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Housing Depreciation Revisited: Hedonic Price Modeling Versus Assessor Estimates

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Abstract

Age and condition driven rates of structural depreciation for single-family housing based on hedonic price modeling representing the perceptions of home buyers/sellers are compared to tax assessor depreciation estimates for 47,000 homes in Sarpy County Nebraska. A hedonic price model with age specified as linear generated depreciation rates 11% below assessor rates with differences ranging from 43% lower to 13% higher across four classes of home values. A quadratic-age specification generated depreciation 39% above assessor rates with a range of 15% to 162% higher. A third model, with both quadratic-age and age-condition interaction variables, generated depreciation 27% higher than assessor rates with a range of 8% to 128%. If the goal of hedonic-based housing depreciation modeling is to converge with assessor-derived depreciation estimates based on widely used proprietary cost estimation software and data, then a linear model specification with respect to home age is recommended. Regardless of functional forms chosen, quantile regression where depreciation is estimated across different classes of home values is recommended for all types of hedonic depreciation models.

Keywords

structural housing depreciation, hedonic price models, quantile regression, tax assessment

A major impediment to the use of the cost approach for valuing single-family residential housing is the lack of subjective and accurate estimates of age-driven structural depreciation defined as physical wear and tear that can potentially be offset by periodic maintenance and/or the replacement of housing components, combined with potential functional obsolescence resulting from missing or outdated home features. The three traditional approaches to calculating housing depreciation are the economic age-life method, the breakdown or unit-in-place method, and various applications of the market extraction method (Stadig, 2011; Appraisal Institute, 2014).

In the economic age-life method, it is assumed that depreciation is linear and in its most basic form is calculated simply by dividing effective age by life expectancy. The approach is limited by the subjectivity in determining both effective age and expected life, particularly when different homes have varying levels of maintenance and upgrades. Therefore this method is typically only used by appraisers and/or assessors requiring a secondary or back-up cost approach valuation to support comparable sales and/or income approach-based valuations.

The breakdown or unit-in-place method is a more comprehensive way to measure deprecation since it usually requires a detailed inspection of the characteristics and condition of homes. In addition to the costly data inputs based on proprietary data sources required with this approach, it is extremely time consuming and usually requires interior home inspections, meaning that the approach is rarely used to estimate depreciation for large numbers of homes. Such an increased effort would most likely occur when appraisers are heavily relying on the cost approach to value a home (e.g., in cases where there are no suitable comparable sales) and/or when tax assessors rely on the cost approach as the primary assessment approach in a jurisdiction that would most likely occur in areas with relatively new and homogenous housing stock.

Finally, the market extraction method to estimate depreciation can be undertaken using several alternative approaches: observing depreciation rates among different types and ages of homes (the life-cycle model); pairwise analyses that compare homes that differ only with respect to age; and statistical techniques including repeat sale and/or hedonic price models that utilize multiple regression to isolate the effect of home age and condition (maintenance) on home prices while accounting for other housing and market characteristics. The major advantages of market extraction approaches, which are discussed in greater detail in the next section, are that they are usually based on large sample sizes and that they measure depreciation from the perspective of buyers and sellers (i.e., the market) while removing the potentially subjective opinions of third person evaluators. However, these statistically advanced modeling approaches may be limited by the fact that accurate property condition measures are not often accounted for by housing transaction sales databases.

Most of the published research on structural housing depreciation was undertaken in the 1980s and 1990s and in fact, the last known published housing depreciation study is from 2008 and focused on the housing market in Stockholm, Sweden (Wilhelmsson, 2008). This depreciation research scarcity has generally coincided with the cost replacement approach being widely dismissed, at least in the United States, as a preferred appraisal valuation technique for single-family housing. However, the cost approach continues to be used by tax assessors and appraisers particularly as a secondary or reference valuation approach for newer residential housing and/or special use properties, which are not amenable to other valuation approaches. The cost approach including depreciation estimates, has continued to be refined and improved by the three major cost replacement data vendors (Marshall and Swift, RS Means, and Xactware) and is now frequently incorporated within the computer-assisted mass appraisal (CAMA) systems of many county tax assessors (IAAO, 2010).

