A Comparison of Citywide Additive, Multiplicative, and Hybrid Condo Models

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Abstract. The City of Calgary recently commissioned the development of three MRA models for residential property: an additive, a multiplicative, and a non-linear model. One set of models was developed for single-family properties and a second set for condominiums and town homes. The purpose of the project was to compare results from the three approaches to help determine which would provide better accuracy and uniformity in the City=s future valuation efforts. Using all validated sales over a two-year period, citywide MRA models were developed using each of the three modeling approaches. In each case a random sample of sales was selected as a holdout group to objectively test and compare model result using sales ratio statistics.

This paper describes the results of the research effort for condominiums and town homes[1]. While all three modeling approaches achieved good results, the multiplicative model performed best. Of course, each approach can (and will) be improved by developing separate models for property groups stratified on the basis of type and location.

Database, Sales Edits, and Methodology

The database contained 15,662 sales from July 1999 through June 2001. The sales had not been edited to remove or identify invalid transfers and sales prices ranged from $1,000 to $10 billion. The sales were screened electronically in a multi-stage process to remove non-market and invalid transfers to the extent possible. The following sales were removed for purposes of the project:

$ Sales below $35,000 or above $1 million (some of the lower value sales were parking stalls);

$ Duplicate transactions, for which the sale date, price, and all other data were identical;

$ Repeat sales in which the transactions took place within five months of

1 For a discussion of the results for single-family properties, see Robert J. Gloudemans, *A Comparison of Three Residential Regression Models: Additive, Multiplicative, and Hybrid*, Proceedings of the 2002 URISA and IAAO CAMA/GIS Conference, April 2002.

each other;

$ Transfers of commercial condominiums;

$ Transactions for which the current assessment-to-sales ratio was below 0.50 or greater than 1.50 (2.7% of remaining sales).

After removing these sales, the database contained 14,080 sales. Finally, because the relative desirability of neighborhoods was not available, neighborhoods with less than 10 sales were excluded (there were only 85 such sales). The final database contained 13,995 usable sales for analysis. Although some valid transfers were inevitably removed during the electronic editing process and some non-arm=s-length transfers undoubtedly still remained, the edited data provided a sound base for purposes of the project.

To provide a control group to objectively compare results from the three modeling approaches, the database was randomly split into a model and test group.[2] The test group consisted of a random sample of 2,500 parcels from the 13,995 sales available, a sample large enough to thoroughly evaluate results by size, age, and various subgroups of property. The other sales (11,495) were retained in the model group and used to develop the models. Sales ratio statistics were calculated on both the model and test groups.

Each model was developed in a series of steps. First, a Abase@ model was developed using variables for living area, building type, age, community or neighborhood, and sale date. Second, a full exploratory model was developed using all available property characteristics. The final model was produced by purging the model of any variables with unreasonable coefficients, or by combining and weighting variables for similar features. For example, variables for location next to a major street or freeway were combined. When complete, the models were saved and applied to the holdout group and sales ratio analyses conducted on both the model and holdout samples.

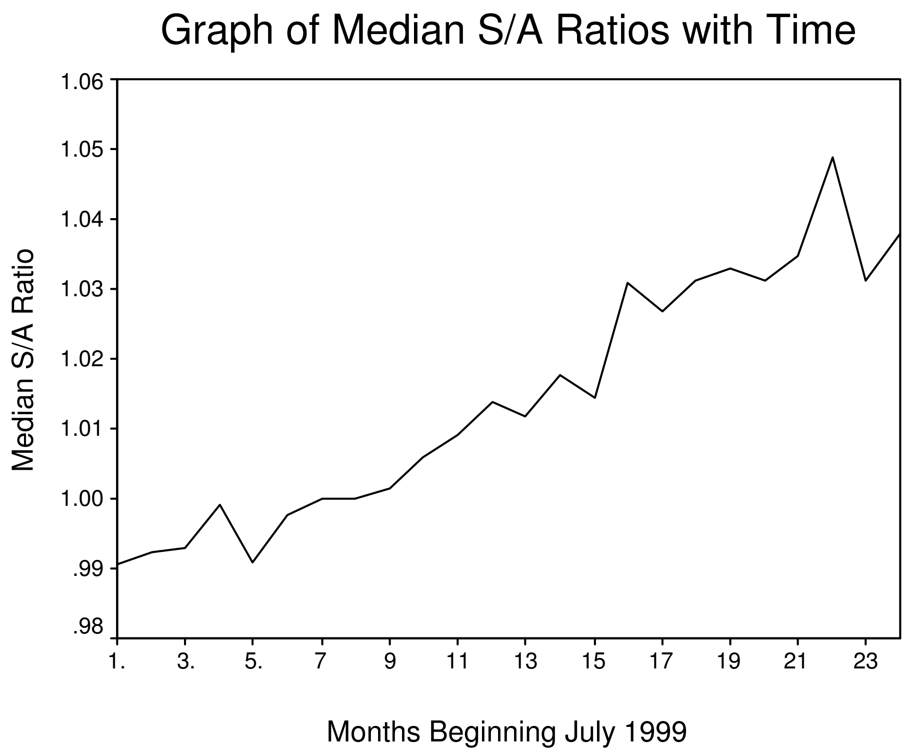
Additive Model

Additive models are easiest to calibrate and the most frequently used in mass appraisal. In an additive model, the contribution of all components is added. Each component can employ transformations (e.g., raising a variable to a power

[2] Without a control group, modeling methods that overly fit or “chase” sales tend to show up as artificially good (location response techniques can be particularly prone in this direction).

or multiplying two variables together), but the contribution of all components is *added*. Thus, adjustments can be expressed on a per-square foot or per-square meter basis (by multiplying a quality variable by a size variable), but percentage adjustments to land, building, or total property values are not feasible.

