Market Calibration of "Cost" Models

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IAAO and URISA Conference
Integrating CAMA and GIS

February 15-18, 2005
Savannah, Georgia

Abstract

Although the benefits of regression analysis and market modeling are well known, a practical limitation of high concern to potential users is how to interface models, once developed, into their Computer Assisted Mass Appraisal (CAMA) systems. How do jurisdictions that have used the cost approach in the past interface models developed with SPSS or other statistical packages into their cost-oriented CAMA systems? This paper will demonstrate how the District of Columbia successfully addressed this issue to implement a highly improved and accurate valuation system.

Like many jurisdictions, the District has utilized a combination of the cost approach and market trending for the appraisal of residential properties. The District's CAMA software, *Appraisal Vision*® by Vision Appraisal Technology, contains the cost approach and an interface with SPSS for modeling. While the District desired to implement MRA, it also wanted to maintain its familiar cost structure, both for value explanation purposes and in order to avoid system modifications or reprogramming. However, the District's cost models are "hybrid" models that contain a combination of rates, size and depreciation curves, and multipliers and therefore cannot be calibrated by traditional additive or multiplicative MRA.

Undeterred, the District used SPSS's "Nonlinear" MRA procedure to calibrate their cost structure using sales data in what can be called a fully "market calibrated cost model". Although somewhat more complex, nonlinear MRA permits the user to calibrate virtually any model structure, thus supporting more sophisticated (complex) model structures and, importantly, fit models to a desired structure (rather than vice versa). Introduction of market calibrated cost models allowed the District to improve model performance and valuation accuracy without modifying its current CAMA system and without additional software or programming costs.

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Acknowledgments: the authors wish to acknowledge the support and encouragement of Thomas W. Branham, Chief Assessor within the Government of the District of Columbia, who has spearheaded the various technological and methodological improvements achieved in the District over the past several years. Without his leadership, vision, and on-going support, this paper would not have been possible.

1. Background

The District of Columbia's assessment process has undergone a number of major changes in recent years. Prior to the tax year (TY) 2002 reassessment, the District was on a three-year reappraisal cycle. Before the adoption of this "triennial" cycle, the District primarily utilized market trending for many years. Beginning with the TY 2002 reassessment (which was conducted during calendar year 2000), the District began transitioning to an annual cycle. One-third of the District (Tri-group 1) was reassessed that year, two-thirds (Tri-groups 1 and 2) the following year, and all properties were reassessed in 2002 for TY 2004. This, of course, necessitated increased workloads and market analysis.

At the same time the District implemented new CAMA software (*Appraisal Vision*®) and a series of related technical advances, including GIS, digital property images and sketches, and aerial oblique photography.

Appraisal in the District has always been challenging. Many properties are very old and have either become dilapidated or, at the other extreme, have undergone complete renovations. Values vary greatly over short distances and neighborhoods are in constant flux and transition. Because some of the oldest properties are in the best locations, there is an overall negative correlation between year built and price: the older the year built, the higher the value (at least on average). What's more, since 2000, the market in the District has been among the hottest in the country, with residential values rising well in excess of 1% per month over the past 5 years. Values that increased at historically high rates one year and were expected to top out the next have continued to go up at least as much the following year.

Through TY 2003 the District had appraised residential properties through a combination of the cost approach and trend factors. The cost approach had become increasingly strained as costs and market prices grew increasingly out of sync, and depreciation became increasingly hard to estimate. In addition, there are virtually no vacant land sales from which to develop land values.

In order to better reflect the market and improve valuation accuracy, the District began to examine the use of multiple regression analysis (MRA). Although pilot additive and multiplicative models both yielded improved results (particularly the latter), a traditional implementation of such models was eschewed in favor of a hybrid cost model structure for several reasons:

- *Appraisal Vision®* interfaces with SPSS and supports additive MRA; however, the District desired a more complex hybrid model reflective of the current cost structure, which was considered both sound and flexible.
- Assessors were familiar with cost valuation, but were less comfortable with MRA.
- The District assessment staff was growing accustomed to using the new system and its table-driven cost approach.
- Finally, the public understands the cost approach.