There are two objectives of this present research: To generate updated estimates of single-family housing depreciation since the last published studies on this topic are over 10 years old, and to compare depreciation estimates based on hedonic price models (representing the perceptions of buyers and sellers) with tax assessor estimates of depreciation based on exterior home inspections, reviews of remodeling permit data, and cost replacement data services.

This study is relevant for several reasons. First, it has been over a decade since price appreciation estimates for single-family housing in the U.S. market has been reported and it might be the case that housing construction method and materials and/or maintenance levels and costs have changed in that time frame. Second, this is the first known study where hedonic modeling-based estimates of housing depreciation representing the perceptions of buyers/sellers are directly compared to assessor estimates of depreciation based on objective (i.e., third party) inspections of property condition. Potential discrepancies between these two sets of depreciation estimates might indicate cases of inequitable tax assessment or alternatively cases of irrational perceptions of home buyers/sellers regarding the costs to repair and maintain properties. Therefore, this research is expected to be of interest to home buyers/sellers, appraisers, and tax assessors and for a variety of local, state, and federal agencies, including the U.S. Army Corps of Engineers and the Federal Emergency Management Agency who are searching for low-cost approaches to estimate structural replacement costs for existing structures across large geographic areas for a variety of disaster mitigation planning activities (Shultz, 2015).

This research is made possible due to the existence of a somewhat unique database of depreciation estimates for over 47,000 homes made by the Sarpy County, Nebraska Assessors Office, which relies primarily on the cost approach to assess single-family housing in this mostly suburban southern portion of Omaha. In fact, no other studies of housing depreciation are known to have had access to such a comprehensive depreciation database. The hedonic price modeling used in this research is closely aligned with the approaches of several past studies that have quantified the effect of dwelling age on sale prices.

Background

The Cost Approach and the Role of Depreciation

The cost approach to valuing real estate has been almost completely ignored in the academic literature in the last decade particularly in relation to the valuation of single-family residential properties after it was demonstrated to be less reliable than comparable sales-based valuation approaches (Dotzour, 1990; Dotzour and Freitag, 1995). In both appraisal and tax assessment practice, the cost approach is often limited to special use properties that do not have comparable sales and/or do not generate rental income, and to newer single-family residential construction, which is relatively easy to depreciate (Moore, 2006, 2012). The cost approach begins with the calculation of the reproduction or more commonly, the replacement (i.e., new construction) cost of a structure through a variety of approaches ranging from highly generalized dollar per square foot estimates, to unit-in place calculations where specific structural characteristics are accounted for (Appraisal Institute, 2014). Replacement cost values are then lowered by accounting for depreciation (either physical, functional, and/or economic), and then increased by adding the value of the lot/land plus additional improvements.

In recent years, the cost approach has been refined and promoted by the three major vendors of cost replacement data: Marshall and Swift (now owned by Core-Logic), RS Means, and X-Estimate, who all offer online cost approach valuation services (Shultz, 2014). These firms base their cost estimates on periodic regional surveys of home builders and material suppliers, and/or insurance companies. The Marshall and Swift cost data are embedded within many assessor CAMA systems and are the most common data used by appraisers valuing single-family residential housing. In contrast, RS Means has traditionally enjoyed a dominant market share among the non-residential construction industry, while X-Estimate is heavily utilized by the property insurance industry. Several federal agencies, particularly the U.S. Army Corps of Engineers and the Federal Emergency Management Agency, are currently looking for ways to quickly and cheaply collect replacement cost data across large areas of the country to facilitate disaster management planning activities (Shultz, 2015).

