [15].

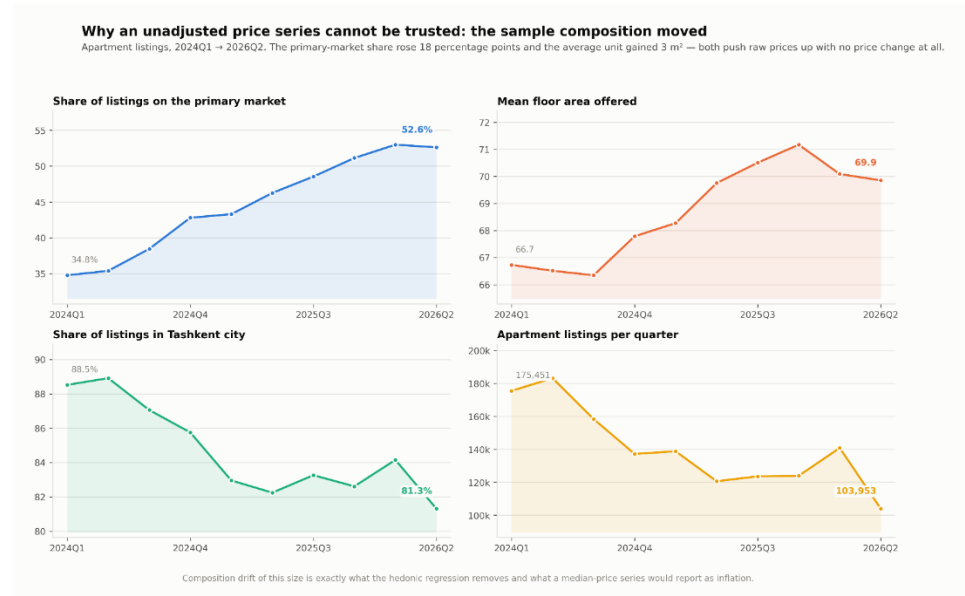


Figure 3. Shifts in sample composition by market type, floor area and region.

Source: author's calculations.

Aggregation weights

Quality-adjusted stratum indices are aggregated with annual expenditure weights whose value component is the product of the stratum's mean listing price and the number of notarial transactions, normalised within the aggregation group (Figure 4). Aggregation is a weighted arithmetic mean of within-year indices; a stratum with no observations in a quarter receives zero weight and the remaining weights are renormalised. Because listing prices are not transaction prices, the weights are a transaction-count-anchored proxy value measure. Weights from year y apply to year $y+1$; as 2023 listing prices were unobserved, the 2024 mean listing price proxies the 2023 price component.

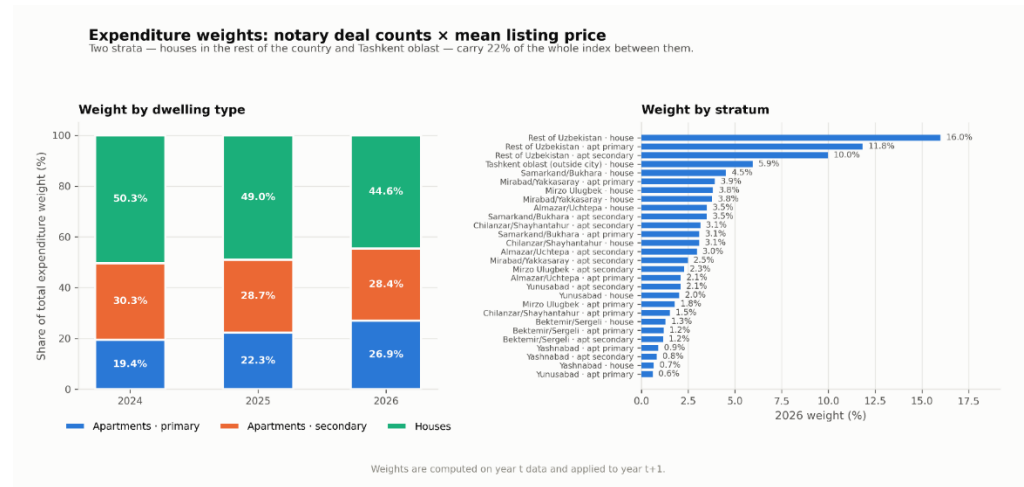


Figure 4. Structure of aggregation weights: number of notarial transactions × mean listing price.