If only MRA, with all of its analytical power and efficiency, could be used to calibrate the District's cost model!

2. Nonlinear Regression

Nonlinear regression analysis (NLR) held the solution. Basically, NLR is a regression methodology for calibrating hybrid models consisting of both additive and multiplicative components. All cost models are hybrid in structure: some components are added and some are multiplied. Further, relationships are often nonlinear, that is, follow curves rather than straight lines (e.g., size adjustments and depreciation curves). Unlike additive and multiplicative MRA, NLR will calibrate virtually any hybrid structure as long as it is well formulated (high multicollinearity can cause problems). SPSS NLR (contained in the add-on Regression Models to SPSS) was used to calibrate the District nonlinear models.

In building an NLR model, the model builder first writes the equation being calibrated in terms of (a) variables and (b) coefficients. The variables must exist in the database; the coefficients are assigned temporary names. Here is a simple example of an NLR model:

SP = lrate*LSQFT * LSIZ_FAC^lsiz_exp + brate * SFLA * (1-EFFAGE/200)^age_exp

where LSQFT = land size, LSIZ_FAC = land size/median land size, SFLA = living area, and EFFAGE = effective age. Variables are in capital letters and coefficient names are in lower case. Provided the variables are resident on the working data file and the statement is syntactically valid, SPSS will calibrate the model and return values for the coefficients based on the usual regression criteria of least squares. The resulting model might look as follows (although actual results are displayed in table format as will be illustrated shortly).

SP = 18.50*LSQFT * LSIZ_FAC^-.525 + 72.94 * SFLA * (1-EFFAGE/200)^.344

Notice that the model has no constant (although the model builder could optionally add one), so that the value is decomposable into its land and building portions. In this case, the model indicates economies-of-scale for lot size, e.g., the base land rate of $18.50 falls as properties increase in size relative to the median size. Also, the multiplier for percent good (1-EFFAGE/200) is dampened, e.g., the indicated multiplier for a property with an effective age of 50 years is .75^.344 = .906.

Of course, real world examples are much more complex, employing many more variables and coefficients. NLR is similar to "feedback" in that the algorithm must be calibrated by an iterative process (we found 10 to 30 iterations to be typical). However, NLR differs from feedback in the following ways:

- Being regression, it is calibrated based on minimization of the squared (not absolute) errors;
- The calibration algorithm is standard rather than proprietary, so that different statistical programs will generate the same results for the same data set;
- Variables are not categorized as building or land or as additive or multiplicative (although such distinctions are implicit in the model);
- No prior structure is imposed - one can formulate and calibrate any equation that makes valuation sense.

Unfortunately, like feedback, NLR produces limited diagnostics. It reports an R-squared value and standard error and confidence intervals for the regression coefficients, but not the standard error of estimate or t-values. In addition, stepwise options are not available. Predicted values can be saved and analyzed with traditional ratio statistics and graphs.

3. The District's Market-Calibrated Cost Approach

3.1 Data Extracts and Conversion to SPSS

The first step in implementing our new approach was to extract the necessary sales and property characteristics from the CAMA database. Three files were extracted:

- Regression extract file. *Appraisal Vision*® software has a facility for extracting selected data to an SPSS data file. The procedure works well for numeric data and automatically decomposes various "sub-area" fields (such as basement, main, and upper floor areas) that are carried as "codes" (e.g., BAS or UBM) and associated number of "units" (usually square feet) to separate fields in SPSS. Three lines of tabular data such as this…

Code	Description	Gross Area	Effect.Area	Living Area
FUS	Upper Story, Finished	795	795	795
BAS	Main Building Area	795	795	795
UBM	Basement, Unfinished	795	199	0

  …are easily converted to a single case in SPSS…

pid	bas	fus	ubm
7489	795.00	795.00	795.00

- Supplemental text and sale date file. The above facility does not provide for exporting date fields and it automatically extracts text variables to SPSS as binaries (since some District grade designations contain alpha characters, they could not be extracted as numeric). These data fields were extracted as a text file for import to SPSS.

