Coming of Age: Renovation Premiums in Housing Markets

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Coming of Age: Renovation Premiums in Housing Markets

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Abstract

We rely on novel textual analysis of real estate listings and identify renovated dwellings in a data set of Norwegian transactions to estimate the renovation premium in an urban housing market. The renovation premium is estimated by classical regression approaches as well as random forests models. The strength of the latter is that it allows for a more complex interplay between the renovation premium and explanatory variables. We find a significant positive renovation premium of 5-7 percent for renovated dwellings and a negative premium of 9-10 percent for unmaintained/neglected dwellings. These averages mask significant variation in these premiums over time. In particular, there is a counter-cyclical effect. In a hedonic price model, omitting renovation has implications for estimated short-term house price growth. We also find that unmaintained dwellings tend to transact more in the fourth quarter, indicating that parts of seasonal price variation reported in the literature are due to compositional variation with respect to renovation. This composition effect tends to bias price movement estimates downward, if uncontrolled for, as unmaintained dwellings tend to transact at a significantly lower price.

Keywords:

Renovation, hedonic estimation, house price indices, real estate listings, random forest

JEL: O18, R30, E60, E31,

Introduction

The housing market is of keen interest for households and policymakers alike. Houses constitute the major wealth component for most households. Moreover, as the last financial crisis made us painfully aware, the housing market is not just a passive receiver of shocks. It can be the originator of an economic downturn with dire consequences. Houses transact infrequently and are heterogeneous with respect to characteristics. Consequentially, monitoring the housing market is far from easy, a recurrent issue within macroprudential policy.

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A house is a classic example of a bundle of characteristics, and where the prospective buyer's willingness to pay reflects the aggregated value of these characteristics. Hedonic models, where house prices are explained by a wide array of house characteristics, like location, size, number of bedrooms, etc., dates back to Rosen (1974).

A challenge for house price models and house price indices is controlling for composition variation. We know that a wide array of hedonic characteristics influence transaction prices, but some more than others. Size and location are more important for the transaction price than a fireplace and an extra bathroom. In this hierarchy of determinants of price, renovation is high on the list but seldom included due to data limitations. The listing of dwellings for sale online may change this.

Online listings often state that a dwelling is newly renovated as this information is likely to attract interested parties. Online listings include photos, and poorly maintained dwellings are easy to spot. The wording, in this case, tends to focus on a unit's potential and attract interested parties that are comfortable with a major renovation. Consequentially, these listing texts shed information about the renovation and the maintenance level of the dwelling for sale. We pair transaction data with their listings text and, through text analysis, classify dwellings into four groups, unmaintained, fully renovated, partially renovated, and none of the first three.

We study the renovation premium in an urban housing market for five years (2014-2019). The time period contains a boom followed by a bust and thus allows us to address the potential time variation of the renovation premium, particularly whether it is pro- or countercyclical. The analysis relies on two novel datasets, mainly a listing dataset and in addition a detailed prospectus dataset of homes in Oslo, Norway¹.

We find a premium for the fully renovated (in the 5 to 7 percent range) and a negative premium for the unmaintained (in the 9 to 10 percent range). The sign of these average effects are unsurprising but gloss over interesting temporal variation. For example, heated housing markets in the sense of price appreciation diminish both the positive premium of the fully renovated dwellings and the negative premium of the unmaintained. The effect is especially strong for the fully renovated, and in a heated market, markets are not distinguishing renovated from non-renovated dwellings in terms of pricing. Another interesting finding is a systematic quarter-to-quarter variation, where the 4th quarter sees more unmaintained dwellings changing hands.

This composition effect tends to bias price movement estimates downward, if uncontrolled for, as unmaintained dwellings tend to transact at a significantly lower price². Moreover, this *renovation bias* has implications for the seasonal variation observed in house price indices.

The major takeaway from our analysis is the importance of renovation as a price determinant. Failure to control for renovation leads to significant biases of housing price levels and indices. Unfortunately, these are not only considerable but also tend to vary over time

¹The listing dataset contains a brief description of the house for sale. The prospectus dataset used for validation contains detailed information about the characteristics of the house and any renovations done.

²We estimate the "rebate" to be in the 9 to 10 percent range.

and across space.

It is important to stress that the incentive to renovate is higher in attractive areas since the expected gain from renovation exceeds the cost by a greater margin (Gyourko and Saiz 2004). In other words, we expect a spatially clustered vintage effect (W. C. Randolph 1988) that creates challenges for estimations of the renovation premium. We address this concern by applying flexible random forest techniques as well as classical hedonic-based regression approaches.

The literature on renovation and renovation premiums in the housing market is sparse. The lion's share of academic contributions concerns neighborhood effects. These may be related to positive spillover effects (Wilson and Kashem 2017) or externalities. One externality regards sustainability, and that renovation may have a negative impact on the environment, at least in the short run (Liu et al. 2020). The other concerns energy efficiency (McLean, Horváth, and Kiss 2013), as renovation often gives more energy-efficient dwellings. McLean, Horváth, and Kiss (ibid.) estimate a renovation premium of 9.4 percent for the Hungarian housing market. In the case of the Taiwanese market, C.-c. Lee, Liang, and Chen (2017) estimate the renovation premium per area unit (ping³), but the focus is urban regeneration, rather than the isolated effect of renovation on dwellings in an area with a mix of dwellings with respect to age. Our paper, in contrast, considers small-scale, household-initiated renovation or lack thereof. Both spillover effects and environmental externalities are likely to play a minor role in our case. The direct impact of a renovation that involves improved energy efficiency is likely to be part of the renovation premium.

The literature on renovation and repeat sales indices is more extensive. An essential requirement for a repeat sales index is that the home remains unchanged between sales. Several research studies have examined the extent to which renovations affect repeat sales indices. McMillen and Thorsnes (2006) estimated a repeat sales index (median quantile) for Chicago for the period 1993-2002 and found that the index overestimated price growth by 9 percent without renovation controls. Bourassa, Cantoni, and Hoesli (2013) find an even larger overestimate (14 percent) for Louisville, Kentucky (1988-2010) for their repeat sales index. Bogin and Doerner (2019) find that overestimation tends to be severe in central areas due to an uneven concentration of renovation activity.

For the broader role of housing quality, early contributions appeared at the same time as the seminal work of Rosen (1974) on attribute prices on bundled goods. Two of these are Sweeney (1974) and Cubbin (1974).

The remainder of the paper is organized as follows. [Data description and Renovation classification](#) describes the data and renovation classification. [Methodology for Assessing the impact of renovation](#) discuss measurement and outline empirical strategies. [Results Empirical analysis](#) reports results for the renovation premium. [Temporal variation in the Renovation premium](#) consider temporal heterogeneity in the renovation premium, and [Renovation-bias in estimated House price growth](#) estimates the "renovation bias" in short

³1 ping = 3.305 m².

term house price growth. [Additional tests and Robustness analysis](#) perform additional tests. [Conclusion](#) concludes.

Data description and Renovation classification

Institutional detail and data description

Most real estate transactions in Norway are arm's length brokered sales. The seller contacts a broker who puts the house on the market. The broker is also responsible for preparing the sales prospectus and listing, and when the house is placed on the market, the listing and sales prospectus are available online. The broker also organizes an open house and manages the ascending-bid auction, which usually takes place on the first business day after the open house. Bids are submitted by telephone or electronically, and each bid is legally binding.

The *listing data* contains the main text of the listing and a wide range of characteristics for 10,350 transacted properties in Oslo, Norway. The dataset was acquired from Eienomsverdi ASA, a private company that collects all transactions in the Norwegian housing market and provides price valuations based on the automated valuation method (AVM) for banks and brokers, considered the best valuation by market agents and the government. In addition, the listing data includes zip codes, geographic coordinates, and both the transaction price and the AVM price valuation. It covers the period from primo 2014 to medio 2019. Table 1 provides summary statistics for the main variables. The dwellings have a mean age of 54.6 years, mean size of 79.7 square meters, and the majority of transactions are apartments (85.5 percent).

Renovation classification

The main focus of this paper is on quality-enhancing renovations and neglect in the context of home sales. Compared to previous work, we also extract information on renovations within the structure, such as kitchen and bathroom⁴.