The depreciation component of the cost approach continues to be a major challenge to the accuracy of cost approach valuations. The simplest and most common depreciation strategy is to divide a building's effective age (chronological age adjusted for upgrades and improvements) by its expected typical life. But calculating the effective age for buildings without detailed interior inspections and/or records of improvements and upgrades is highly subjective and problematic. In 2012, Marshall and Swift undertook a major effort to refine depreciation estimates based on their internal (and not publicly disclosed) research on depreciation observed in the market place and the assumption that many structures follow non-linear depreciation life cycles. Their strategy for their customers to estimate depreciation quickly and/or for large numbers of homes (i.e., mass appraisal) is to estimate the condition and quality of homes (using nine classifications ranging from bad to excellent) and then to use Marshall and Swift depreciation tables that account for condition and quality, as well as home age, style, and framing and/or foundation materials. Unfortunately specific Marshall and Swift depreciation approaches are highly proprietary and kept somewhat secretive.

Research on the Nature of Housing Depreciation

The scarcity of research on the cost approach has coincided with an even smaller amount of published studies dealing with housing depreciation. In fact, the most recent known housing depreciation study was published in 2008 and focused on how levels and types of maintenance influenced age driven housing depreciation in Stockholm, Sweden (Wilhelmsson, 2008). The study used a hedonic price model with transaction data to quantify how both outdoor and indoor maintenance interacted with an age variable influencing housing prices. A log-polynomial model was estimated with depreciation defined as being a function of age, age-squared, and age-maintenance interaction variables (separately for indoor and outdoor maintenance, which were only represented dichotomously) to indicate whether or not maintenance for particular homes was needed based on surveys of homebuyers. Well maintained properties were found to depreciate by 0.77% per year versus 1.10% for poorly internally or externally maintained properties. Annual depreciation rates were found to be non-linear, and decreasing with age, and locational (spatial) effects were not found to influence depreciation. No attempts were made to estimate depreciation rates by housing value sub-categories.

Harding, Rosenthal, and Sirmans (2007) used a repeat sales model to quantify depreciation rates based on the American Housing Survey over the 1983 to 2001 period. Although the authors mention the possibility that depreciation is likely to be endogenous to house value, they did not formally test for this relation, but instead, focused on quantifying age and maintenance factors using a two-stage least squares model that was able to account for the non-linear effects of age and separate depreciation values with and without maintenance. Over the 18-year period of the study, homes were found to depreciate on average by 2.5% per year, of which approximately 0.5% was related to maintenance represented by owner maintenance expenses, but it was not made explicitly clear if the maintenance data were specific to repeat sale properties or inferred from American Housing Statistics.

A series of earlier studies used hedonic price modeling with transaction data to quantify annual price depreciation in various U.S. locations. The earlier studies from the 1980s are extensively reviewed by Malpezzi, Ozanne, and Thibodeau (1987), who concluded that housing depreciation rates varied substantially across studies and that this was likely due to alternative methods, data sources, and time periods. But in general they found that annual average depreciation decreases with age at declining rates and average 0.9% in early years to 0.28 in later years (around 20 years old).

In the 1990s, there were seven known housing depreciation studies focused on different U.S. housing markets. Goodman and Thibodoeau (1995) used a hedonic price model with transaction data in Dallas, Texas to quantify age-related depreciation using alternative functional forms (ordinary least squares and general least squares and a polynomial representation of age). They concluded that age and depreciation were non-linear, indicating the importance of second order effects of age when calculating depreciation. Clapp and Giaccotto (1998) separated age-derived depreciation by cross-sectional depreciation effects and demand driven effects and found that depreciation rates were highly dependent on temporal effects. Knight, Miceli, and Sirmans (2000) concluded that required maintenance did not have a major impact on depreciation rates because sellers required repairs at the time of sales brought homes up to typical maintenance levels. This finding has not been replicated in later studies and was explicitly refuted in several later studies, particularly Wilhelmsson (2008). Finally, Smith (2004) found that location and sold year had large effects on economic depreciation rates and that it was critical to remove land values from depreciation analyses. It is interesting to note that no known prior has attempted to evaluate housing depreciation rates calculated by appraisers or other third persons not associated with sale transactions.