- Extra features file. Unlike "sub-areas", the CAMA software does not decompose extra features (such as detached garages) into separate data fields. Extra features and outbuildings were also extracted in text format, read into, and normalized in SPSS (one column per attribute).

SPSS syntax was written to aggregate the data from the regression facility extract with the data from the two text files.

3.2 Replication of Cost Model

In order to calibrate the CAMA software's cost structure, it was imperative to ensure that the NLR formula correctly replicates the cost model's algorithms as implemented in the District. This requires precise understanding of how the cost model works, something often taken for granted by users of cost systems. Except for several unimportant nuances, the District's cost system has the structure shown in Exhibit 1.

[Insert Exhibit 1 about here]

LV = LandRate * Adj_Fact * LotSize * LSizeFac (Note: one LandRate per NBSub)

Adj_Rate = (BaseRate + Ext_Adj + Roof_Adj + Floor_Adj + Heat_Adj + Cool_Adj) * BsizeFac

RCN = (Adj_Rate*Eff_Area + BathRate*Baths + FP_Rate*FP + BsmtRate*Bsmts + PorchRate*Porches) * GradeFac * NbSubFac

TV = LV + RCN*PerGood*Reno_Fac*Cond_Fac + OXF_Value

evaluate market relationships, determine candidate regression variables, and flag outliers. Exhibit 2 contains a list of property characteristics available for potential use, all of which were used in the existing cost model. We determined to evaluate which were significant in the District market and potentially eliminate those that were not, provided they were not considered essential in value explanations. In exhibit 2, asterisks indicate those variables that proved significant in models and were calibrated by NLR. The symbol "c" indicates variables that were constrained based on cost tables; they were not modeled.

[Insert Exhibit 2 about here]

3.4 Preliminary Models

As mentioned, NLR does not support stepwise modeling procedures and, because it operates on an iterative basis, takes much longer to run than conventional MRA (a typical run with 5,000 sales and 100 variables may take several to10 minutes depending on computer processing speeds). Accordingly, we used multiplicative regression analysis to determine the final variable set, as well as to develop time adjustments. The model for the TY 2006 used sales from January 2002 through July 2004. Exhibit 3 below shows the final multiplicative model (for exposition, only the first five NBHDs are shown; variables that begin with an "L" are logarithms).

[Insert Exhibit 3 about here]

3.5 NLR Models

Exhibit 4 below shows the SPSS syntax used to run the initial NLR model (only the first five neighborhoods are shown). The first part of the syntax shows the names and starting values for each coefficient. The model uses these values in its initial iteration and subsequently refines them in order to calibrate the optimal model in terms of minimizing the squared errors (differences between actual and predicted values). In the third paragraph the modeler declares the dependent variable (TASP), assigns a name to the predicted values (which are saved to the data file), and sets the convergence criteria, including maximum number of iterations.

[Insert Exhibit 4 about here]

Exhibit 5 shows the output produced by the initial NLR model. The model converges after 26 iterations and produces an R-square of .957. Notice that the output includes the coefficient, standard error, and 95% confidence intervals for each variable. Many of the coefficients (such as those for neighborhoods, grades, and condition) are multipliers or factors. Many others are per-square-foot rates. Some, such as those for bathrooms and fireplaces, are dollar amounts. Still others (those ending in "exp") are exponents that calibrate size adjustment curves, in which case the negative values indicate economies of scale. Sales ratio statistics are shown at the bottom of the exhibit.