One challenge in creating a renovation classification is that it is essentially a continuous variable. A new house is "renovated" and begins its journey toward "unmaintained". As a dwelling ages, its quality deteriorates in two ways. First, everything from plumbing fixtures to window frames is subject to natural deterioration. Second, after a certain amount of time, the materials and construction become outdated and no longer reflect the current zeitgeist. Owners may decide to do a partial renovation or a full renovation. To distinguish these cases, we constructed a renovation variable with two positive values for partial renovation (1) and full renovation (2) and one negative value for neglected renovation (-1). Since we are unable to estimate renovation more precisely for the entire dataset, we use a scale as a proxy.

A combination of machine search and a careful reading of all listings was undertaken to assign one of the values 2, 1, 0, or -1 to the renovation variable. About half of the

⁴This allows us to capture more renovations than in studies that only capture remodeling renovations in the form of additional rooms or additional living space or renovations that require a building permit.

Table 1 Summary Statistics for prices and Key housing characteristics for listing data. Prices in million NOK. N=10,350

Statistic	Mean	St. Dev.	Min	Max
Transaction price	4.5	2.3	1.0	33.0
AVM price valuation ^a	4.6	2.2	1.1	20.1
Size in m ²	79.7	49.0	14	757
Dwelling age	54.6	36.5	-2 ^b	214
Average area income	4.34	0.68	2.80	5.99
Average area education	0.47	0.11	0.27	0.76
	No. of obs	Percent		
<u>Dwelling type:</u>				
Apartment	8,845	85.5		
Single family	554	5.4		
Multi family	851	8.2		
New	100	1.0		
<u>Ownership type:^c</u>				
Regular owner	5,448	52.6		
Coop	4,384	42.4		
Regular owner in part	518	5.0		
<u>Location:^d</u>				
Central	3,921	37.9		
West	4,403	42.5		
East	2,026	19.6		
Total	10,350	100		

The table shows summary statistics for the full data set. The three subsets of this full dataset used in the analysis are summarized in Appendix I. 1 NOK= 0.11 USD on January 7, 2022. Notes: *a.*The AVM price is produced by Eiendomsverdi ASA and available for a smaller set of the data (N=5,809). *b.*New properties sold two years before completion. *c.*In a coop, the purchaser own a right to live in her unit. A regular owner owns her unit. *d.*See table 12 for the list of Oslo suburbs in each of the three categories.

properties classified as renovated (48 percent) had "renovated" in their list text⁵. Whether the renovation is interpreted as full or partial depends on whether or not it includes the most expensive rooms to renovate, as well as the timing of the renovation, and the overall impression of the extent of the renovations. A new kitchen and bathroom and described as "fully renovated" received a score of 2. In contrast, only a kitchen and described to have "some renovations" received a score of 1. 89 percent of dwellings classified as unmaintained had "unmaintained" in their list text.

The fairly brief descriptions in the listings may result in many dwellings being classified with a 0 renovation score. To address this concern, we used a second dataset of prospectuses with extensive detail to see if the distribution of renovation scores differed greatly from the distribution based on the listing dataset⁶.

Classification results

Overall, we find a share of 12.4 percent renovated (7.0 percent fully renovated) and 8.7 percent unmaintained, based on information in the listings. Our results for "fully renovated" are roughly comparable to those of McMillen and Thorsnes (2006), which find a renovation share of transactions associated with issued building permits in Chicago of 10.7 percent over 1993-2002. However, these results are significantly larger than those of Bogin and Doerner (2019)⁷.

In addition, we can shed some light on the distribution of renovated house transactions over time. Figure 1 shows the quarterly distribution of sales by renovation class. The highest combined renovation share of sales for a single quarter is 26 percent in 2016-Q4 (so neutral non-renovated homes, denoted R0, account for 74 percent), and the lowest is 13 percent in 2018-Q3. There is evidence of systematic quarter-to-quarter variation, where the 4th quarter (Q4) sees more unmaintained dwellings changing hands, with an average of 11 percent of sales compared to 7-8.5 percent in Q1-Q3⁸. This composition effect may bias price movement estimates downward, if uncontrolled for, as unmaintained dwellings tend to transact at a significantly lower price⁹.

Finally, we find notable differences in age and price per square meter between renovation levels. According to these results, renovations are closely related to the age of the unit at the time of sale, and older dwellings are increasingly likely to be renovated¹⁰. This accords with the findings in B. S. Lee, Chung, and Kim (2005). These results are summarized in Table 2.

⁵Other much-used markers are e.g. "completely new kitchen, bathroom and floors", or just a recent year (kitchen, bathroom and floors from 2018).

⁶See details in Table 11 in Appendix I.

⁷The authors find a 0-2 percent renovation share for transacted dwellings in large U.S. cities. Their study likely measures extensive renovations, such as whole-unit remodeling, so we expect its estimates to be lower.

⁸These details can be found in Table 10 in Appendix I.

⁹The sample length used in this analysis should preferably be extended to conclude confidently.

¹⁰By contrast, the highest proportion of unmaintained dwellings are found to be between 31 and 50 years old, and the proportion is subsequently lower for younger and older units, resulting in a reversed U-shape for the share of unmaintained units by age.

Fig. 1 The Renovation Class of House transactions by share of sales between 2014-Q1 and 2019-Q2. N=10,350

The figure shows the quarterly results of a classification of sales by renovation level based on real estate listings in Oslo, Norway. Notes: R-1 ~ unmaintained, R0 ~ neutral, R1 ~ partially renovated, R2 ~ fully renovated.

Table 2 Classification Results. The number of House transactions in each Renovation class (frequency in percent) in the listing data set (top) and the Age distribution by Renovation class (bottom). N=10,350

Description	Renovation class	No. of obs (percent)			
Fully renovated	2	723 (7.0 %)			
Partially renovated ^a	1	558 (5.4 %)			
Neutral	0	6,736 (65.1 %)			
Unmaintained	-1	902 (8.7 %)			
Less than 10 years old		1,431 (13.8 %)			
Age group	Price ^b per m ²	Unmaintained	Renovated ^c	No. of obs	
<11	69.3	0.000	0.008	1,784	
11-30	60.3	0.050	0.056	1,198	
31-50	46.7	0.149	0.109	1,775	
51-60	53.8	0.120	0.153	1,522	
61-70	59.9	0.110	0.132	1,114	
71-90	69.4	0.106	0.178	1,394	
91-120	69.3	0.083	0.246	940	
>120	73.8	0.074	0.236	623	

The table summarizes our results for renovation shares in real estate transactions. Notes: *a*. Partial renovation usually includes costly rooms such as kitchen and bathroom, but not a full renovation. Neutral units are neither renovated nor unmaintained. *b*. Price per m² in 1,000 NOK. *c*. *Renovated* combines partially and fully renovated units.

Methodology for Assessing the impact of renovation

Define the *observed renovation premium* as the expected increase in the equilibrium house price for an average renovation, derived from the well-known hedonic equilibrium price function $P = f(X, \varepsilon)$. The price function maps the relationship between the observed and unobserved to the economist attributes, respectively (X, ε) , and the house price (P). The implicit price reflects the marginal willingness to pay for renovation (Rosen 1974).

We build on (W. Randolph 1988; W. C. Randolph 1988) in our understanding of how renovation combines with closely related attributes such as residential depreciation and overall quality of a unit in the price function. In this view, residential depreciation can be defined as the value of the portion of unmeasured quality change caused by aging alone¹¹. A renovation is a discrete upward shift in the aging/quality depreciation curve. The interpretation for the hedonic relationship is that measurements of age depreciation are expected to capture, unobserved to the economist, renovations in addition to age-only depreciation. This is consistent with Diewert, Haan, and Hendriks (2015), which defines the net depreciation rate as the "true" gross depreciation rate of the house less an average renovation appreciation rate.

Because the fraction of measured age depreciation that is attributable to renovation or quality of materials is unobserved, and for simplicity, we focus our analysis on the observed renovation premium (according to our classification), which we refer to below as the *renovation premium*. However, infer from this discussion that there are potentially important interactions, correlated characteristics, and nonlinear effects in the hedonic relationship, especially when considering the isolated impact of renovation/neglect on the house price. As a measure of the gain in house valuation performance from our renovation indicator, we consider the loss in predictive performance with and without renovation information included as characteristics.

The study area is a metropolitan region. The following sections present empirical strategies for identifying and examining the renovation premium and the prediction gains from including the renovation information.