Source: author's calculations.

Hypothesis testing design

H1 is tested by measuring, for every stratum–q/q link estimated in more than one overlapping window, the revision range (largest minus smallest estimate) in percentage points and reporting its distribution and the share of links below the 0.25, 0.5, 0.75 and 1.0 percentage-point thresholds. H2 is tested by comparing the hedonic apartment index with raw median and geometric-mean price-per-square-metre series on the common base 2024 average = 100 over consecutive quarters. H3 is tested by comparing adjusted R^2 , the share of time-dummy coefficients significant at the 5 percent level and the mean standard error of time-dummy coefficients between apartment and house models. The sensitivity of model fit to Cook's Distance filtering is assessed by comparing R^2 before and after filtering for all 196 models.

3. Results

Model diagnostics and segment differences (H3)

Across the 196 regressions of the 2024Q1–2026Q2 audit the mean adjusted R^2 is 0.684 and the median 0.720; Cook's Distance filtering removed 5.78 percent of observations on average. Fit and the precision of time-dummy coefficients are higher for apartments: 81.5 percent of 378 apartment time-dummy coefficients are significant at the 5 percent level, against 60.0 percent of 210 house coefficients. The mean standard error of time dummies is 0.0039 for apartments and 0.0131 for houses (Table 3, Figure 5). These diagnostic differences are consistent with H3, although attributing them solely to the richer attribute set would require a separate controlled re-specification test.

Table 3. Empirical diagnostics of RTD hedonic models, 2024Q1–2026Q2.

Segment	Number of models	Mean adj. R^2	Adj. R^2 range	Cook filter, %	Time dummies significant at 5%, %
Apartments	126	0.753	0.619–0.869	5.84	81.5
Individual houses	70	0.561	0.382–0.759	5.67	60.0
Total	196	0.684 (median 0.720)	0.382–0.869	5.78	73.8

Source: author's calculations.

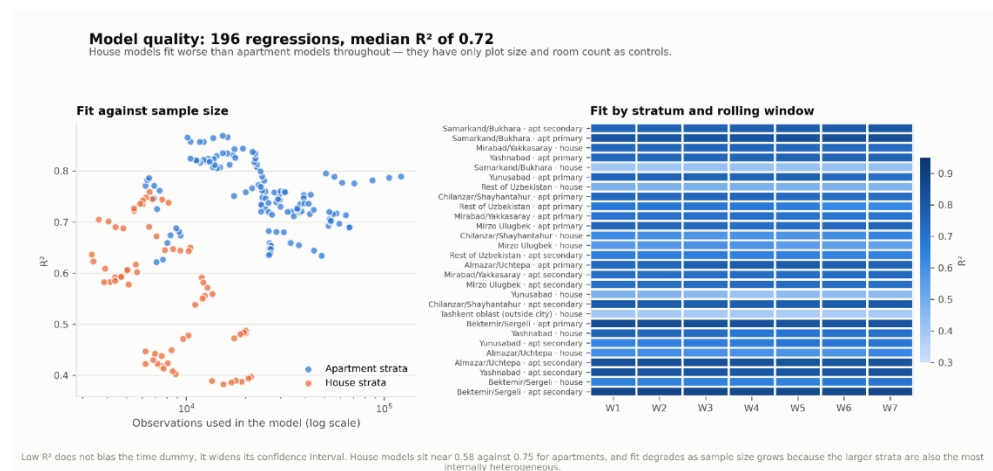


Figure 5. Model quality across 196 regressions and stability across rolling windows.

Source: author's calculations.

Adjusted R^2 alone is therefore insufficient: coefficient signs, standard errors, influential observations, stratum size and the stability of time coefficients across adjacent windows must be monitored jointly. The significance of a time-dummy coefficient is not a criterion of whether price change “exists” but an indicator of the precision of the estimated time effect.