[Insert Exhibit 5 about here]

As with any model, results were evaluated and a number of variables modified or constrained. Constraints can be included in an NLR model by simply hard-coding the coefficient (rather than adjusting the dependent variable as in additive and multiplicative models). Even with these constraints, the final NLR model produced a COD of 11. 4, the same as the initial model.

3.6 "Predict" Statement

Although the model has been completed at this point and sales ratios run on the predicted values, it is good practice to write syntax, known to SPSS users as a "Predict Statement", to reproduce the transformations and final model algorithm. The Predict statement can be run standalone without rerunning the model to produce the same results. It shows all required calculations and ensures that everything is correct and accounted for. It also allows the modeler to modify the algorithm, e.g., to change a coefficient or to smooth adjustments for the various values of an attribute, such as grade or condition. If sales ratio analyses reveal a potential problem, e.g., a neighborhood is out of line, often the problem can be addressed and ratios rerun without rerunning the model.

Exhibit 6 contains the complete Predict Statement for the TY 2006 residential model (again, syntax for other than the first five neighborhoods has been suppressed). It shows exactly how values are calculated and allows any modifications to be simulated and tested. Refinements made in the Predict Statement lowered the COD marginally to 11.3 (good results in a heterogeneous, urban market such as the District of Columbia).

[Insert Exhibit 6 about here]

3.7 Interface with the CAMA Cost Tables

The final step is to update the CAMA tables with the new rates and factors established during the modeling process. Specifically, this includes updating the land and building base rates, size and depreciation adjustments, various additions to the base rates, multipliers, and unit-in-place adjustments. In some cases, Excel algorithms have been written to convert curvilinear adjustments developed by NLR to the series of discrete adjustments required by the cost system. It is also beneficial to replace tedious, manual data entry with electronic updates using ODBC and tables derived from the SPSS output.

Of course, once the necessary updates have been accomplished, properties can be "costed" for valuation purposes. Exhibit 7 shows an example of a cost printout produced by the system.

[Insert Exhibit 7 about here]

4. Progress and Future Applications

The District began using market-calibrated cost models in 2002 for TY 2004 and has now completed its third successive annual revaluation using this approach. Improvement has been steady as experience is gained, complementary technologies are introduced, and data quality is improved. The COD for residential properties has improved substantially over each of the last three years. Seventy percent of residential properties were modeled for TY 2006 and the percentage will grow as additional properties are inspected and converted from a trending approach.

The District has also used MRA to value its considerable inventory of residential condominiums (almost 40,000 units) over the last three years. The market for condominiums has been active and the inflation rate even higher than observed for other residential properties. Over 8,000 sales were available for calibration of the TY 2006 model. A direct, multiplicative model is used for condominiums (no attempt is made to replicate a cost approach).

As time permits, the District is also pursuing modeling of various commercial properties. We have already developed pilot models for apartments and warehouse properties.

Exhibit 1 - Washington, D.C. Cost Structure

LV = LandRate*Adj_Fact*LotSize*LSizeRat**LSiz_Exp (Note: one LandRate per NBSub)

Adj_Rate = (BaseRate+Ext_Adj+Roof_Adj+Floor_Adj+Heat_Adj+Cool_Adj)*BsizeFac

RCN = (Adj_Rate*Eff_Area+BathRate*Baths+FP_Adj*FP)*GradeFac*Wall_Fac*NBSubFac

TV = LV + RCN*PerGood*Reno_Fac*Cond_Fac + OXF_Valu

Exhibit 2 - Characteristics Tested in Model Development

- Property type: detached, town/row home, duplex, 2-4 family, 2-4 unit conversion (*)
- Grade (*)
- Year built (*)
- Remodel type and year (*)
- Interior, exterior, and overall condition (*)
- Stories (c)
- Exterior wall(c)
- Roof (c)
- Floor (c)
- Heat and air conditioning (c)
- Kitchens
- Full and half baths (*)
- Extra bath fixtures
- Fireplaces (*)
- Pool (*)
- Kitchen style (c)
- Bathroom style (c)
- Lot size (*)
- Main and upper floor living areas (*)
- Finished and unfinished basement areas (*)
- Attached, detached, and basement garage areas (*)
- Open, screened, glass, and finished porch areas (*)
- Deck and patio areas (*)
- Cost value of other miscellaneous features and outbuildings (c)
- Land/site adjustments (a)