Methods and Data

This study focused on evaluating assessor-derived depreciation for all 47,157 homes in Sarpy County, Nebraska for the 2013 assessment year. The county encompasses the southern portion of the Omaha metropolitan area and has a population of around 166,000. This depreciation data obtained from the Sarpy County Assessor office includes replacement cost new values and depreciation estimates, along with typically collected housing characteristics data (size, age, total value, condition, and quality). The availability of cost replacement data for an entire population of homes in an assessment jurisdiction is not common but is available here because much of the real estate development in the county has occurred in the last 15 years as a result of suburban Omaha growth trends, which allows the county to rely heavily on the cost replacement approach to assess all classes of properties and particularly so for single-family residential and special use properties. In fact, the Marshall and Swift cost estimation software is included in the county's CAMA system to generate structural replacement costs based on relatively detailed structural characteristics and condition data collected by the assessor's office.

The assessor calculates three distinct depreciation rates, all as a percentage of replacement cost values: physical, functional, and economic depreciation. Physical depreciation representing general wear and tear and expected required general maintenance are based on exterior site inspections, combined with remodeling permit data reviews, to assign a building condition code based on nine Marshall and Swift defined building condition classifications (ranging from bad to excellent). These condition classifications are not used to calculate effective age based physical depreciation estimates (effective age divided by life expectancy) but rather, more complex calculation tables developed and provided by Marshall and Swift are used to estimate physical depreciation based on tabular-based combinations of building age, condition, and physical characteristics.

Functional depreciation is used to represent the functional obsolescence of home features, and, in particular, missing or damaged key features of homes such as a lack of a garage or basement based on values contained in the Marshall and Swift Home Repair and Remodel Cost Guide. For this study, functional depreciation values for new housing were ignored as missing features for newly constructed homes are considered pending or forthcoming and functional depreciation (for existing homes) is combined with physical depreciation. That is, no efforts were made to distinguish between functional and physical depreciation. As well, economic depreciation, which the Sarpy County assessor uses as an adjustment factor to ensure that depreciated structural replacement values within particular market segments converge with average sale price values, was not included with depreciation analyses in this study.

The Characteristics and Determinants of Assessor Calculated Depreciation

A primary focus of this study was to evaluate how annual depreciation calculations (cumulative depreciation divided by age) vary by the age and value of homes as previous studies have found that annual depreciation rates decline with home age (due to remodeling and repair), as well as home value since wealthier homeowners have an increased ability and more of a financial incentive to maintain their home values. To begin, depreciation rates are compared across home age and value classifications. Of particular interest is how the Sarpy County Assessor mean annual depreciation rates differ from those of previous U.S.-based housing depreciation studies and whether these depreciation rates vary across home age and value. Then, a multiple regression model is estimated where annual depreciation is regressed against home age, home style, value, size (total square feet), and assessor made condition and quality measures. The dependent and explanatory variables in this model are summarized in Exhibit 1. This dataset (the homes of Sarpy County) are relatively newer than homes in much of the country (average age of only 28 years), and are likely to have a higher frequency of single-story home designs (70% of the total) as the county is highly suburban.

Exhibit 1. Variables Used with a Regression Model to Quantify the Determinants Assessor-Calculated Depreciation (n = 41,217)

	Description	Mean	Std. Dev.
Dependent Variable			
Dep_Yr	Depreciation per year (cumulative depreciation divided by home age)	0.007	0.002
Explanatory Variables			
AGE	Home age (years)	28	21
T_SF	Total square footage	2,679	906
COND	Home condition (9 Marshall & Swift based categories: Bad (10) to Excellent (60)	31	3
QUAL	Home quality (9 Marshall & Swift Based Categories: Bad (10) to Excellent (60)	33	5
d_1_story	Whether a home is 1 story	0.7 (n = 28,851)	0.5
d_split_bi	Whether a home is bi-level or a split level	0.1 (n = 4,121)	0.2
d_2_story	Whether a home is a 2 story	0.2 (n = 8,242)	0.4
d_3_story	Whether a home is a 3 story	0.1 (n = 4,120)	0.3
total_val	The total assessed value ($)	165,858	73,912