Graphical analyses showed the relationship between time of sale and price to be approximately linear, as illustrated below by the line graph of median sale-to-appraisal (S/A) ratios with month of sale. Therefore, a single variable, MONTHS (coded 1 to 24), was employed to capture time trends. Two seasonality variables were also created and tested: winter (November through February) and spring/fall (March, April, September, and October). Summer, which includes the base assessment date in Alberta of July1, was held out as the reference period. The model



The first model developed was a "base" model with variables for property type (town homes served as the base), quality/size (one size variable for each quality class), effective age, time, seasonality, and community or neighborhood codes (one typical community served as the base). Experimentation showed that raising the age variable to the .75 power and multiplying by square meters, so as to produce an adjustment per square meter, provided the best fit. The time variable was also best expressed on a per-square meter basis.

Next an exploratory model was developed using all candidate variables. Although the key variables all performed as expected, some secondary size variables, namely a binary variable for 3+ bedrooms and patio/balcony variables, entered with negative coefficients and were removed from subsequent models. The former may reflect economy-of-scale factors, as three or four bedrooms units would tend to be among the largest in terms of living area. In addition to size, quality, and effective age, variables for finished basement area, fireplaces, floor level, view, river, two-story and three-story units (negative adjustment), and separately titled parking were particularly strong, as were many of the community variables.

The model indicated a time trend over the 24-month period of 0.29 percent per month, while the seasonality variables were insignificant. Thus, all sales were adjusted forward to the assessment date (1 July 2001) at the rate of 0.29% per month (sales occurring in June 2001 received a half-month adjustment). For comparability, the same time-adjusted sales prices were used in the multiplicative and hybrid models as well.

Exhibit 1 below shows the final additive model (for brevity, only the last several community code binaries are shown). The appendix provides variable definitions. The dominant variables in the model are the "pseudo-binaries" for the quality classes (fair, average, good, excellent, and luxury), each expressed on a per square meter basis. Many of the property type and location-related variables are also strongly significant.

As shown below, the model produced a median of 1.002 and COD of 8.93. When applied to the test sample of 2,500 sales, these same statistics median were 1.003 and 9.23, respectively. The slight deterioration in the COD reflects the model's slightly better fit to the sales from which it was developed. Although 11,495 sales were used to develop the model, coefficients for community, certain style, and other variables with relatively few sales reflect only those sales. This underscores the importance of maintaining good sample sizes and not creating variables for which too few sales can be expected.

Final Additive Model

RATIO

TEST	N	Median	Mean	Minimum	Maximum	Std. Deviation	COD
.00	11495	1.0020	1.0112	.5181	2.0370	.12140	8.93
1.00	2500	1.0033	1.0120	.5957	1.7501	.12440	9.23
Total	13995	1.0024	1.0114	.5181	2.0370	.12193	8.98

Multiplicative Model

Multiplicative models have several advantages. They readily accommodate percentage adjustments and they efficiently calibrate nonlinearities. Also, because the models are in logarithmic format, the range of the dependent variable is considerably reduced, meaning that more equal weight is given to each property and the influence of outliers is reduced. On the negative side, logarithms are involved, making the math more complex, and inherently additive relationships can be difficult to accommodate. All things considered, multiplicative models would seem particularly well suited to condominiums, since economies-of-scale can be substantial, there are relatively few size variables, and land size is not relevant. Percentage adjustments should adapt well to the range of values and taking logarithms will afford similar weight to each sale, so that the model will not be overly influenced by premium properties.

Secondary size variables (other than living area) were converted to multipliers by dividing them by main living area (SIZETOTL) and adding one. For example, basement area was expressed as the multiplier:

$$1 + \text{BSMTARET}/\text{SIZETOTL}$$

The model then calibrates the exponent for the variable, which would be expected to be greater than zero but less than one. In this case, the exponent calibrated by the final model is .111, meaning that basement area is worth roughly 11 percent as much as main living area. A similar variable for finished basement area has an exponent of .137 (a binary variable for walkout basement was also significant in the final model). Exhibit 2 contains the final multiplicative model (again, for brevity, only several of the community binaries are shown).

Binary variables are readily accommodated in multiplicative models, requiring no additional transformations. For them, the model calibrates associated multipliers. For example, with average construction quality serving as the base, the final model calibrated multipliers of .929 for fair quality, 1.075 for good quality, 1.252 for excellent quality, and 1.759 for luxurious (the multipliers are found by taking the exponential or antilog of the regression coefficient). Similarly, the multiplier for full view (VWF) is 1.085, for complex security (COS) is 1.016, and for commercial, multi-family, or industrial influences is .972.