Note: * = calibrated from models; (c) = constrained based on cost; (a) = appraiser-determined

Exhibit 3 - Final Multiplicative Model

Model Summary

Model: 14

R	R Square	Adjusted R Square	Std. Error of the Estimate
.982	.965	.964	.14398

Model: 14

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
(Constant)	9.544	.064		148.923	.000
LLSZ2000	.105	.005	.098	19.711	.000
LEFFSQFT	.415	.008	.216	49.093	.000
SFD	.065	.007	.039	8.887	.000
SM_APT	-.190	.010	-.059	-18.583	.000
Q10	-.253	.062	-.010	-4.099	.000
Q20	-.049	.015	-.010	-3.273	.001
Q35_40	.036	.007	.018	5.232	.000
Q45_50	.063	.009	.034	7.034	.000
Q55_60	.103	.010	.049	10.423	.000
Q65_70	.170	.011	.065	15.222	.000
Q75	.194	.016	.041	11.968	.000
Q80	.249	.015	.063	17.029	.000
Q85	.334	.019	.056	17.557	.000
Q90	.389	.021	.054	18.667	.000
Q95	.388	.028	.035	13.810	.000
Q100	.525	.038	.033	13.762	.000
Q105	.568	.058	.023	9.801	.000
Q110	.508	.061	.019	8.302	.000
Q120	.666	.049	.032	13.673	.000
LPERGOOD	.050	.025	.008	2.039	.041
COND_1	-.199	.023	-.019	-8.534	.000
COND_2	-.123	.011	-.027	-11.203	.000
COND_4	.097	.005	.056	21.114	.000
COND_5	.159	.007	.071	24.452	.000
COND_6	.199	.012	.050	16.985	.000
LBATHFAC	.724	.059	.049	12.232	.000
FP	.022	.002	.027	8.784	.000
POOL	.085	.015	.013	5.626	.000
LPARBSMT	.198	.015	.038	13.562	.000
LFINBSMT	.040	.015	.007	2.722	.007
LUNFBSMT	.131	.012	.031	10.896	.000
LGARAGE	.127	.045	.008	2.830	.005
LDETGARZ	.179	.032	.014	5.561	.000

Model: 14

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
LCOP_POR	.117	.032	.009	3.592	.000
LSEP_POR	.209	.049	.010	4.262	.000
LGEP_POR	.208	.040	.013	5.200	.000
LDECK	.087	.044	.005	1.996	.046
GUT_PCT	.097	.018	.012	5.373	.000
MAJR_PCT	.056	.010	.013	5.414	.000
REMD_PCT	.020	.007	.007	2.805	.005
NB1A	.119	.025	.011	4.771	.000
NB1B	.121	.017	.019	7.260	.000
NB1C	.122	.017	.019	7.290	.000
NB2A	-1.087	.022	-.131	-48.714	.000
NB2B	-1.015	.020	-.151	-51.176	.000
NB3	-1.051	.024	-.119	-43.474	.000
NB4A	.088	.026	.008	3.392	.001
NB4B	.062	.034	.004	1.811	.070
NB4C	.115	.041	.007	2.839	.005
NB5A	-1.012	.030	-.081	-34.043	.000
NB5B	-1.159	.024	-.122	-48.913	.000
…..	…..	…..	…..	…..	…..
MO_3Y_1	.013	.000	.119	27.088	.000
MO_3Y_2	.016	.000	.192	48.423	.000
MO_3Y_3	.011	.000	.135	34.356	.000
MO_3Y_4	.091	.018	.013	5.058	.000