Hedonic Regression to Estimated Depreciation

To accomplish the second task of this paper, three alternative semi-logarithmic hedonic price models are estimated using sales transaction data for the 2012–2013 period and compared to assessor calculated depreciation. The three alternative specifications differ slightly with regard to the functional form used to represent age: age being treated as linear versus quadratic following the model specification [as demonstrated by Goodman and Thibodeau (1995)], and a third model, which contains both an age-quadratic variable and two age-condition interaction variables similar to the specification previously undertaken by Wilhelmsson (2008). For each of the three alternative specifications, the model is first estimated using all 41,217 housing sales over the 2012–2013 period and then, via quantile regression with separate regressions for four distinct classes of home values to account for endogeneity between housing values and depreciation.

The age linear model specification is:

$$\text{Ln}\ (P_i) = \beta_0 + \beta_1 AGE + \beta_2 T\_SF + \beta_3 WALK\_BASE + \beta_4 FIREP + \beta_5 Garage + \beta_6 COND + \beta_7 QUAL, \tag{1}$$

where Ln (P_i) is the natural log of the reported selling price of the ith house based on data from the Omaha Area Board of Realtors' Multiple Listing Service (MLS) over the 2010–2013 period; *Age* is the age of the house in years; *T_SF* is total square feet; *WALK_BASE* is whether a home has a walk-out basement; *FIREP* is whether a home has a fireplace; *Garage* is garage stalls; *COND* is the assessor condition ranking for the house (1–8); and *QUAL* is the assessor quality of construction ranking for the house (1–8).

The quadratic-age model specification is identical to model 1 except that it includes both the age (*AGE*) and age squared (AGE^2) variable to account for non-linear age effects and depreciation and is calculated by:

$$\partial V/\partial AGE = \beta_1 AGE + \beta_2 AGE^2. \quad (2)$$

The final model specification has two age-condition interaction variables and an age-squared variable. The first interaction variable interacts home age with a dichotomous (dummy) variable indicating whether a home has been given a below average condition rating (<30) while the second interaction variable relies on a dummy variable indicating whether a home has received an above average condition ranking (>35). The resulting depreciation estimates for this model are calculated by:

$$\partial V/\partial AGE = \beta_1 AGE + \beta_2 AGE^2 + \beta_3 AGE\_BAD\_COND + \beta_4 AGE\_EXC\_COND. \quad (3)$$

Quantile regression is undertaken in each of these three model specifications by estimating the regression separately for four classes of home values: less than \$100,000, between \$100,000 and \$159,999, between \$160,000 and 224,999, and homes valued at \$225,000 or higher. This quantile regression based on home value is justified based on the hypothesis that depreciation is endogenous with respect to home values.

Finally, depreciation estimates from each of the alternative hedonic price model specifications were compared to assessor-calculated depreciation estimates for all home types and across four classes of home values for the cases of quantile regression specifications. Since this was the first known attempt to compare assessor versus hedonic-derived depreciation estimates, it was not hypothesized a priori whether or not these alternative depreciation estimates would converge or which of the alternative model specifications would generate results closest to the assessor-derived estimates. No attempts were made to determine which of the two sources of depreciation are correct or superior because they are each based on different methodologies, data sources, and perspectives. However, if particular hedonic model specifications generate depreciation estimates that are very similar to the depreciation estimates reported by the Sarpy County Assessor, this would indicate that the convergent assessor and buyer/seller perceptions of depreciation are likely a reasonable good (i.e., representative) measure of depreciation.