Age adjustments require conversion to a percent good factor in multiplicative and hybrid models. Age was raised to the .75 power (optimal transformation in the additive models), divided by 100, and subtracted from 1. For example, the initial percent good factor calculated for a 50-year old building is .812 (1 - 50^.75/100). As shown in exhibit 2, the final model calibrated an exponent of 1.624 for the variable, so that units in a 50-year old building would have a final multiplier of .713 (.812^.1.624). Note that in a condominium model, with no separation of land and building values, the depreciation adjustment is applied to the entire property (whereas in a single-family model it would be explicitly applied to the building component).

An examination of exhibit 2 shows that the lead and most important variable in the model is the logarithm of living area (LSIZE). The variable has an associated exponent of .625, indicating considerable economies of scale. The adjustments for low and high rise apartment style condominiums are negative (town homes are the base). Unlike patios and balconies, decks emerge as positive contributors. Value decreases with the number of units in the complex but increases with floor level. End units command a modest 1% premium. The various location influence variables behave as expected. North-facing (EXN) and south-facing (EXS) units show a 2% and 0.7% decrement, respectively. An approximately 5% adjustment is indicated for swimming pools (SWM).

As shown below, the final multiplicative model produces a median of 1.001 and COD of 8.14 for the model group and 1.002 and 8.43 for the holdout group. The CODs are substantially better than those achieved by the additive model (8.93 and 9.23). Exhibit 3 shows graphs of the ratios against key property characteristics for the holdout sample. Horizontal and vertical equity appear very good.

Final Multiplicative Model

RATIO

TEST	N	Median	Mean	Minimum	Maximum	Std. Deviation	COD
.00	11495	1.0008	1.0059	.4689	1.6784	.10913	8.14
1.00	2500	1.0018	1.0059	.5791	1.6350	.11279	8.43
Total	13995	1.0011	1.0059	.4689	1.6784	.10979	8.20

Hybrid Model

Hybrid model combine the best features of additive and multiplicative models, allowing the model builder to specify both additive and multiplicative relationships. There are, however, two drawbacks to hybrid models. First, software is comparatively limited and hybrid models are more difficult to calibrate. In particular, calibration requires an iterative, processor-intensive process. Second, the models do not contain the full range of features and diagnostics available with standard MRA. For example, stepwise options are not available and t-value are not directly reported. Fortunately, SPSS contains a nonlinear MRA module, which was used to specify and calibrate the hybrid models developed for the project.

Because condominiums are not meaningfully decomposable into land and building values and because they contain few size variables, hybrid condominium models are quite similar in structure to multiplicative models, that is, most components constitute *general qualitative* factors that apply to the entire property. The primary difference is in the treatment of secondary size variables: basement areas, garage size, patios, balconies, decks, fireplaces, and swimming pools. These features constitute additive components of a hybrid model, whereas (as previously explained) multipliers were created for them in the multiplicative model. Thus, the contribution of these variables is added together and adjusted for the various quality-related and location variables. In addition, a building size factor (BSIZEFAC) was developed and calibrated for main living area. This factor was computed by dividing living area by 95 (standard size). In the final model, an exponent of -.247 was calibrated for the factor. This implies, for example, that a unit twice as large as the average would have a rate per square meter that was 87% as much (2^-.247 = .870). Similarly, a unit that is three-fourths as large would have a rate per square meter that is 14.2 % higher (.75^-.247 = 1.142). This reflects the usual economy-of-scale factors observed in real estate markets.

The equation produced by the final hybrid model is shown in exhibit 4 (again only the first few community code variables are shown). The base rate is $1,567 per square meter, which is adjusted for size as explained above. To this is added the contributory value of basement finished areas (BDA), walkout basements (WLK), decks (DCKS and DCKC), garage areas, fireplaces, and pools. The sum of the quantitative items is then adjusted for the various qualitative factors, such as age, building type, style, location features, and community codes.

The final hybrid model produces a median of 1.002 and COD of 8.73. When applied to the holdout sample of 2,500 sales, the corresponding statistics are 1.001 and 9.06, respectively. While better than those of the additive model, the CODs fall significantly short of the corresponding CODs of 8.14 and 8.43, respectively, achieved by the multiplicative model. The deterioration is likely attributable to abandonment of the logarithmic base used in the multiplicative models, which gives more equal weight to each sale and avoids fitting high-value sales at the expense of low-value sales when there are few observations for a property feature.

Conclusions

All three models consistently produced median ratios near 1.000 for both the model and test data sets. CODs were as follows:

	Model File	Test File
Additive Model	8.93	9.23
Multiplicative Model	8.14	8.43
Hybrid Model	8.73	9.06

Clearly the multiplicative model produced the best uniformity of the three approaches. There are likely a number of reasons for this. First, the approach develops percentage adjustments for qualitative and location variables, which adapt well to a heterogeneous citywide database. Second, the model efficiently calibrates an economy-of-scale adjustment. Of course, hybrid models also include these features (additive models do not). However, because they utilize logarithms, multiplicative models give more equal weight to each sale, which helps fit better the lower end of the market and tends to improve the COD, in which each sale is afforded equal weight. This may be more of an advantage than has been recognized in the literature. Interestingly, the multiplicative model also produced the best CODs for single-family properties as well (see previous citation), despite the theoretical merits and greater flexibility of hybrid models. Finally, apparently multiplicative models sacrifice little (if anything) in treating secondary size variables (basements, garages, etc.) as multipliers through ratio variables.