Excluded Variables[n]

Model: 14

					Collinearity Statistics
	Beta In	t	Sig.	Partial Correlation	Tolerance
LPATIO	.000	-.101	.920	-.001	.910
ROW_END	.001	.312	.755	.004	.889
LFOP_POR	.001	.588	.557	.007	.907
XKITCHEN	.002	.709	.478	.008	.958
COSM_PCT	-.002	-.835	.404	-.010	.962
CONV_APT	.002	.756	.450	.009	.635
DUPLEX	.003	.877	.381	.010	.534
LFEP_POR	.002	.929	.353	.011	.954

n. Dependent Variable: LTEMP_SP

Exhibit 4 - Syntax for Initial NLR Model

```
MODEL PROGRAM
N1A=1 N1B=1 N1C=1 N2A=1 N2B=1 N3=1 N4A=1 N4B=1 N4C=1 N5A=1 N5B=1 LANDRATE=50
LSZ1_EXP=-.50 LSZ2_EXP=-.50 LSZ3_EXP=-.50 LSZ4_EXP=-.50 BASERATE=100 DPLXRATE=100
CL23RATE=100 CL24RATE=100 CL12RATE=100 ENDRATE=0 BATHRATE=12000 FPRATE=500
POR_RATE=50.60 FBP_RATE=50 FBB_RATE=40 BGR_RATE=30 BSIZ_EXP=-.25 SIZ23EXP=-.25
GRAD10=1 GRAD20=1 GRAD3540=1 GRAD4550=1 GRAD5560=1 GRAD6570=1
GRAD75=1 GRAD80=1 GRAD85=1 GRAD90=1 GRAD95=1 GRAD100=1 GRAD105=1 GRAD110=1
GRAD120=1 COND1=1 COND2=1 COND4=1 COND5=1 COND6=1 GUT=1 MAJORREN=1 REMOD=1
COSMETIC=1 PGD_EXP=1 DETGAR_R=53.03 POOLRATE=46000 XF_FACT=1.15.

COMPUTE ESP =
N1A**NB1A*N1B**NB1B*N1C**NB1C*N2A**NB2A*N2B**NB2B*N3**NB3*N4A**NB4A*N4B**NB4B
*N4C**NB4C*N5A**NB5A*N5B**NB5B
*( LANDRATE  * (SIZEGRP1*(LOT_SIZE/1500)**LSZ1_EXP + SIZEGRP2*(LOT_SIZE/1500)**LSZ2_EXP
   + SIZEGRP3*(LOT_SIZE/1500)**LSZ3_EXP + SIZEGRP4*(LOT_SIZE/1500)**LSZ4_EXP)
   * LANDFAC1 * LANDFAC2 * LOT_SIZE
+ ((BASERATE*ROWHOME+DPLXRATE*DUPLEX+CL23RATE*SM_APT+CL24RATE*CONV_APT
   + CL12RATE*SFD+ ENDRATE*ROW_END+EXT_ADJ+ROOF_ADJ+FLOORADJ+HEAT_ADJ
   +COOL_ADJ) * BSIZERAT**BSIZ_EXP * SIZ23RAT**SIZ23EXP * EFF_AREA + BATHRATE*(BATHS-
   + .67*HBATHS2) + FPRATE*FP + POR_RATE*LINPORCH + FBP_RATE*FBP + FBB_RATE*FBB
   + BGR_RATE*BGR)
   *GRAD10**Q10*GRAD20**Q20*GRAD3540**Q35_40*GRAD4550**Q45_50*GRAD5560**Q55_60
   *GRAD6570**Q65_70*GRAD75**Q75*GRAD80**Q80*GRAD85**Q85*GRAD90**Q90*GRAD95**Q95
   *GRAD100**Q100*GRAD105**Q105*GRAD110**Q110*GRAD120**Q120
   *COND1**COND_1*COND2**COND_2*COND4**COND_4*COND5**COND_5*COND6**COND_6
   *GUT**GUT_PCT*MAJORREN**MAJR_PCT*REMOD**REMD_PCT*COSMETIC**COSM_PCT
   *PERGOOD**PGD_EXP)
  + DETGAR_R*DETGARZ + POOLRATE*POOL + XF_FACT*(XF_OTH+OUTB_OTH).

NLR TASP /OUTFILE='C:\TEMP\SPSSFNLR.TMP'/PRED=ESP /SAVE=PRED
 /CRITERIA=ITER(25) SSCON(.001).
```