A classical linear regression model

As a benchmark specification, we estimate a classical log-linear regression that has become standard in the hedonic house price literature (see Xiao 2017, for a recent review). The house price model includes dummies for renovation level, along with a set of characteristics. We then extend the benchmark specification to include interaction terms between characteristics such as renovation and location and location and age of the unit. These interaction regressions highlight spatial variation in the renovation premium and the age distribution of dwellings. Our regression specification is:

$$\log P_i = \beta_0 + \beta_1 \log(\text{Size}_i) + \sum_{\forall s \in S} \beta_s D_{is} + \sum_{\forall l \in L} \beta_l N_{il} + \sum_{\forall k \in K} \delta_k R_{ik} + \varepsilon_i \quad (1)$$

¹¹See W. Randolph (1988), p. 12.

Where P_i is the house price, $Size_i$ is the area (in sqm.), D_{is} are either dummy variables or dummy interaction variables, $s \in$ (dwelling type, ownership type, dwelling age cohort, sales quarter, administrative area dummies and/or price zone dummies), N_{il} are administrative area fixed effects, $l \in$ (income level, education level), and R_{ik} are renovation indicators $k \in (-1, 1, 2)$. The delineation of the age cohorts and log-form of house size was proposed in a preliminary analysis by a random forest algorithm¹². ε_i is an error term. The coefficients of primary interest are estimates of the renovation premium, δ_k .

The model data¹³ are split into an estimated set S_T containing 70 percent of the data and an out-of-sample set S_O containing 30 percent.

A Random Forest algorithm

The hedonic theory provides little guidance about the functional form of the relationship, especially relevant when there are likely to be non-linear effects or complex interactions among characteristics. A growing body of literature uses more flexible methods to value real estate. Several studies conclude that the use of a non-parametric random forest algorithm improves predictive performance in house price models (Yoo, Im, and Wagner 2012; Čeh et al. 2018; Bogin and Shui 2020) or when dealing with other challenging prediction problems (Auret and Aldrich 2012), although several caveats remain when interest concerns consistent and stable coefficient estimates (Mullainathan and Spiess 2017).

The random forest algorithm is a particularly interactive class of models that builds a random ensemble of decision trees by bootstrapping. We use the methodology described in (Breiman 2001) with cross-validation to select an optimal complexity level that maximizes prediction accuracy without overfitting. Candidate variables for each decision tree split are drawn randomly from the complete set of variables, making each tree distinct¹⁴. The random forest and classical regression models use the same set of independent variables in the random forest to ensure comparability of inferences.

We compare predictive performance out-of-sample. The squared correlation coefficient (R2 and adjusted R2) and root mean square error (RMSE) are among the most commonly used measures of accuracy, where $RMSE = \sqrt{\frac{1}{N_O} \sum_i (lP_i - \hat{lP}_i)^2}$ and weights larger errors more heavily than smaller errors.

Spatial aggregation

A well-documented challenge in regression methods such as hedonic estimation arises from spatial dependence and spatial heterogeneity when models do not adequately capture spatial structure or omits essential variables (Anselin 1990; LeSage and Pace 2009). To obtain robust estimates of the spatial price premium, we construct standard administrative area districts from zip codes and noncontiguous *price zone* dummies. The price zones are estimated using a flexible aggregation method that allows us to find spatially distant areas with

¹²Details are available upon request.

¹³See Table 13: (3) Hedonic Model data (1) with price zones.

¹⁴See details in Appendix II.

similar location premiums. See details in Å. Sommervoll and D. E. Sommervoll (2019)¹⁵. The prize-zone algorithm can be summarized as follows:

1. Estimate an auxiliary hedonic house price regression.
2. Use a grid to partition Oslo into rectangular cells.
3. Restrict the number of submarkets to be fixed at 12.
4. Search for maxima for the auxiliary hedonic regression (here R^2) by varying the spatial aggregation of the cells using a genetic algorithm, a variant of gradient ascent.
5. The final result is an aggregation of 370 zip codes to 12 submarkets, represented by a 370-dimensional vector $(7, 2, 7, 1, 12, \dots)$ with cells estimated to have the highest location premium in price zone nr. 12 and the lowest in price zone nr. 1.

Interpreting the difference, while administrative areas capture neighborhood amenities such as the quality of schools, the price zones capture amenities *across space*. This is because the price zones, in many cases, aggregate unobserved amenities such as the most attractive and sunny locations with the best transportation access in the best price zones¹⁶.

To evaluate the spatial implementation and compare regression models, we test for spatial autocorrelation by estimating the global Moran’s I statistic on model residuals (see Moran 1948, LeSage and Pace 2009). It uses the location of dwellings, where location is a pair of latitude and longitude coordinates $\{lat_i, lon_i\}$, and is defined as:

$$\text{Moran's I} = \frac{N_T}{\sum_i \sum_j W_{ij}} \frac{\hat{\varepsilon}' W \hat{\varepsilon}}{\hat{\varepsilon}' \hat{\varepsilon}}$$

Where N_T is the number of units in the estimating data set, $\hat{\varepsilon}$ is the estimated residuals matrix, and W is an $N \times N$ spatial weight matrix that defines the spatial relationship between pairs of observations i and j . The definition of W is crucial for measuring spatial autocorrelation, as it implies a conjecture of how observations are related in space. We believe local autocorrelation is the main potential issue and construct a set of spatial weight matrices W_r of different ranges within 0.1 - 1.5 km as contiguity matrices¹⁷ using the great circle distance around each dwelling as calculated by the Haversine formula. Dwellings within each cutoff distance receive an equal weight in the final row-standardized $W_r, \forall r \in (0.1, 0.5, 1.0, 1.5)$.

Results Empirical analysis

The renovation premium in the classical model

Table 3 reports results for the effects of three levels of renovation on price. We include a comparison for the classic regression model with area dummies and fixed effects (column 1)

¹⁵The method employed is described in 4.1 Genetic algorithm, p.243-.

¹⁶Maps showing both spatial aggregations is documented in Figure 7 in Appendix I.

¹⁷Dwellings outside the cutoff distance receive the weight zero.

and one that also includes price zone dummies (column 2)¹⁸. Column 3 shows the results for the model in column 2 without the renovation variable. Column 4 shows the results with interaction terms between dwelling age and area, and column 5 also adds interactions between renovation class and area¹⁹.

Across the different specifications in columns (1)-(5), the results suggest a significant positive average renovation premium²⁰ in the range of 5.4-6.1 percent for fully renovated (R2), and a negative premium in the range of 9.1-9.5 percent for unmaintained (R-1) dwellings²¹. The coefficient for partial renovation (R1) is slightly positive but close to zero in most cases. This could be due to the difficulty distinguishing "somewhat" renovated from neutral (R0).

To interpret the economic magnitude of the average renovation premium, we focus on the results in column 2. Expressed in market prices, a renovation premium of 5.7 percent implies a premium of NOK 255,800 (USD 28,100) for the average-priced dwelling sold in the middle of the period. A negative premium of 9.2 percent for neglected properties means a discount of NOK 414,100 (USD 45,600). These are substantial sums for the average working person, who earned an average of NOK 522,700 per year before taxes in the middle of the period²².

When omitting renovation information in column 3, this is seen to scale the other model-coefficients, such as the age penalties. This is consistent with age-renovation correlations. Including dwelling age and area interactions in column 4, the average marginal effect (AME) renovation premium for fully renovated is estimated to 5.9 percent. The AME estimate for unmaintained units is similar to the previous. Column 5 displays area-specific renovation premiums, suggesting spatial variation²³. In addition to the possibility of heterogeneous "treatment effects" of renovations, such patterns may be due to systematic geographically heterogeneous "treatments," i.e., the size and monetary value of the renovation. It is likely that investments are larger in high-end areas due to more expensive tastes and higher expected resale values, so *fully renovated* does not mean the same on average for different locations.

Improvements in prediction performance. Comparison of the random forest and the classical model

The random forest algorithm achieves moderately higher overall performance than the classical regression model out-of-sample, such as a decrease in RMSE from 0.128 to 0.115 in Table 4 Panel B, columns 1 and 7. R squared increases from 0.898 to 0.918. However, the random forest is also found to reduce spatial dependence in the residuals for all sets of

¹⁸The generalized variance inflation factor (VIF) scores remain low for all coefficients, and about 1.05-1.08 for the renovation coefficients.

¹⁹All models are estimated with robust standard errors (White). The Breuch Pagan $\sim \chi_p^2 = 432.7$ in (2) with $p = 59$ degrees of freedom.