Some of these advantages will be ameliorated when sales are stratified by type (town home versus condominium) and location. Still, the general advantages will persist and should be recognized in determining modeling strategies. Although there is some added complexity in the mathematics of multiplicative models, gaining the required proficiency (which is not formidable) may well be worth the effort.

Finally, while the results achieved here are clearly very good, better results can be achieved once town homes and condominiums are stratified and separate models developed (Calgary uses stratified models for actual valuation purposes). Clearly the value of living area will differ geographically and different amenities are more important in some areas than in other. Waterfront influence, for example, can differ among areas of a city - both on an absolute *and* percentage basis. Thus, while a multiplicative model is probably the best choice for a single "global" model for condominiums and town homes, one can likely improve equity further by developing several appropriately stratified models (regardless of model structure.

Exhibit 1 - Final Additive Model

Model: 28

R		R Square	Adjusted R Square	Std. Error of the Estimate
MODEL = 1.00 (Selected)	MODEL ~= 1.00 (Unselected)			
.941	.930	.886	.885	19279.76753

Model: 28

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	71486.200	1606.085		44.510	.000
LOWRISE	-19325.018	1306.117	-.164	-14.796	.000
HIRISE	-30619.897	1695.063	-.178	-18.064	.000
RENT_OWN	20390.208	3015.180	.028	6.763	.000
CMB	8613.995	3687.507	.007	2.336	.020
SAD	10325.198	1568.565	.026	6.583	.000
PST	12661.102	878.053	.093	14.420	.000
AMENUNIT	4058.538	1615.635	.010	2.512	.012
FEE_SIMP	8383.498	1711.364	.019	4.899	.000
CDO4PLEX	-4167.884	1819.032	-.008	-2.291	.022
PLEX2_SS	3295.756	1130.098	.014	2.916	.004
DETACHED	19059.186	4530.611	.014	4.207	.000
STACKED	-9729.177	1104.093	-.040	-8.812	.000
BMT_UNIT	-24760.948	7535.718	-.011	-3.286	.001
PENTHSE	54663.941	4289.452	.043	12.744	.000
SPLIT	-17473.047	1769.276	-.041	-9.876	.000
STY_15	-28907.101	6231.568	-.015	-4.639	.000
STY2_25	-16843.656	930.971	-.143	-18.093	.000
STY_3	-30031.482	1668.096	-.075	-18.003	.000
FAIR_SM	948.311	27.642	.169	34.307	.000
AVE_SM	1035.216	13.688	.845	75.630	.000
GOOD_SM	1146.332	11.389	1.101	100.651	.000
EXC_SM	1448.868	11.998	.729	120.763	.000
LUX_SM	2357.110	20.506	.424	114.949	.000
BED1	-3624.014	604.457	-.023	-5.995	.000
BSMTAREA	43.101	12.184	.023	3.538	.000
WLK	4836.828	975.451	.019	4.959	.000
BDA	200.301	14.639	.060	13.683	.000
DCKS	1617.364	675.003	.011	2.396	.017
DCKC	4410.141	1079.492	.016	4.085	.000
FPL	4997.098	443.480	.048	11.268	.000

Coefficients[a,b]

Model: 28

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
AGE75SM	-23.404	.806	-.193	-29.028	.000
UNITS	-38.594	3.563	-.053	-10.833	.000
FLOOR	1713.065	118.782	.075	14.422	.000
ENDUNIT	1207.076	623.984	.007	1.934	.053
ELV	4411.089	840.415	.037	5.249	.000
EXN	-1639.395	609.938	-.010	-2.688	.007
EXW	1791.330	673.678	.009	2.659	.008
VWF	16351.813	1085.514	.059	15.064	.000
VWP	3354.847	1565.597	.007	2.143	.032
RIV	35043.477	2568.935	.047	13.641	.000
RIP	23941.342	5246.712	.015	4.563	.000
BIK	13408.081	2799.936	.017	4.789	.000
LRT	-15115.780	6284.965	-.008	-2.405	.016
CMI	-4022.240	1134.576	-.012	-3.545	.000
TRAFF_MF	-3607.325	750.753	-.016	-4.805	.000
COS	3749.794	886.826	.018	4.228	.000
SWM	13481.762	1026.085	.055	13.139	.000

a. Dependent Variable: TASP

b. Selecting only cases for which MODEL = 1.00

Exhibit 2 - Final Multiplicative Model

Model: 22

R				
MODEL = 1.00 (Selected)	MODEL ~= 1.00 (Unselected)	R Square	Adjusted R Square	Std. Error of the Estimate
.946	.940	.895	.894	.10914