Results

The Characteristics of Assessor Calculated Depreciation

Across all 47,217 homes in Sarpy County, the average annual depreciation is 0.7% (Exhibit 2), which is very similar to previously reported depreciation estimates for single-family residential housing with the exception of the depreciation rates estimated by Harding, Rosenthal, and Sirmans (2007), which were closer to 2.5% per year. However, the use of this 0.7% average annual depreciation rate for all homes would likely result in many inaccurate depreciation estimates for subsets of homes because depreciation rates in

Exhibit 2. Average (Mean) Annual Assessor Calculated Depreciation by Age and Value of Homes

	All Values	<\$100k	\$100k–\$160k	\$160k–\$225k	>\$225k
All Years	0.7%	0.5%	0.7%	0.9%	0.9%
<5 years	1.0%	2.0%	1.1%	1.1%	0.9%
6–20 Years	0.09%	1.2%	1.0%	1.0%	0.9%
21–50 years	0.06%	0.6%	0.6%	0.6%	0.6%
51–70 years	0.05%	0.5%	0.5%	0.5%	0.4%
>70 years	0.04%	0.4%	0.3%	0.3%	0.3%

Exhibit 3. Multiple Regression Results: The Determinants of Assessor Calculated Annual Depreciation Estimates

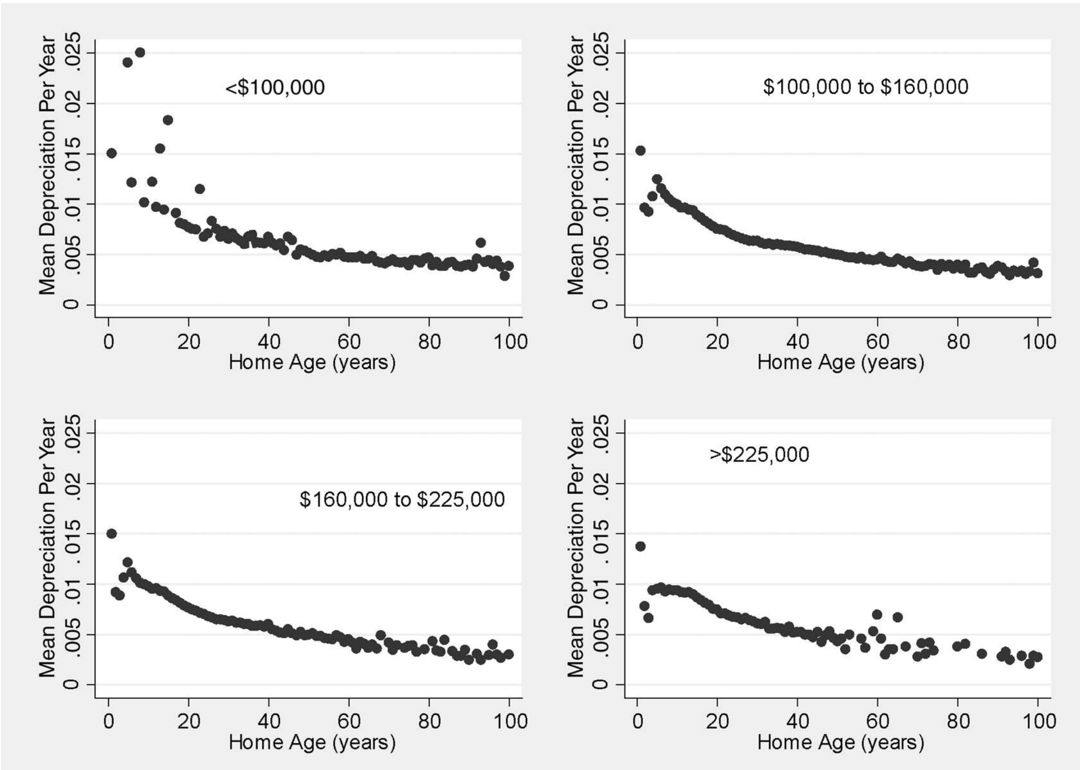
Variable	Para. Est.	Std. Error
Intercept	0.18997	0.00009
AGE	−0.00010	3.44e-07
T_SF	1.32e-07	1.40e-08
COND	−0.00022	2.19e-06
QUAL	−0.00006	2.26e-06
d_1_story	0.00037	0.00002
d_split_bi	0.00101	0.00003
d_2_story	0.01112	0.00114
d_3_story (omitted)		
Total_Value	−6.56e-10	2.12e-10

Notes: There are 47,113 observations. The root mean square error is 0.00129. The adjusted R^2 is 0.73. The F-value is 16,119.