²⁰A joint heteroskedasticity robust linear F-test of regression model (1) rejects the null hypothesis that all renovation coefficients are zero by a large margin: $F = 6.447$ (p-value<0.001).

²¹The following transformation is used to interpret the coefficient as the percent change in price: $(\exp(\hat{\delta}) - 1) \times 100$.

²²Official income data is gathered from Statistics Norway. [Source](#).

²³The table includes a few interaction terms to illustrate.

Table 3 Regression Results: Classical linear model

<i>Linear and Interaction models</i>					
Dependent variable: log(Price)					
	LIN A	LIN AP	LIN AP No R	INT 1	INT 2
	(1)	(2)	(3)	(4)	(5)
log(Size)	0.698*** (0.006)	0.695*** (0.006)	0.689*** (0.006)	0.698*** (0.006)	0.697*** (0.006)
R-1	-0.100*** (0.007)	-0.096*** (0.007)		-0.097 [†]	-0.098 [†]
R1	0.006 (0.007)	0.012 (0.007)		0.014* (0.007)	0.015* (0.007)
R2	0.053*** (0.007)	0.055*** (0.007)		0.059 [†]	0.051 [†]
<u>Age(8)</u>					
Age2	-0.081*** (0.008)	-0.074*** (0.007)	-0.077*** (0.007)		
Age5	-0.123*** (0.007)	-0.109*** (0.007)	-0.117*** (0.007)		
Age8	-0.082*** (0.008)	-0.082*** (0.008)	-0.084*** (0.009)		
<u>Rk×Area(12)</u>					
R-1×A4 (Central)					0.102*** (0.014)
R-1×A7 (West)					0.085** (0.029)
R2×A4 (Central)					0.052*** (0.015)
R2×A7 (West)					0.080** (0.027)
Time, structural	<i>x</i>	<i>x</i>	<i>x</i>	<i>x</i>	<i>x</i>
Area (A)	<i>x</i>	<i>x</i>	<i>x</i>	<i>x</i>	<i>x</i>
Price zone (P)	—	<i>x</i>	<i>x</i>	<i>x</i>	<i>x</i>
Area×Age	—	—	—	<i>x</i>	—
Robust errors ^a	<i>x</i>	<i>x</i>	<i>x</i>	<i>x</i>	<i>x</i>
Est. parameters	52	63	60	130	154
Observations	5,742	5,742	5,742	5,742	5,742
Adjusted R ²	0.891	0.902	0.896	0.906	0.906

The table presents results for classical hedonic models including the effects of three levels of renovation, R-1, R1, and R2. Each column represents a separately estimated regression. Notes: Includes Administrative area dummies (A), Administrative area and Price zone dummies (AP), No Renovation indicator (No R), Area-Renovation interaction terms (INT 1), and in addition Area-Unit Age interaction terms (INT 2). [†]These are average marginal effects (AME) in the interaction models. ^aWhite. Significance level: *p<0.1; **p<0.05; ***p<0.01.

spatial variables, indicating its superiority in capturing spatial structure and heterogeneous effects. This accords with McMillen (2010), which argues that problems with functional form may lie behind any observed spatial autocorrelation and suggests the use of flexible methods. The random forest achieves slightly higher out-of-sample performance than in-sample²⁴, evidence that the predictor is not overfitting to the estimation data²⁵.

The inclusion of the price zone dummies is found to reduce spatial dependence, as evidenced by lower spatial autocorrelation of the residuals (see the results of the Moran’s I test in Panel A). Note that we use a test based on fairly fine-scaled spatial aggregations (100 meter-1.5 km circle around each dwelling), and expect some shortcomings of the spatial dummies. The spatial autocorrelation is estimated to be positive and strongest at a radius of 100 meters around each dwelling. Although significantly different from its theoretical mean (close to zero), Moran’s I test statistics between 0.026-0.162 (first column) and 0.012-0.117 (fourth column) are considered low²⁶.

When we exclude the renovation variable in the linear model there is a modest decrease in adjusted R-squared overall, where it reduces from 0.902 to 0.896 (columns 1 and 4). RMSE increases from 0.128 to 0.131. This is not straightforward for the random forest, as estimating the model with and without a variable could also lead to a change in the estimated function, so the overall effect on model performance could be a mixture of both. Nonetheless, model performance changes to a similar extent. Because of the issues with partial estimates noted above, we restrict attention to the magnitude of the estimated parameters in the classical models.

The marginal improvement in adjusted R squared by including the renovation variable is larger in the top and bottom quartiles of the house price distribution, as seen for the linear model in P25 when comparing the second and fifth columns of Table 4 where it increases from 0.604 to 0.629. This larger tail effect is consistent with the discussion in McMillen and Thorsnes (2006).

The takeaways from Table 4 are, first, that spatial dependence is not expected to be a major concern for our preferred model specifications in columns 1 (classical) and 4 (random forest). This supports our results for the renovation premium in Table 3. Second, the overall gain in model performance from including the renovation indicator is similar for the classical model and the more flexible random forest, with larger gains in the tails of the house price distribution. This could imply that the impact of including the renovation indicator in the house price index, which is based on overall (average) market development, will be more considerable in areas with cheaper and more expensive dwellings.

A model with professional AVMs

A challenge to hedonic valuation is that unobserved characteristics may be correlated with the house price and characteristics of interest. This is relevant for the probability of renovating a house and could lead to inconsistent estimates of the renovation premiums

²⁴Not reported for brevity.

²⁵See a discussion in Hastie, Tibshirani, and Friedman (2009).

²⁶The Moran’s I statistic ranges from -1 to 1, with 1 indicating perfect positive spatial autocorrelation.

Table 4 Moran's I (in-sample) and Model performance (out-of-sample)

Panel A: Moran's I ^a . Spatial autocorrelation of residuals/prediction errors. In-sample (N _T =5,742).								
Dist. ^b	Linear			Random Forest (RF)			Neighbors	
	A, P	A	No spatial	A, P	A	No spatial	Mean	Min, Max
0.1	0.162	0.227	0.415	0.117	0.174	0.392	6.6	0, 39
SD	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)		
0.5	0.081	0.175	0.452	0.044	0.107	0.356	95.2	0, 254
SD	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)		
1.0	0.043	0.107	0.408	0.020	0.060	0.322	318.4	2, 820
SD	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)		
1.5	0.026	0.066	0.369	0.012	0.034	0.290	643.6	3, 1508
SD	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)		
Panel B: Model performance ^c w./w.o. renovation (R). Out-of-sample (N _O =2,461)								
Metric	Linear R		Linear No R		RF R		RF No R	
	Overall	P25, P75	Overall	P25, P75	Overall	P25, P75	Overall	P25, P75
R ²	0.900	0.638, 0.761	0.896	0.614, 0.750	0.921	0.678, 0.776	0.915	0.661, 0.757
Adj. R ²	0.897	0.629, 0.755	0.893	0.604, 0.744	-	-	-	-
RMSE	0.128	0.127, 0.154	0.131	0.132, 0.158	0.115	0.103, 0.138	0.118	0.106, 0.143

The table reports the results from Moran's I tests on regression residuals for the classical model and prediction errors for the random forest algorithm in Panel A. Panel B shows results for model performance. Notes: *a.* Panel A reports Moran's I test statistics and standard deviation in (). The expected Moran's I-values= 0.000.. and P-values<0.001 in all cases.*b.* This is the Haversine distance in kilometers. The spherical distance is based on a radius *r* of the earth of value *r*=6,378.137 km. All neighbors within the given distances are given equal weight in the contiguity weight matrix. The mean number of neighbors within the relevant distance is reported under *Neighbors*, along with the min and max. *c.* Performance measures are reported for the overall case and the top (P75) and bottom (P25) quartiles of the house price distribution.