Sensitivity of model fit to Cook's Distance filtering

The audit workbook stores R^2 before and after filtering for every stratum–window model. The mean share of influential observations is 5.78 percent (median 5.74 percent). Plain R^2 rises from a mean of 0.613 before filtering to 0.685 after filtering, a mean change of +0.0717 and a median change of +0.0738. In apartment models R^2 rises from 0.690 to 0.753 (+0.0628) and in house models from 0.474 to 0.561 (+0.0878). In 80.1 percent of the 196 models the gain is at least 0.05 and in 10.7 percent at least 0.10. The filter thus materially affects fit. Because the workbook does not retain pre-filter time-dummy coefficients and raw microdata are outside the audit package, no index-level claim is made that RPPI links are unchanged with and without the filter.

Quality mix and the quantitative importance of quality adjustment (H2)

The hedonic apartment index was compared with raw median and geometric-mean price-per-square-metre series on the common base 2024 average = 100. The gap is not confined to a single quarter. In 2025Q1 the hedonic index differs from the raw median and geometric-mean series by 3.64 and 4.04 index points, in 2025Q2 by 2.96 and 2.17 points and in 2025Q3 by 3.04 and 2.33 points (Figure 6). The descriptive two-point criterion is therefore exceeded against both raw benchmarks in three consecutive quarters, 2025Q1–2025Q3. The comparison demonstrates the practical importance of quality adjustment, but the whole gap between the hedonic index and the raw series cannot be interpreted causally as the quality-mix effect alone, because the series also differ in adjustment, aggregation and specification; the result is treated as diagnostic evidence consistent with H2.

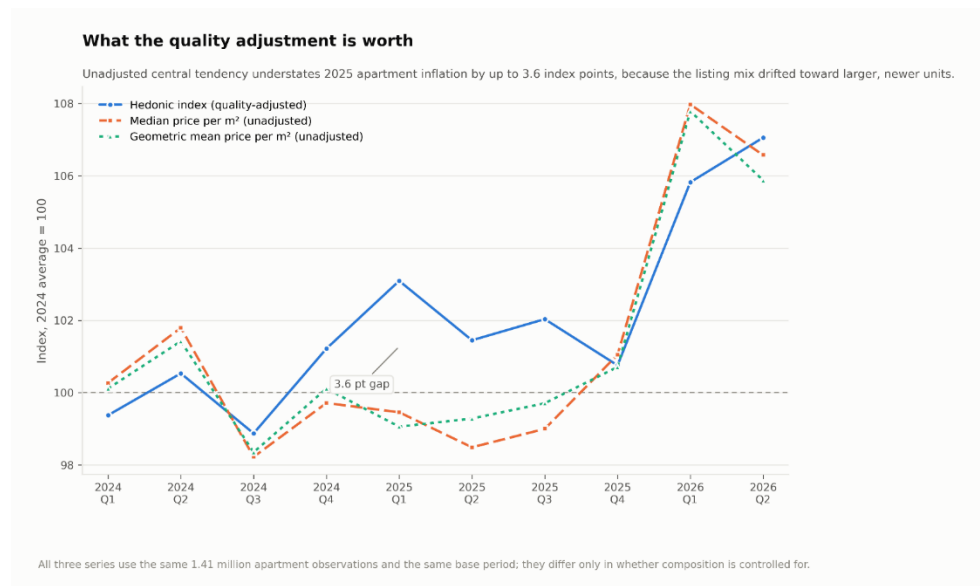


Figure 6. The value of quality adjustment: hedonic index versus median and geometric-mean price series.

Source: author's calculations.

RPPI dynamics, 2024Q1–2026Q2

On the base 2024 average = 100 the national RPPI reached 106.772 in 2026Q2. In the same quarter the all-apartment index stood at 107.057, the primary-market apartment index at 110.854, the secondary-market apartment index at 104.297 and the individual-house index at 106.123. Year-on-year growth ranged from 2.03 percent for houses to 7.08 percent for primary apartments, with the national index at 3.95 percent (Table 4, Figures 7 and 8).