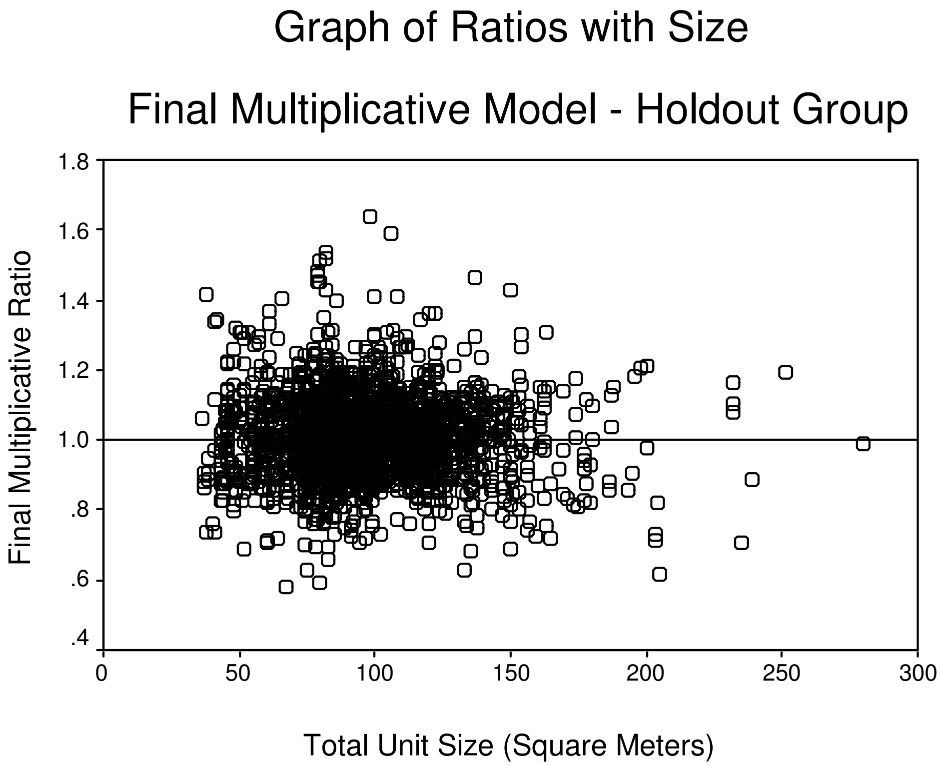
Model: 22

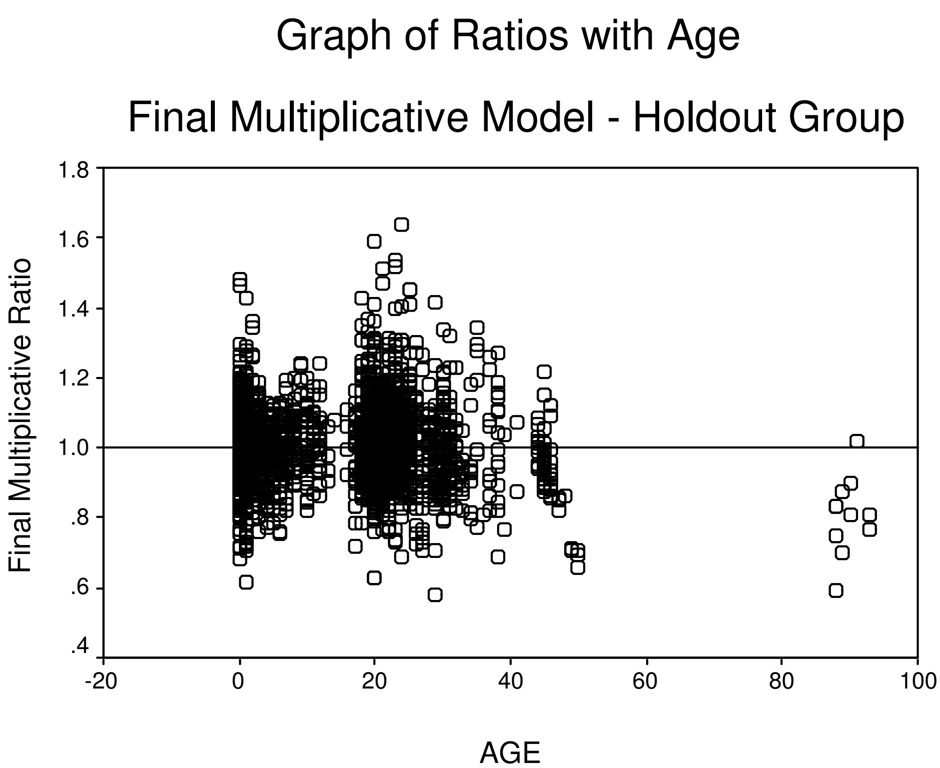
	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
(Constant)	9.123	.031		297.576	.000
LSIZE	.625	.007	.533	95.481	.000
LOWRISE	-.074	.009	-.106	-8.382	.000
HIRISE	-.138	.011	-.136	-12.825	.000
RENT_OWN	.204	.017	.047	11.883	.000
RENT_SYN	.041	.024	.005	1.753	.080
SAD	.069	.009	.029	7.736	.000
PST	.081	.005	.102	16.037	.000
Q_FAIR	-.074	.011	-.026	-6.937	.000
Q_GOOD	.072	.004	.103	19.298	.000
Q_EXC	.225	.010	.129	22.887	.000
Q_LUX	.565	.022	.094	26.145	.000
AMENUNIT	.028	.009	.012	3.020	.003
FEE_SIMP	.053	.010	.021	5.496	.000
PLEX2_SS	.028	.006	.020	4.296	.000
PLEX2_BB	-.049	.010	-.017	-4.970	.000
DETACHED	.111	.026	.014	4.324	.000
STACKED	-.059	.007	-.041	-8.734	.000
BILEVEL	.098	.011	.043	9.223	.000
BMT_UNIT	-.185	.043	-.014	-4.351	.000
PENTHSE	.123	.024	.016	5.057	.000
SPLIT	-.068	.010	-.027	-6.601	.000
STY_15	-.109	.035	-.010	-3.065	.002
STY2_25	-.078	.006	-.113	-13.427	.000
STY_3	-.134	.010	-.057	-13.868	.000
BED1	-.015	.004	-.017	-4.275	.000
LBSMTRAT	.111	.011	.071	10.465	.000
LBFINRAT	.137	.012	.055	11.664	.000
WLK	.017	.006	.011	3.158	.002
DCKS	.008	.004	.010	2.164	.030
DCKC	.024	.006	.015	3.951	.000
LGARRAT	.194	.021	.052	9.272	.000
LLINFP	.545	.053	.043	10.308	.000