Sarpy County vary substantially with respect to home age and value (Exhibit 3). Similar to the summary findings of Malpezzi, Ozanne, and Thibodeau (1987), average annual depreciation in Sarpy County decreases with age at declining rates with new homes (less than four years old) depreciating at 1% per year, homes 21 to 50 years old depreciating at 0.6% per year, and the oldest homes (>70 years old) depreciating at 0.5% per year (Exhibit 4). This declining depreciation with age is likely a result of older homes receiving periodic upgrades and improvements (i.e., re-modeling efforts) and supports the use of non-linear functional forms to represent age in hedonic price models used to estimate depreciation.

It can also be seen from both Exhibits 2 and 4 that the magnitude at which annual average depreciation declines with age is highly dependent on the home values in question. For example, the lower valued homes (\$100,000) have depreciation rates that vary from 2% (newer homes) to 0.4% (oldest homes), which represents a 500% decrease. This trend is not as strong for other home value classes; for example, those with the highest valued

Exhibit 4. Annual Depreciation by Home Age and Total Home Valuation Classes



homes (>$225,000) that are newest and have an annual depreciation of 0.9% versus 0.3% when they are greater than 70 years old, which represents only a 33% decrease. This justifies the use of quantile regression with regard to home value in the hedonic price models used to estimate depreciation. It also demonstrates that for non-parametric analyses, housing depreciation rates need to be evaluated by both age and value, which has not been done in many past studies. For example, while in general (across all ages of homes) as home values increase, their annual rates of depreciation increase (from 0.5% for lowest valued homes to 0.9% for the highest valued homes). However, this relation does not hold for all classes of home ages. For example, with newer homes depreciation rates decrease substantially (by almost half) as homes age, while only very slight decreases in depreciation with changing home values occurs for homes aged 6 to 20 years old.

Regression Modeling to Quantify the Determinants of Assessor Calculated Depreciation

The results of the regression model to quantify the determinants of assessor calculated annual depreciation are summarized in Exhibit 3. The model provides explanatory power for 73% of the variation in annual depreciation and all of the explanatory variables are statistically significant at the 99% level of confidence and have their expected directional

Exhibit 5. Hedonic Price Model Regression Statistics for Calculating Depreciation

	Linear in Age		Quadratic in Age		Quadratic w/Age/Condition	
Variable	**Para. Est.**	**Std. Error**	**Para. Est.**	**Std. Error**	**Para. Est.**	**Std. Error**
Intercept	10.3664	0.04287	10.38498	0.04234	10.76655	0.02603
T_SF	0.00184	5.10e-06	0.00186	5.03e-06	0.00019	5.09e-06
Garage	0.11812	0.00578	0.10660	0.00582	0.10789	0.00588
d_WALK_BASE	0.03430	0.00689	0.03114	0.00680	0.03081	0.00688
d_FIREP	0.08046	0.00784	0.08659	0.00776	0.0850	0.00784
QUAL	0.02036	0.00089	0.02012	0.00088	0.01995	0.00891
COND	0.01112	0.00114	0.01271	0.00113		
AGE	−0.00657	0.00019	−0.01037	0.00043	−0.00960	0.00042
AGE^2			0.00005	0.00043	0.00004	5.16e-06
AGE_COND25					−0.00170	0.00041
AGE_COND35					0.00179	0.00034
Constant	10.3664	0.04287	10.38495	0.04234	10.76655	0.02603
RMSE	0.1732		0.1709		0.1727	
Adj. R^2	0.82		0.83		0.83	
F-value	2,387		2,158		1,870	

Note: The number of observations is 3,552.