Table 4. Main aggregate RPPI indicators in 2026Q2.

Indicator	2026Q2 index (2024 = 100)	QoQ, %	YoY, %
National RPPI	106.772	+1.255	+3.950
All apartments	107.057	+1.165	+5.527
Primary-market apartments	110.854	+0.720	+7.083
Secondary-market apartments	104.297	+1.599	+4.168
Individual houses	106.123	+1.370	+2.029

Source: author's calculations.

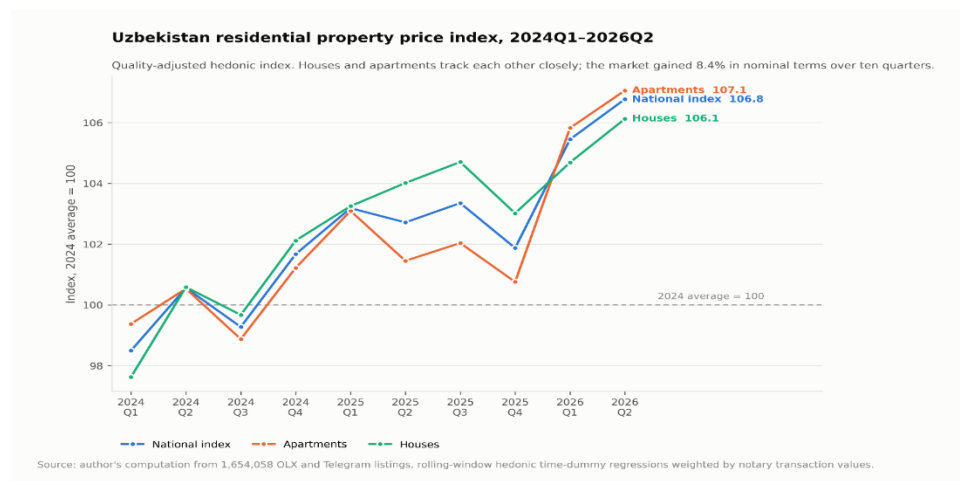


Figure 7. Uzbekistan RPPI: national index, apartments and individual houses, 2024Q1–2026Q2. Source: author's calculations.

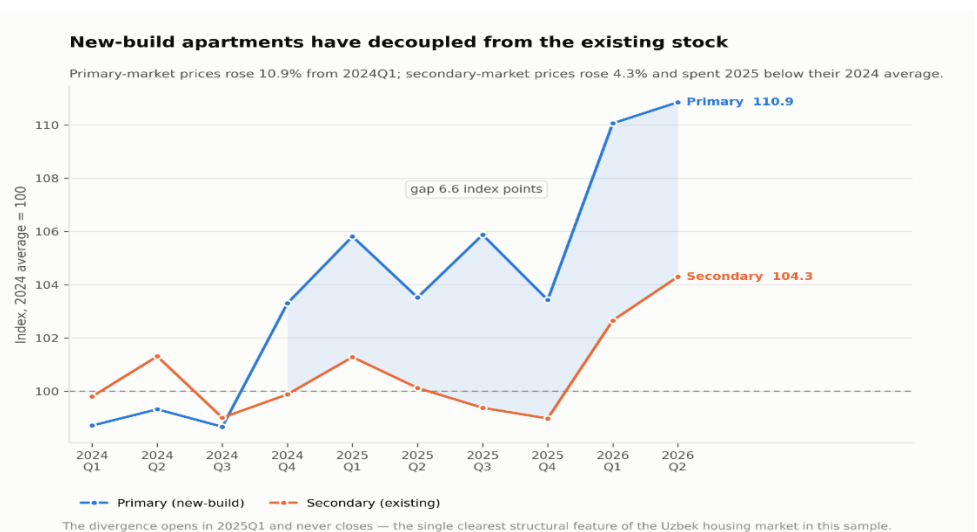


Figure 8. Divergence of primary- and secondary-market apartment indices. Source: author's calculations.