Model: 22

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
LPCTGOOD	1.624	.047	.244	34.797	.000
LUNITS	-.020	.002	-.056	-11.201	.000
LFLOOR	1.066	.072	.074	14.795	.000
ENDUNIT	.010	.004	.010	2.708	.007
IRC	-.017	.005	-.011	-3.213	.001
ELV	.040	.005	.057	8.355	.000
DUM	-.016	.008	-.006	-1.894	.058
EXN	-.020	.004	-.020	-5.451	.000
EXS	-.007	.004	-.007	-1.857	.063
VWF	.082	.006	.050	13.579	.000
GLF	.041	.018	.008	2.283	.022
RIV	.158	.014	.036	10.927	.000
RIP	.140	.030	.015	4.735	.000
LAK	.135	.064	.007	2.097	.036
BIK	.047	.016	.010	2.972	.003
LRT	-.123	.036	-.011	-3.433	.001
CMI	-.028	.006	-.014	-4.344	.000
TRAFF_MF	-.023	.004	-.018	-5.500	.000
COS	.016	.005	.013	3.261	.001
SWM	.050	.006	.034	8.491	.000
COMM_ABB	-.356	.034	-.033	-10.566	.000
COMM_ACA	-.142	.009	-.062	-15.837	.000
COMM_ALB	-.334	.029	-.036	-11.574	.000
COMM_ALT	-.076	.012	-.024	-6.358	.000
COMM_ARB	-.190	.013	-.052	-14.907	.000

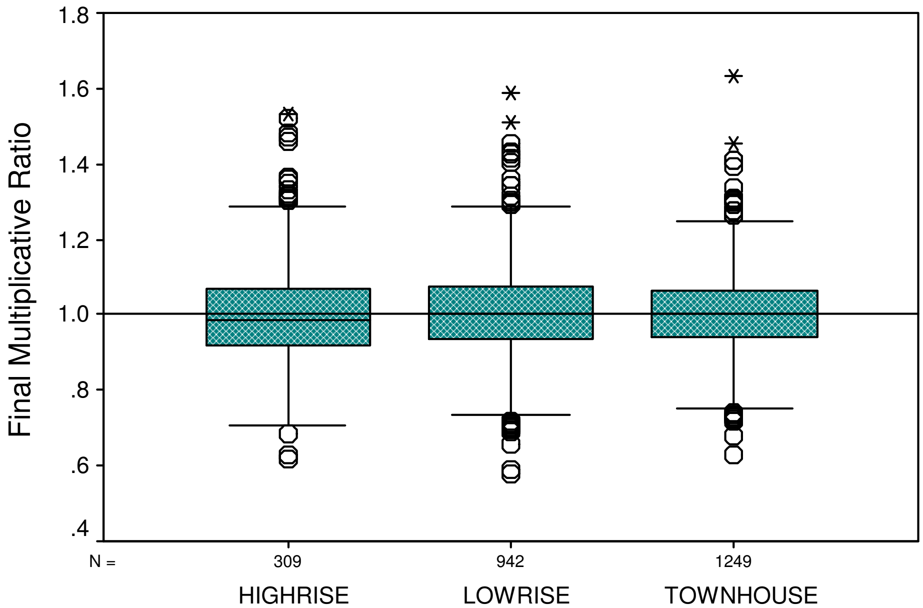
Exhibit 3 – Plots of Multiplicative Ratios (Holdout Group)