(see a discussion in Bajari, Fruehwirth, Timmins, et al. 2012). To illustrate, omitting unit-specific characteristics such as a fireplace and balcony may be correlated with expected resale value and thus the decision to renovate or not renovate prior to sale. To address this issue, we collected external price valuations used by market participants and produced at the time of sale. The AVMs are based on all transactions in the Norwegian housing market (including those outside Oslo) and on a more comprehensive set of hedonic characteristics. We use the following strategy, for all $i \in (1, \dots, N_V)$:

1. Regress the valuation price $\log P_{AVM,i}$ on our set of hedonic characteristics. Variable interpretations are the same as for model (1):

$$\log P_{AVM,i} = \bar{\beta}_0 + \bar{\beta}_1 \log(Size_i) + \sum_{\forall s \in S} \bar{\beta}_s D_{is} + \sum_{\forall l \in L} \bar{\beta}_l N_{il} + \sum_{\forall k \in K} \bar{\delta}_k R_{ik} + \bar{\epsilon}_{AVM,i} \quad (2)$$

2. Calculate the vector of residuals $\hat{\epsilon}_{AVM,i}$
3. Estimate the hedonic classical model including the orthogonalized residuals, $\hat{\epsilon}_{AVM,i}$, our estimate of unobserved price-determining characteristics:

$$\log P_i = \bar{\beta}_0 + \bar{\beta}_1 \log(Size_i) + \sum_{\forall s \in S} \bar{\beta}_s D_{is} + \sum_{\forall l \in L} \bar{\beta}_l N_{il} + \sum_{\forall k \in K} \bar{\delta}_k R_{ik} + \hat{\epsilon}_{AVM,i} + \epsilon_i \quad (3)$$

Due to dataset variations²⁷, the classical model is re-estimated in column (1), resulting in a lower premium for full renovation estimated at 4.4 percent²⁸. Results for the other premiums are similar.

Table 5 Regression Results: Controlling for a richer set of characteristics

	<i>Dependent variable:</i>		
	log(Price)		
	LIN	AVM	VAL
	(1)	(2)	(3)
R1	−0.005 (0.007)	−0.005 (0.006)	—
R2	0.043*** (0.007)	0.043*** (0.006)	—
R-1	−0.095*** (0.007)	−0.095*** (0.005)	—
$\hat{\varepsilon}_{AVM}$	—	0.768*** (0.022)	—
AVM	—	—	0.990*** (0.004)
Time, structural	<i>x</i>	<i>x</i>	
Area (A)	<i>x</i>	<i>x</i>	
Price zone (P)	<i>x</i>	<i>x</i>	
Robust errors (White)	<i>x</i>	<i>x</i>	<i>x</i>
Observations	5,809	5,809	5,809
Adjusted R ²	0.909	0.945	0.935

The table contains results for the hedonic model with an instrument for omitted characteristics. Each column represents a separately estimated regression. Notes: LIN is the same specification as LIN AP in Table 3, AVM includes the residual from an auxiliary regression of a model with external valuations as the dependent variable, VAL is the regression of price on the AVM alone. Significance level: *p<0.1; **p<0.05; ***p<0.01.

Column 2 contains the results of model (3) estimated with OLS. It is evident that these results strengthen our previous findings for the renovation premiums. The renovation coefficients are identical up to two decimal places and more stable, suggesting that our estimates are robust when we control for the extensive price-determining characteristics in the AVM valuation. The quality of the AVM valuation is also reflected in the large increase in R squared from 0.909 to 0.945 (0.935 without our hedonic characteristics in column 3).

Our results for fully renovated dwellings are lower than the estimates in McLean, Horváth, and Kiss (2013)) of 9.4 percent for Hungary. Importantly, when comparing our point estimates with existing evidence, one must keep in mind the differences in the renovation data²⁹.

²⁷Details in Appendix I. A notable difference is that the AVMs are dominantly in place for regular owner-dwellings and that a smaller share are located centrally.

²⁸The transformation from estimate to percent is described in section [Results Empirical analysis](#).

²⁹See the discussion in [Classification Results](#).

Temporal variation in the Renovation premium

The time period for which we have access to renovation information contains a boom followed by a bust and thus allows us to address the potential time variation of the renovation premium, particularly whether it is pro- or countercyclical. As demonstrated by Zabel (2015) for Boston in the U.S., temporal variation can lead to substantial differences in estimated implicit prices. In this section, we examine the temporal variation in the renovation premium and compare the trajectory of the premium with the housing market cycle. This is also of interest to the literature on economic behavior.

In addition to the benchmark linear hedonic model and the nonparametric random forest considered earlier, we estimate a rolling-window version of model (1). For this purpose, the estimation sample is split into three adjacent parts. Each resulting predictor is used to predict its time window out-of-sample³⁰. The adjacent window approach is useful for studying parameter variation. The random forest index results are used to determine breakpoints for the rolling window model.

Methodologically, temporal aggregation is the primary purpose of house price index (HPI) construction. To study temporal variations in the renovation premium, our procedure is to trace out the renovation premium over time by estimating the HPI by renovation class and computing their ratios. Since interest lies in level movements for a bundle of characteristics, it is convenient to consider a Laspeyres price index³¹. Each price index, defined as $I_{x_i \in S_B}^{0-t}$ for any period t relative to period 0, is obtained by predicting the classical linear, rolling-window, and random forest models on a fixed set of house transactions at the beginning of the period, S_B ($N_B = 954$), named the base period. The characteristics of the base period, $x_i \in S_B$ where $B=2014-15$, are held constant and reassessed subsequent periods³². It is essential that the composition of the characteristics is reasonably evenly distributed and that the base period set is sufficiently large. Fortunately, both the renovation classes and the other characteristics appear to be largely balanced in S_B and later periods, with some small variations³³.

Figure 2 shows separate house price indexes by renovation class (right) and the corresponding renovation premium (left). One particular feature stands out. The premiums vary considerably in this volatile market period when considering the random forest model (a), allowing for such variability. Panel (e) and Table 6 column (1)-(3) give results for the rolling window model that support the time variation trend in the renovation pre-

³⁰This can be regarded as an extreme case of a rolling window approach, which typically builds overlapping estimation windows in each model (see Hill, Melser, and Syed 2009).

³¹There are several other candidates, but not all are equally appropriate for models estimated on hedonic characteristics and for comparison across regression models. For example, the Paasche index involves changing the actual bundles and their prices. Thus, the movement of the index is determined in part by changes in the prices of the characteristics and in part by composition effects. For instance, to what extent the house price increases in part because the price per square meters increases and in part because the "median" house is 3 square meter larger is considered a concern, depends on the analysis at hand. In this analysis, the Laspeyres index seems to be the most appropriate.

³²This is the *hedonic imputation index* for the Laspeyres type with constant characteristics (set). See Silver et al. (2016).

³³Variations include a gradual increase in the mean age of the properties and a slight tendency toward a more central location in later periods.

Fig. 2 Renovation Premiums in a housing market (left). Separate hedonic House price Indexes by Renovation class (right)

The figure displays our results for the temporal variation in the renovation premiums. Notes: The renovation premium in period t (figures on the left) is defined as the difference between the estimates of the HPI level of fully renovated (R2) and neutral (R0) units at t , for out-of-sample HPI predictions (right-hand side). Similarly for R-1. The confidence interval for the renovation premium is twice the standard error of the differences in the average predictions. The random forest uses the jackknife median standard errors of the predictions.

Table 6 Regression Results: Rolling window model^a

Dependent variable: log(Price)			
	LIN Normal Q1.14-Q4.15	LIN Boom, Bust Q1.16-Q2.17	LIN Normal Q3.17-Q2.19
	(1)	(2)	(3)
log(Size)	0.715*** (0.009)	0.655*** (0.010)	0.702*** (0.010)
R1	0.012 (0.010)	0.008 (0.015)	0.012 (0.013)
R2	0.068*** (0.011)	0.015 (0.012)	0.065*** (0.012)
R-1	-0.098*** (0.011)	-0.084*** (0.012)	-0.106*** (0.011)
Time, structural	<i>x</i>	<i>x</i>	<i>x</i>
Area (A)	<i>x</i>	<i>x</i>	<i>x</i>
Price zone (P)	<i>x</i>	<i>x</i>	<i>x</i>
Robust errors (White)	<i>x</i>	<i>x</i>	<i>x</i>
Observations	2,132	1,552	2,058
Adjusted R ²	0.900	0.896	0.895

The table contains results for hedonic regression models. Each column represents a separately estimated regression. Notes: *a.*The Rolling Window model is estimated for three adjacent time periods in each column. Significance level: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

mium found by the random forest model. During the boom-bust period, the premium on full renovation is not significantly different from zero. Consequentially, if we exclude the boom-bust periods in the rolling window model, the average R2 premium increases to 6.7-7.0 percent. The discount on unmaintained units is also reduced during the boom-bust period, although the reduction is smaller in magnitude than for fully renovated dwellings. Panel 2d shows the equivalent index for the classical linear model, where the price development by renovation class are multiplicative shifts from each other, consistent with the log-linear form of the model.