The difference between the primary and secondary segments reached 6.56 index points in 2026Q2 (110.854 against 104.297). Interpreting the aggregate “apartments” index without tracking the individual market segments may therefore smooth over cyclical signals. Stratum indices differ substantially from one another: in the same quarter some regions and segments show growth while others decline (Figure 9). The national index should consequently be read as a measure of central tendency, and model monitoring must continue across all 28 strata.

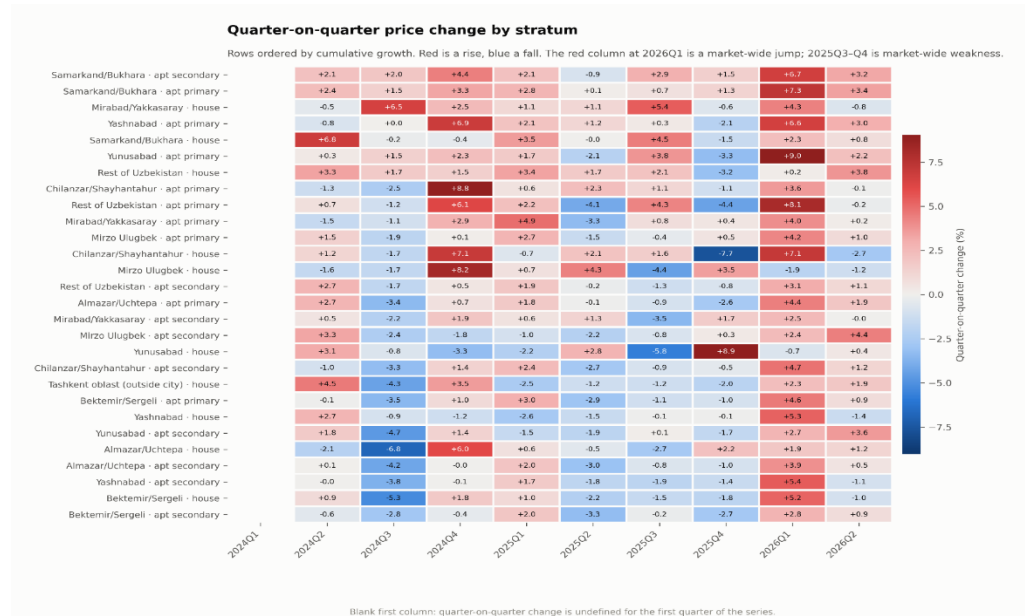


Figure 9. Quarter-on-quarter quality-adjusted price changes across 28 strata. Source: author's calculations.

Operational stability in overlapping four-quarter windows (H1)

H1 was tested by re-estimating the same stratum and the same adjacent-quarter link in different overlapping four-quarter windows. Over 196 repeated stratum-q/q combinations the revision range averages 0.301 percentage points, with a median of 0.191 and a 90th percentile of 0.710 percentage points. The median revision is 0.156 percentage points for apartments and 0.309 for houses. At the practical 0.5-point criterion, 85.7 percent of apartment links and 72.9 percent of house links fall below the threshold (Table 5).

Table 5. Revision range of identical stratum-q/q links across overlapping four-quarter windows.

Q/q link	Repeated estimates per stratum	Mean revision, p.p.	Median, p.p.	Maximum, p.p.
2024Q2→2024Q3	2	0.113	0.067	0.798
2024Q3→2024Q4	3	0.311	0.196	1.297
2024Q4→2025Q1	3	0.383	0.286	1.016
2025Q1→2025Q2	3	0.318	0.242	1.007
2025Q2→2025Q3	3	0.288	0.203	0.959
2025Q3→2025Q4	3	0.349	0.241	1.416
2025Q4→2026Q1	2	0.345	0.161	2.505

Source: author's calculations.

Threshold sensitivity shows that this conclusion does not hinge on the 0.5-point choice. Across all 196 repeated links the share of revisions below 0.25 percentage points is 60.2 percent, below 0.5 points 81.1 percent, below 0.75 points 90.8 percent and below 1.0 point 97.4 percent. The corresponding shares are 70.6, 85.7, 92.1 and 97.6 percent for apartments and 41.4, 72.9, 88.6 and 97.1 percent for individual houses. This strengthens the within-window stability finding without providing grounds to treat 0.5 percentage points as a universal standard.