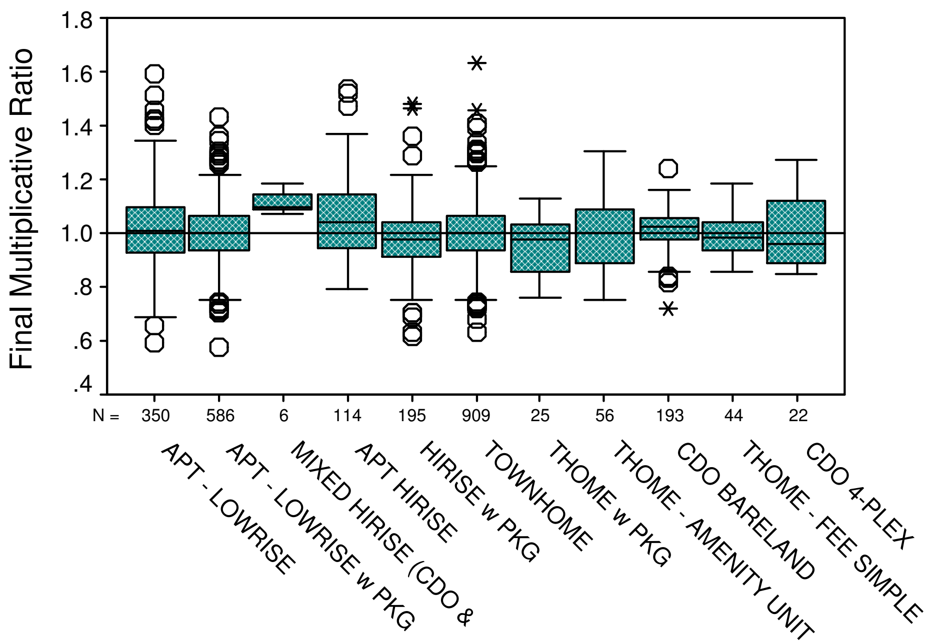
Box Plot of Ratios with Property Type

Final Multiplicative Model - Holdout Group



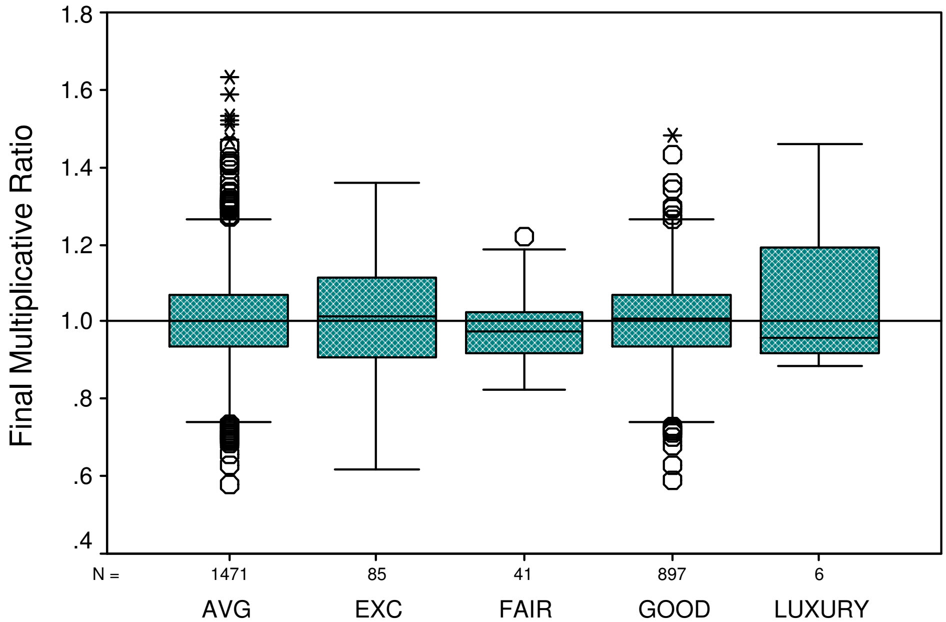
Box Plot of Ratios with Use Code

Final Multiplicative Model - Holdout Group



Box Plot of Ratios with Quality

Final Multiplicative Model - Holdout Group



Graph of Ratios with Value

Final Multiplicative Model - Holdout Group

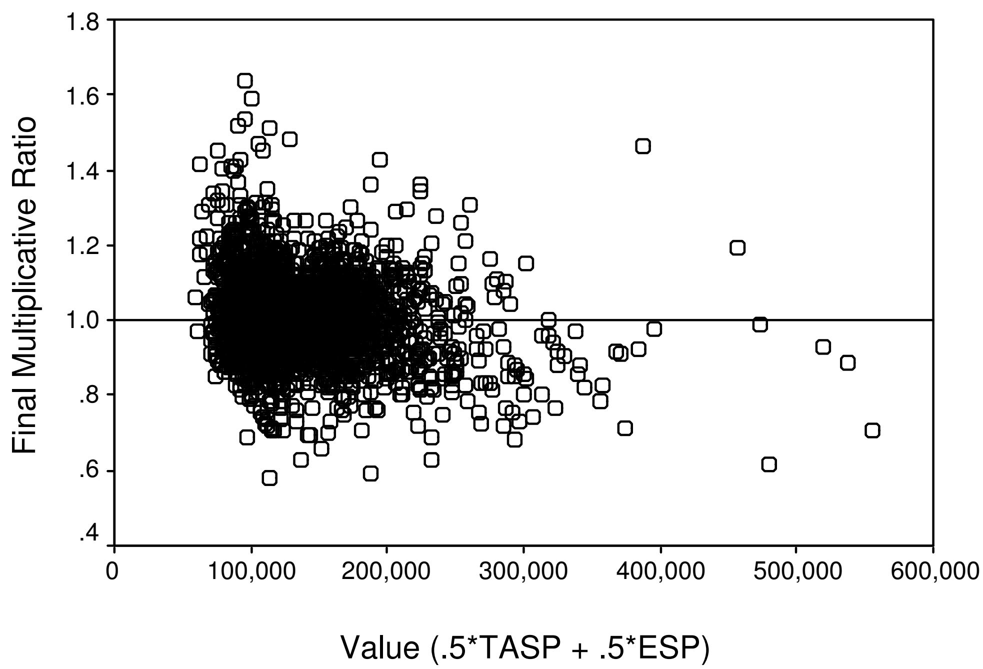


Exhibit 4 - Final Nonlinear Model

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COMPUTE ESP_HYBD= (1567.077*SIZETOTL *
BSIZEFAC**-.24433
+      77.37748   *    BSMTAREA
+      236.3957   *    BDA
+      3657.723   *    WLK
+      3600.757   *    DCKS
+      4573.324   *    DCKC
+      201.3123   *    GARSIZE
+      4932.634   *    FPL
+      7692.388   *    SWM) * PCTGOOD**1.49028
*        .98300   **   LOWRISE
*        .95278   **   HIRISE
*       1.17759   **   RENT_OWN
*       1.02010   **   RENT_SYN
*       1.06469   **   SAD
*       1.08257   **   PST
*        .92834   **   Q_FAIR
*       1.06473   **   Q_GOOD
*       1.27197   **   Q_EXC
*       1.80675   **   Q_LUX
*        .98650   **   BARELAND
*       1.07014   **   FEE_SIMP
*       1.01888   **   MULTI_BB
*       1.02396   **   PLEX2_SS
*        .96503   **   STACKED
*        .95961   **   THREE_LV
*       1.19194   **   BILEVEL
*        .82979   **   BMT_UNIT
*       1.15212   **   PENTHSE
*        .91994   **   SPLIT
*        .86496   **   STY_15
*        .93129   **   STY_2
*        .89062   **   STY_3
*       1.00818   **   FLOOR
*       1.01293   **   ENDUNIT
*        .98532   **   IRC
*       1.03401   **   ELV
```

*	.97554	**	DUM
*	.98470	**	EXN
*	.98515	**	EXS
*	1.01680	**	EXW
*	1.09139	**	VWF
*	1.01466	**	VWP
*	1.04616	**	GLF
*	1.01712	**	GRN
*	1.10017	**	RIV
*	1.12206	**	RIP
*	1.13477	**	LAK
*	1.07529	**	BIK
*	.85470	**	LRT
*	.98425	**	CMI
*	.98674	**	TRC
*	.96257	**	TRAFF_MF
*	1.02897	**	COS
*	UNITS60	**	-.02735
*	.71827	**	COMM_ABB
*	.88942	**	COMM_ACA
*	.70764	**	COMM_ALB
*	.87169	**	COMM_ALT
*	.83941	**	COMM_ARB

Appendix
Variables Used in Models

Additive Model Variables

LOWRISE	Binary variable for low-rise (town homes were the base)
HIRISE	Binary for high-rise
RENT_OWN	Binary for single-owner rental complex
CMB	Binary for combined unit
SAD	Binary for senior adults only
PST	Binary for parking stall included in price
AMENUNIT	Binary for amenity unit
FEE_SIMP	Binary for fee simple ownership