Figures 3 show the renovation premium predictions of the random forest model (figure 2a) along with macro-variables providing information of the housing cycle, as measured by house price growth and housing investment growth. The latter consists of investment in new construction and renovation of all existing homes. These results suggest the renovation premium is counter-cyclical during the boom and bust.

Fig. 3 Renovation premium, House price growth and Housing investment growth

The figures display our results for the renovation premiums compared to the housing market cycle. Notes: House price and residential investment growth are official estimates from Eiendomsverdi ASA and Statistics Norway, respectively. The premium for unmaintained dwellings has been shifted up by 0.07 percentage points for ease of interpretation.

Renovation-bias in estimated House price growth

This section examines the impact of omitting renovation information on house price growth. In the previous sections, we found evidence of differences in the composition of renovated dwellings over time. Moreover, the renovation premium is significant. This may have implications for estimated house price growth.

We calculate the difference in the house price growth estimate for the classical linear model estimated when excluding our renovation information. We compute the quarterly house price growth for the Laspeyres index described earlier, including and excluding the renovation indicator. We use the results in columns 2-3 in Table 3. The absolute deviation in the house price growth estimate is defined as the *renovation-omission bias*:

$$|\Delta \log I_R^{t-(t+1)} - \Delta \log I_{None}^{t-(t+1)}|, \forall t \in \{1, T\}$$

The average absolute deviation in estimated quarterly growth for the city total and smaller strata is displayed in Figure 4 and summarized in Table 7. For the *City total* this is estimated to 0.32 percentage points per quarter, which is 8.08 percent of the average absolute quarterly growth over this period. The results for the Central region are similar. In the East, omitting renovation information leads to a larger deviation in estimated price growth, 0.70 pp. on average, equivalent in absolute terms to 14.83 percent of average quarterly growth³⁴. This finding contrasts with Bogin and Doerner (2019) which proposes the bias in the HPI is greatest in downtown areas of large cities. Most, but not all, quarterly differences are statistically significant (Figure 4)³⁵.

³⁴The direction of the bias is largely in line with differences in the composition of renovation classes.

³⁵Alternatively, one could consider "renovation-adjusted" house price growth, where the different renovation classes are regarded as separate strata weighted by their transaction shares. This method is common practice in the literature on house price indices for type, location, etc. when different segments evolve at

Fig. 4 Quarterly House Price growth, with and without Renovation information

The figure displays results for the quarterly absolute renovation omission bias (%) of the linear classical hedonic model for the City total, the Central strata, and the Eastern strata. Notes: *HPG omitted* omit renovation and *HPG renovation* includes renovation in the hedonic regression.

Table 7 Renovation-Bias in quarterly House Price growth

Strata	Bias ^a (pp.)	Share quarterly	Bias boom ^b (pp.)	Share quarterly boom
Full city	0.32	8.08	0.43	10.78
East	0.70	14.83	0.75	15.89
Central	0.34	8.0	0.61	14.4

The table reports results for the quarterly renovation omission bias (%) of the linear classical hedonic model. See table 12 for the list of Oslo suburbs in each of the categories. Notes: *a*. This is defined as the average absolute change in the quarterly house price growth estimates due to omission of renovation information. The bias is measured in percentage points. *b*. The two right columns show results for 2016 only.

different growth rates.

Additional tests and Robustness analysis

We perform two additional tests. The main takeaway is that our results regarding the renovation premium and counter-cyclical variation hold regardless of sample selection criteria and geographic segmentation. However, as there are likely to be renovations not reflected in the online-listings texts, this is expected to create a downward bias. As such, our estimates can be interpreted as a lower bound of the renovation premium. Excluding the right tail in the error distribution, the temporal variation in the renovation premium is even more substantial.

Adjustments for shortcomings of the renovation classification

Comparing the classification based on listings with a classification based on complete prospectuses, we expect a shortcoming of units classified with renovation status 1 and 2³⁶. Challenges that arise when modeling house prices from failure to account for unobserved factors such as renovations and remodeling are often addressed by researchers by removing the tails in the error distribution (see Bajari, Fruehwirth, Timmins, et al. 2012; Anundsen and Røed Larsen 2018). We hypothesize that the undetected renovated units end up in the top right tail of the error distribution and remove the observations in the top 10 percent of the error distribution based on the classical linear model³⁷. Before removing the top 10 percent, we exclude R1 and R2-observations and also observations from the boom year 2016 from the estimation data. The reason for the latter is that many of the candidate observations to remove are from the boom year, if not excluded. We believe this is related to factors related to market tightness rather than omitted variables such as renovation. The estimation data reduces from 5,742 to 5,322 observations.

Table 8 column 1 shows the results of estimating the classical model on the adjusted dataset for the entire period. The coefficient on partial renovation now has a point estimate of 3.1 percent and is highly significant. The coefficient on full renovation increases by about 2 pp. to 8.0 percent. The reduction in the right tail may have resulted in the neutral class being less noisy than before. However, this is an arbitrary data manipulation, and we are probably removing dwellings that received an unexplained high price (by our model) for reasons unrelated to renovation. The coefficient on the unmaintained characteristic remains the same. Columns 2-4 display the results of the rolling window model for the adjusted data. The pattern of temporal variation in the premium is even stronger than before, with R1-R2 premiums declining more sharply in the boom-bust years.

The takeaways from this exercise are, firstly, that we suspect that our previous R1-R2 estimates are somewhat biased downward, but that the estimates with the adjusted sample in 8 are biased upward. Thus, our results can be interpreted as a lower bound of the renovation premium. Secondly, we gain increased support for our previous finding of counter-cyclical temporal variation.

³⁶See Table 11 in Appendix I.

³⁷See model specification (2) in Table 3.

Table 8 Adjusted sample Regression Results: Classical and Rolling window model^a

	Dependent variable: log(Price)			
	LIN Entire period	LIN Normal Q1.14-Q4.15	LIN Boom, Bust Q1.16-Q2.17	LIN Normal Q3.17-Q2.19
	(1)	(2)	(3)	(3)
log(Size)	0.673*** (0.005)	0.700*** (0.008)	0.643*** (0.009)	0.668*** (0.008)
R1	0.031*** (0.007)	0.032*** (0.009)	0.015 (0.015)	0.038** (0.013)
R2	0.077*** (0.007)	0.098*** (0.011)	0.025* (0.019)	0.092*** (0.012)
R-1	-0.094*** (0.006)	-0.097*** (0.009)	-0.084*** (0.011)	-0.102*** (0.009)
Time, structural	<i>x</i>	<i>x</i>	<i>x</i>	<i>x</i>
Area (A)	<i>x</i>	<i>x</i>	<i>x</i>	<i>x</i>
Price zone (P)	<i>x</i>	<i>x</i>	<i>x</i>	<i>x</i>
Robust errors (White)	<i>x</i>	<i>x</i>	<i>x</i>	<i>x</i>
Observations	5,322	1,946	1,500	1,876
Adjusted R ²	0.921	0.921	0.903	0.922

The table contains results for hedonic regression models on an adjusted dataset where 10 % of the observations in the right tail of the error distribution is excluded. Each column represents a separately estimated regression. Notes: ^aThe Rolling Window model is estimated for three adjacent time periods in each column. Significance level: *p<0.1; **p<0.05; ***p<0.01.

Testing if changes in the renovation premium are driven by changes in the implicit price for centrality

Based on hedonic theory, one could suspect that all implicit prices may exhibit a similar pattern to the renovation premium in times of disequilibrium. Moreover, movements in one implicit price may be confounded by movements in another if not accounted for. HPIs segmented by other hedonic characteristics (such as size and type) were examined for similar patterns of temporal variation using the random forest. Potential heterogeneity in implicit prices for apartments vs. single-family units has received some attention among practitioners. We find that the temporal variation in size- and dwelling type-coefficients are considerably more modest³⁸. However, the average HPI by geographical strata follows a similar but less pronounced pattern where the centrality-premium reduces temporarily during the boom.

From this finding, there is the possibility that the results for the temporal variation of the renovation premiums in figure 2 may in part be driven by shifts in the centrality premium. To address this contingency, we examine the temporal variation of the renovation premium for more homogeneous urban strata. The most central urban area around the CBD (Central), an affluent western suburb (West), and a less affluent eastern suburb (East)³⁹, although this distinction is not exact. Figure 5 displays the renovation premium

³⁸Results are similar for regular owner vs. coop dwellings.