Exhibit 6. Depreciation Results from Alternative Model Specifications

Model	**All Homes**	**<$100k**	**$100–$160k**	**$160k–$225k**	**>$225K**
Assessor (Marshall & Swift)					
Depreciation	0.74%	0.49%	0.68%	0.88%	0.87%
Hedonic Linear					
R^2	0.82	0.28	0.46	0.46	0.56
Depreciation*	0.66%	0.49%	0.68%	0.88%	0.87%
Difference	−11%	−36%	−22%	−43%	+13%
Hedonic Quadratic					
R^2	0.83	0.35	0.47	0.49	0.58
Depreciation*	1.03%	1.28%	0.87%	1.01%	1.58%
Difference	+39%	+162%	+27%	+15%	+82%
Hedonic Quadratic with Age-Condition Interaction					
R^2	0.83	0.33	0.46	0.49	0.56
Depreciation*	0.94%	1.12%	0.73%	1.25%	1.73%
Difference	27%	128%	8%	42%	98%

Note:
*Only statistically significant depreciation results reported.

impacts on depreciation. Omitted explanatory variables suspected to be responsible for 27% of the variation in depreciation remaining unexplained are related to repair/remodeling information that the assessor obtains from building permit data but were not available in the depreciation database.

Age, as expected, has a negative impact on annual depreciation, or alternatively annual depreciation decreases as homes get older. Also as expected, as condition and quality measures increase (improve), depreciation decreases, and similarly, increasing home values are associated with decreasing depreciation. In contrast, larger homes have higher depreciation while all of the three home styles included in the model all positively influence depreciation. The main contribution of this multivariate analysis is to confirm the previously reported non-parametric findings regarding the relationships between depreciation, home age, and value while accounting for a variety of different explanatory variables. These results clearly justify the use of non-linear functional forms to account for home age and to undertake quantile regression by home values when estimating hedonic price models to quantify annual depreciation rates.

Hedonic Price Model Estimates of Annual Depreciation

The first hedonic model specification where depreciation is defined simply as the coefficient on the variable *AGE* generates an R^2 value of 0.82 and an annual depreciation estimate of 0.66 (Exhibit 5). Age and all of the other explanatory variables are statistically significant at the 99% confidence level as impacting sale prices as expected. When the model is run separately for four home value classes (i.e., quantile regression), depreciation estimates range from 0.49% to 0.88%, and are highest among the most highly valued homes (Exhibit 6). The R^2 values of these quantile regressions are markedly lower than the single model for all sales (they range from 0.27 to 0.56), which is most likely due to the relatively small sample sizes of sales in the different home valuation classes. However, the coefficient of *AGE* is statistically significant with all of the models. Overall, across all home values, the hedonic depreciation estimates are 11% lower than the assessor-derived estimates across all homes and these differences range from −43% to plus 13% for the different home value classes.

The quadratic age model specifications have similar R^2 values as the previous age-linear model specification, but depreciation estimates are markedly different (much higher). In fact, overall they are 39% higher than assessor-derived depreciation rates and the range of these differences is 15% to 162% across different home value classes. Finally, the model specifications with age treated as quadratic but with the inclusion of two age-condition interaction variables (age if home condition is below or above average) also have similar R^2 values and depreciation estimates that are lower than the age-quadratic specification, but still markedly higher than the age-linear specification (27% among all homes, and from 8% to 128% across home value classes).

Conclusion

This study demonstrates that tax assessor-generated depreciation estimates based on exterior home inspections and remodeling permit data in conjunction with commonly-used proprietary depreciation approaches are very similar to hedonic price model estimates of depreciation representing buyers/sellers perceptions of how home age and levels of depreciation impact sale prices when age is specified as linear. When quadratic or quadratic-condition interaction specifications are utilized, differences between the assessor and hedonic depreciation results increased. However, since this is the first known study to have compared assessor versus hedonic derived estimates of depreciation, it is considered prudent that the research be replicated in other locations of the country (using depreciation data from different assessors) to confirm these findings.

This research also demonstrates that depreciation estimates based on hedonic modeling or assessor approaches should be segregated across different ages of homes and home values (i.e., quantile regression). Continued research on improving the accuracy of estimating single-family housing depreciation is likely to improve the development of mass appraisal-driven cost approach valuation estimates, which have an important role to play in communities with relatively new housing stock and/or many special use properties, and also in disaster management planning where depreciated replacement cost values need to be estimated for many homes across large geographical areas.

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