CDO4PLEX	Binary for 4-plex
PLEX2_SS	Binary for side-by-side duplex
DETACHED	Binary for detached unit
STACKED	Binary for stacked unit
BMT_UNIT	Binary for basement unit
PENTHSE	Binary for penthouse unit
SPLIT	Binary for split level design
STY_15	Binary for 1.5 stories
STY2_25	Binary for 2 and 2.5 stories
STY_3	Binary for 3 stories
FAIR_SM	Square meters of fair quality units (else 0)
AVE _SM	Square meters of average quality units (else 0)
GOOD_SM	Square meters of good quality units (else 0)
EXC _SM	Square meters of excellent quality units (else 0)
LUX _SM	Square meters of luxury quality units (else 0)
BED1	Binary for one-bedroom units
BSMTAREA	Basement area (square meters)
WLK	Binary for basement walkout
BDA	Basement developed (finished) area (square meters)
DCKS	Standard decks (count)
DCKC	Custom decks (count)
FPL	Fireplaces (count)
AGE75SM	Age to the .75 power x square meters of living area
UNITS	Number of units in complex
FLOOR	Floor level of unit
ENDUNIT	Binary for end unit
ELV	Binary for elevator complex
EXN	Binary for northern exposure
EXW	Binary for western exposure
VWF	Binary for full view
VWP	Binary for partial view
RIV	Binary for facing river
RIP	Binary for facing river park

BIK	Binary for bike path
LRT	Binary for light rapid transit
CMI	Binary for commercial, multi-family, industrial influence
TRAFF_MF	Binary for major road or freeway traffic
COS	Binary for compound security
SWM	Binary for swimming pool

Multiplicative Model Variables (not included in additive model)

LSIZE	Natural log (LN) of living area
Q_FAIR	Binary variable for fair quality
Q_GOOD	Binary variable for good quality
Q_EXC	Binary variable for excellent quality
Q_LUX	Binary variable for luxury quality
LBSNTRAT	LN (1 + BSMTAREA/SIZETOTL)
LBFINRAT	LN (1 + BDA/SIZETOTL)
LGARRAT	LN (1 + GARSIZE/SIZETOTL)
LLINFP	LN (linearized fireplaces)
LPCTGOOD	LN (1 – AGE^.75/100)
LUNITS	LN (UNITS/60)
LFLOOR	LN (1 + FLOOR/100)
IRC	Binary for interior units
GLF	Binary for golf course
LAK	Binary for lake
DUM	Binary for dumpster

Hybrid Model Variables (not included in additive model or multiplicative models)

BSIZEFAC	SIZETOTL/95
BARELAND	Binary for bare land condos
MULTI_BB	Binary for multi-family back-to-back units
PLEX2_SS	Binary for duplex side-by-side units
THREE_LV	Binary for three level units
EXS	Binary for southern exposure
EXW	Binary for western exposure
GRN	Binary for green space
TRC	Binary for collector street