³⁹See Figure 12 in Appendix.

Fig. 5 Strata: Random Forest Renovation premiums

The figure display our results for the temporal variation in the renovation premiums in two urban strata, the most central urban area around the CBD (Central) and a less affluent eastern suburb (East). Note: The methodology is identical to Figure 2.

for the Central and East regions⁴⁰. The methodology is the same as for the full city model⁴¹. The renovation premium shows similar patterns with considerable cyclic variation over the period, implying that our results are robust to lower geographical segmentation.

Conclusion

The housing market involves transactions of dwellings that differ with respect to hedonic characteristics. In principle, there is no limit to the number of dwelling characteristics that may affect market price. On the other hand, the most important determinants of transaction prices are well known. This paper addresses the price determinant, renovation, which is of known importance but seldom included in house price estimation due to data limitations.

We use the text of online-listings⁴² of houses transacted in the Oslo market for the time period 2014 to 2019 and classify dwellings according to four renovation classes⁴³. We find that the renovation premium (fully renovated) is in the 5 to 7 percent range. However, there are potentially renovations not reflected in the online-listing texts. This creates a downward bias, and as such, our estimates can be interpreted as a lower bound of

⁴⁰The estimated R2 premium is highest in the Western, and lowest in the Eastern region, according to these results. The Central region is placed in the middle. A similar pattern emerges for unmaintained properties, which are punished the most in the Eastern region.

⁴¹The out-of-sample dataset for 2014-2015 for the Central region is of size $N_{central, O \in (Q_{114}, Q_{415})} = 493$, whereas the estimating dataset is of size $N_{central, T} = 3,212$. Similarly for the East, $N_{east, O \in (Q_{114}, Q_{415})} = 172$ and $N_{east, T} = 1,098$.

⁴²The listing and prospectus datasets described in Appendix I.

⁴³These are unmaintained, partly renovated and fully renovated. The fourth is the reference category, dwellings that are neither renovated nor unmaintained.

the renovation premium. The negative premium for unmaintained dwellings is somewhat higher, consistently estimated roughly at 9 to 10 percent.

It must be stressed that these average effects gloss over systematic variation over time and space. The time dimension is important along two dimensions. First, it appears to be a variation with the business cycle. The premium is considerably lower in a more heated housing market. This effect is the opposite for the unmaintained. The negative premium is less for unmaintained dwellings in a heated housing market. A natural explanation for this is the income-mortgage effect. The market heat is like a tide that lifts all boats, but the attractive and expensive in several market segments to a lesser extent due to income and mortgage financing limitations. This results in more competition for less attractive and less expensive dwellings. The unmaintained dwellings fall in this category. Moreover, unmaintained dwellings allow for a future renovation and, as such, involve a potential investment smoothing. Equally important, our analysis shows a systematic medium-run temporal variation in price premiums that may bias estimates for house price levels and price indices. Second, our analysis indicates that part of well-known seasonality in house price indices is partly due to composition effects. The frequency of unmaintained dwellings is considerably higher in the fourth quarter, leading to a downward bias in house price indices that do not control for this.

We find an interesting pattern in renovation premium variation geographically. As Bogin and Doerner (2019) we find that the renovation premium varies with centrality and may bias house price levels and indices. They find that a higher renovation activity in central areas is the primary explanation for this bias. In contrast, our results show that the bias tends to be higher in the less central areas, driven by the higher frequency of unmaintained dwellings. There are reasons to believe that both higher renovation frequency in central areas and higher propensity to not undertake necessary maintenance in more distant areas from the city center apply to most cities. As both effects lead to a smaller price difference between central and non-central areas when we adjust for renovation (or lack thereof), this finding has implications for the literature regarding beta and sigma convergence in metropolitan areas Wood, D. E. Sommervoll, and Silva (2016).

Our analysis relies on less than perfect identification of renovation class for the dwellings in question. This calls for caution in the interpretation of the above-mentioned point estimates. However, the importance of renovation as a price determinant is an undeniable takeaway from our analysis. Failure to control for renovation leads to significant biases of housing price levels and indices. Moreover, these are unfortunately not only considerable, they also tend to vary over time and across space.

At a higher level, our analysis of online listing points to a way to control for renovation. Other ways, for example, by the use of computer vision (Yencha 2019), may prove an even more powerful way to measure the degree of renovation and get closer to quality-adjusted price levels and price indices for the housing market. In this sense, our analysis is just an early contribution that shows controlling for renovation is doable and involves significant rewards.

Appendix I

Table 9 Data Preparation prospectus data and Summary Counts listings and prospectus data. Averages and totals.

Panel A: Data Preparation prospectus data	
Data stage	No. of transactions
Raw data	7,212
(1) Data after removal of errors in price variabel	7,205
(2) Data after adjusting (1) for age cohort and time-of-sale ^a	3,485
Panel B: Summary Counts listings data (N=10,350) and prospectus data (N _p =3,485)	
Data counts	No. of words, sections or bytes
Average no. of words per listing text ^b	15.2
Words in total listing texts	156,878
Bytes total listing texts	1,768,700
Sections per prospectus ^c	51.5
Bytes total prospectus texts	16,634,488

Panel A provides a brief overview of the data preparation. Panel B provides a comparison of text length and the richness in vocabulary. The listing data have less text available for text analysis. This makes text analysis easier because the texts are not only shorter but also more standardized. There is also the possibility that renovation/poor maintenance is not reflected in the text. We perform a similar classification based on exceedingly richer information in prospectuses for a smaller subset of dwellings to address this.

Notes: *a.* Stratified re-sampling of transactions by age cohort of dwellings and time-of-sale, matching the distribution of listings. *b.* The listing text is written in the form of keywords. These typically contain condensed information or highlights of the unit, often including information about recent renovations. Summary statistics are based on a full count. *c.* The prospectus texts include, in most cases, an extensive description of the unit and a list of maintenance and renovations.

Table 10 Frequent Words in listing texts and Summary Statistics by Renovation class. N= 10,350

Renovation class	2	1	-1	0	age<10yr	All
No. of obs.	723	558	902	6,736	1,431	10,350
Percent	7.0	5.4	8.7	65.1	13.8	100
+ Renovation indicators^a						
Renovert (Renovated)	482	128	0	35	7	552
Påkostet (Lavish)	68	16	0	8	37	129
Kjøkken (Kitchen)	106	358	20	382	12	
Baderom (Bathroom)	126	284	108	842	81	1,441
Lekker (Gorgeous)	230	100	3	707	303	1,343
Høy standard (High Standard)	62	34	1	360	71	528
Strøken (Flawless)	45	6	0	83	51	185
- Renovation indicators						
Oppussingsobjekt (Unmaintained)	0	0	803	3	0	807
Potensial (Potential)	0	0	145	22	0	167
Sjarmerende/Hyggelig (Charming/Nice)	20	28	19	418	9	494
Moderne (Modern)	37	32	213	202	122	606
Dwelling characteristics						
Transaction price (10^6 NOK)	4.5	3.9	4.7	4.4	5.3	4.5
Transaction price per m^2 (10^3 NOK)	65.5	64.9	51.9	61.2	68.5	61.9
Size in m^2	74.8	63.8	98.7	78.6	81.1	79.7
Dwelling age	74.8	77.8	63.5	60.0	4.4	54.6
Location						
Central	335	265	283	2,515	523	3,921
West	245	213	412	2,921	612	4,403
East	143	80	207	1,481	115	2,026
Quarter of sale (share)						
Q1	0.07	0.055	0.085	0.79	-	2,749
Q2	0.07	0.055	0.085	0.79	-	3,324
Q3	0.07	0.055	0.07	0.80	-	2,230
Q4	0.065	0.05	0.11	0.77	-	2,047

The table provides details on the word frequencies for the different renovation groups in our classification. This can be seen as a first check of the classification since the keywords signaling full renovation should be almost absent for the unmaintained ones and vice versa. The table is encouraging because it shows the desired separation of signaling words. To some degree, these listing texts are essentially advertisements, so there is considerable creativity that presents a challenge for text analysis. A wide range of positive words is used to describe newly renovated homes (gorgeous, flawless, exclusive, lavish). Since most of these words could be cheap talk, a careful reading of all listing texts was undertaken to assess the degree of renovation they reflect. Listings for unmaintained homes generally use a different vocabulary. "Potential" and "charming" are widely recognized as positive ways to describe a poorly maintained dwelling. Notes: *a*. The classification is based on both automated word search and manual control. In particular, some units may be renovated but use different wording. Some that contain the word renovated are clearly not renovated in a way that qualifies for renovation levels 1 or 2.