4. Discussion

The results indicate that the four-quarter RTD architecture in Uzbekistan's quarterly RPPI performs three methodological functions simultaneously: it pools observations over a local time interval, relaxes the assumption of long-run constancy of attribute coefficients, and integrates new-period data into the existing index series with limited revision.

The first finding concerns cross-window revision. A median revision of 0.191 percentage points in repeated stratum-q/q links shows that the architecture operates in a relatively stable manner in most cases. However, revisions reaching 2.505 percentage points in some strata show that aggregate stability can conceal local model problems. Official production should therefore monitor stratum-level revision, standard errors and sample coverage alongside the national index.

The second finding concerns the practical importance of quality adjustment. Gaps exceeding two index points between the hedonic index and the raw median and geometric-mean series were observed in three consecutive quarters, 2025Q1–2025Q3. This is strong diagnostic evidence consistent with the need for quality adjustment in a market with a changing composition of listings. At the same time, because the hedonic and raw series differ in specification and aggregation, the whole gap cannot be interpreted as the causal effect of quality mix alone.

The third finding is that model diagnostics differ across segments. Apartment models show higher adjusted R^2 and lower time-dummy standard errors, whereas house models carry higher uncertainty. This calls for segment-specific monitoring; the precise cause requires a separate controlled test of attribute set, market heterogeneity and sample properties.

Five limitations apply. First, prices are asking prices from online advertisements, not transaction prices: the bargaining gap is unobserved, and the 2024 mean listing price served as a proxy for the unavailable 2023 component of the 2024 weights. Second, a reproducible key for raw data collection and cross-platform, property-level deduplication is not retained in the audit workbook, so complete duplicate removal is not asserted (Lyons; Kolbe et al.; Loberto et al.). Third, the sample fell by 40.9 percent over the period and house attributes are more limited than apartment attributes, raising thin-market and omitted-variable risks. Fourth, pre-filter time-dummy coefficients are not stored and inference rests on conventional OLS standard errors without documented robust or clustered alternatives, so significance shares are read as descriptive precision diagnostics. Fifth, three-, five- and six-quarter windows were not estimated on the same microdata; the

four-quarter architecture is assessed as operationally stable within the existing system, not as empirically optimal.

5. Conclusion

This study assessed the methodological and empirical properties of the four-quarter rolling time-dummy hedonic architecture applied in Uzbekistan's quarterly residential property price index, using 1,654,058 listings for 2024Q1–2026Q2, 28 strata, seven overlapping windows and 196 stratum–window regressions.

All three hypotheses are supported in general terms. The median cross-window revision of identical stratum–q/q links is 0.191 percentage points, with 85.7 percent of apartment links and 72.9 percent of house links below 0.5 points (H1), although stratum-level monitoring must continue. The hedonic–raw gap exceeded two index points against both benchmarks in three consecutive quarters (H2), confirming quality adjustment as a necessary element of a constant-quality RPPI without attributing the whole gap to quality mix. Mean adjusted R^2 of 0.753 for apartments against 0.561 for houses, with significance shares of 81.5 and 60.0 percent (H3), shows that diagnostics differ by segment without establishing attribute count as the cause. The 2026Q2 divergence between primary (110.854) and secondary (104.297) apartment indices underlines the need to publish segment sub-indices alongside the aggregate.

The main scientific contribution lies not in proposing the four-quarter window as a new method but in the comprehensive empirical evaluation of its operational properties through cross-window revision, segment-specific diagnostics, raw–hedonic gaps consistent with quality mix and Cook-filter model-fit sensitivity. In practical terms, official RPPI production should regularly monitor sample coverage by stratum, time-dummy standard errors, influential observations, cross-window revision and segment-specific model fit. The four-quarter rolling time-dummy approach can thus be assessed as a methodologically coherent and practically applicable local estimation architecture for a quarterly constant-quality RPPI in Uzbekistan's heterogeneous housing market, while its empirical superiority over three-, five- or six-quarter alternatives remains to be established by a dedicated robustness test.

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