Table 11 Validation: Renovation Classification Results between 2017-Q2 and 2019-Q2. Shares and volumes. Prospectuses (P) and Listings (L)

	R-1 (P)	R-1 (L)	R0 (P)	R0 (L)	R1 (P)	R1 (L)	R2 (P)	R2 (L)
<i>Shares</i>								
2017-Q2	0.10	0.08	0.58	0.80	0.15	0.05	0.17	0.07
2017-Q3	0.08	0.09	0.54	0.78	0.20	0.04	0.18	0.09
2017-Q4	0.12	0.11	0.62	0.78	0.13	0.04	0.13	0.07
2018-Q1	0.12	0.09	0.52	0.79	0.19	0.05	0.16	0.07
2018-Q2	0.10	0.09	0.59	0.81	0.16	0.04	0.15	0.06
2018-Q3	0.12	0.04	0.58	0.87	0.15	0.05	0.15	0.03
2018-Q4	0.19	0.11	0.55	0.77	0.11	0.06	0.15	0.06
2019-Q1	0.08	0.10	0.60	0.78	0.14	0.05	0.18	0.07
2019-Q2	0.09	0.08	0.58	0.78	0.20	0.06	0.14	0.08
Total	0.11	0.09	0.57	0.80	0.16	0.05	0.15	0.07
<i>Volumes</i>								
2017-Q2	20	47	110	472	29	29	32	44
2017-Q3	12	41	80	357	30	19	27	42
2017-Q4	18	50	92	352	19	17	19	33
2018-Q1	18	41	78	364	29	22	24	32
2018-Q2	20	52	114	480	31	25	28	35
2018-Q3	21	23	100	452	26	27	25	18
2018-Q4	24	41	68	290	14	23	18	24
2019-Q1	11	46	85	343	20	21	25	31
2019-Q2	10	30	67	274	23	21	16	28
Total	154	371	794	3,384	221	204	214	287

The table compares the renovation classifications for the listing and prospectus datasets. To make the comparison valid, the transactions in the prospectus data are adjusted for differences in the timing of sales and the age distribution of the properties. We find that the share of R-1, the unmaintained properties for sale, is strikingly similar, for each quarter and overall. Thus, the listing text appears to be adequate for capturing dwellings needing renovation. The story for R1 and R2 is less reassuring. In the case of fully renovated units, the proportion in the prospectus data set is 15 percent, compared to 7 in the listing data set. Although these are different data sets, they are from the same area and cover the same period. The share is less than one-half in the prospectus dataset, consistent with the fact that only half of the fully renovated units are identified by the listing dataset. Notes: In the validation stage, a fixed share of 40 percent (20 percent $\times$ 2 with replacement) of the transactions in the adjusted prospectus data (N=3,485) is randomly selected each quarter and classified by the same criteria as for the listing data.

Table 12 Oslo Suburbs. Administrative areas by Strata

Strata	Administrative area with area number
Central	1.Frogner, 2.Grünerløkka, 3.Sentrum, St. Hanshaugen, 4.Sagene, 5. Gamle Oslo
West	6.Ullern, 7.Vestre Aker, 8. Nordre Aker, Marka, 11.Nordstrand
East	9. Bjerke, 10.Alna, 11.Østensjø, 12.Søndre Nordstrand, Stovner, Grorud

Notes: To achieve a sufficient volume of transactions in each area, Sentrum, Marka, Søndre Nordstrand, and Stovner are merged with nearby areas or areas with similar location premiums.

Fig. 6 The share of Renovated transacted dwellings by Administrative area between 2014-Q1 and 2019-Q2. Left: Renovated (R1-R2). Right: Unmaintained (R-1)

Notes: The figure maps the spatial distribution of the share of renovated transacted dwellings for the five year period. According to these findings, renovation shares R1-R2 are positively associated with urban location (left graph), with the highest shares in central, high-end suburbs. Unmaintained sales are more common in low-income southern and eastern suburbs (right panel). For example, renovated dwellings are more frequent in area 3 which includes the city center. Unmaintained units are more frequent in area 12, the cheapest housing areas in the city. The numbering corresponds to Table 12. Oslo's large most Northern administrative area, including mainly recreational zoning areas, is excluded from the map (Marka).

Fig. 7 Transactions in Administrative areas (by color) and non-contiguous Price zones (by color). N=8,203

Notes: The administrative areas in figure (a) are described in Table 7. The price zones in figure (b) are constructed based on the methodology described in Å. Sommervoll and D. E. Sommervoll (2019).

Table 13 Data Preparation listing data

Data stage	No. of transactions
Raw data	11,683
Hedonic data after removal of non-housing transactions (commercial, vacation-property, contracts, lots, whole buildings)	11,372
Hedonic data after removal of data with errors in price-variables ^a	11,284
Hedonic data after renovation classification ^b	10,842
Hedonic model data after removal of missing model variables	10,642
(1) Hedonic model data after excluding 2013-transactions ^c	10,350
(2) Hedonic model data (1) with geographical coordinates	9,186
(3) Hedonic model data (1) with price zones	8,203

Notes: *a.*90 transactions were recorded with very low transaction prices and were removed. *b.*442 transactions were removed because the text of the listings contained very limited information, and classification by renovation status was not possible based on the information reported. *c.*2013-data was removed due to few transactions per quarter.

Table 14 Checks for Balances: Summary Statistics estimating data, out-of-sample data, and data with AVMs. Prices and Key housing characteristics. Prices in million NOK

Statistic	Mean	St. Dev.	Min	Max
Estimating data. $N_T=5,742$				
Transaction price	4.5	2.25	1.1	32.5
Size in m ²	75.7	46.0	14.0	757.0
Dwelling age	57.1	37.7	-1 ^a	176.0
Sold before 2016 (share)	37.1			
Apartments (share)	88.7			
Regular owner (share)	54.7			
Located centrally ^b (share)	55.9			
Out-of-sample data. $N_O=2,461$				
Transaction price	4.4	2.1	1.1	21.0
Size in m ²	74.6	44.5	15.0	397.0
Dwelling age	57.9	37.4	0	188
Sold before 2016 (share)	38.8			
Apartments (share)	89.7			
Regular owner (share)	54.5			
Located centrally (share)	55.4			
Data with AVMs. $N_V=5,809$				
Transaction price	4.65	2.3	1.0	33.0
AVM price ^c	4.6	2.2	1.1	20.1
Size in m ²	80.2	49.0	14	757
Dwelling age	53.5	36.5	-2 ^a	214
Sold before 2016 (share)	39.7			
Apartments (share)	85.7			
Regular owner (share)	74.8			
Located centrally (share)	47.1			

Notes: 1 NOK= 0.11 USD on January 7, 2022. *a.*New dwellings sold before completion. *b.*See Table 12 for the list of Oslo suburbs in each of the three categories. *c.*The AVM price is a professional price estimate from Eiendomsverdi ASA.

Appendix II

Random forest details

Random forest algorithms require hyperparameters that control how many decision trees are grown, how many variables are included in each split (mtry), and how small each terminal node of the tree can be (node size). The chosen performance measure minimizes the predictions' root mean squared error (RMSE). To find the optimal set of hyperparameters, we run a loop of hyperparameter combinations using 5-fold cross-validation.

Although regression tree models often use categorical data in their natural form, it is worth considering whether alternative coding can improve performance. In this case, including all variables in numerical form produces the best predictive results. The best performing models, in the sense of no significant gains in model performance (R squared or RMSE) from altering the hyperparameters, is found around the parameter set where the number of trees is about 1,000, as this is demonstrated to be sufficient to achieve a stable error rate in our case (see the discussion in Leo (2001)), mtry is 5-6, and the final node size is 5. With a node size beyond 6, performance is reduced. The final hyperparameters used are mtry=5, nodesize=5, trees=1,000. The infinitesimal jackknife for bagging is used to estimate the standard errors. The Ranger, Caret and RandomForest packages in R are used to estimate the models. Reported estimation results are based on the Ranger package (see Wright and Ziegler 2015).

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