Exhibit 5 - Initial NLR Model

Run stopped after 26 model evaluations and 11 derivative evaluations.
Iterations have been stopped because the relative reduction between
successive residual sums of squares is at most SSCON = .00100000

Nonlinear Regression Summary Statistics   Dependent Variable TASP

Source	DF	Sum of Squares	Mean Square
Regression	150	3.618843E+15	2.412562E+13
Residual	7142	5.873069E+13	8223283076.99
Uncorrected Total	7292	3.677573E+15	
(Corrected Total)	7291	1.387883E+15	

R squared = 1 - Residual SS / Corrected SS =   .95768

Parameter	Estimate	Asymptotic Std. Error	Asymptotic 95 % Confidence Interval Lower	Upper
N1A	1.008406626	.027206610	.955073613	1.061739640
N1B	1.021834800	.018459538	.985648637	1.058020963
N1C	1.024030149	.017770060	.989195567	1.058864731
N2A	.320486121	.026510948	.268516810	.372455432
N2B	.350183352	.020471101	.310053931	.390312772
N3	.331761653	.026573222	.279670267	.383853039
N4A	.875385208	.017222570	.841623869	.909146547
N4B	.855779002	.018238233	.820026663	.891531342
N4C	.851760191	.019005041	.814504682	.889015700
N5A	.377857954	.033619671	.311953440	.443762467
N5B	.320326910	.029089415	.263303041	.377350780
LANDRATE	194.94344870	5.266438288	184.61966975	205.26722765
LSZ1_EXP	-.815268060	.013588724	-.841905985	-.788630135
LSZ2_EXP	-.582878155	.014086138	-.610491159	-.555265152
LSZ3_EXP	-.441416808	.015084539	-.470986972	-.411846644
LSZ4_EXP	-.338762947	.065111186	-.466400158	-.211125737
BASERATE	60.115956861	4.268542084	51.748350044	68.483563678
DPLXRATE	57.707624343	4.429529392	49.024434719	66.390813967
CL23RATE	39.126961848	3.585260963	32.098788414	46.155135282
CL24RATE	59.800984750	4.262819470	51.444595950	68.157373549
CL12RATE	78.229257573	5.254617571	67.928650727	88.529864419
ENDRATE	.784041320	.918728589	-1.016938839	2.585021479
BATHRATE	16299.716638	1101.0443287	14141.343627	18458.089649
FPRATE	4154.1758344	789.44198097	2606.6357208	5701.7159481
POR_RATE	20.555808258	6.559438180	7.697366535	33.414249982
FBP_RATE	38.877911212	2.781903743	33.424555883	44.331266541
FBB_RATE	-2.112786116	3.211764690	-8.408796225	4.183223993
BGR_RATE	54.121502648	8.337729127	37.777083943	70.465921352
BSIZ_EXP	-.025930782	.021626489	-.068325107	.016463543
SIZ23EXP	-.050817380	.157730717	-.360016304	.258381544
GRAD10	-.059995285	.715654972	-1.462891004	1.342900435
GRAD20	.860040207	.097321521	.669261199	1.050819215
GRAD3540	1.132956014	.035736021	1.062902828	1.203009199
GRAD4550	1.227646687	.038483387	1.152207850	1.303085524

GRAD5560	1.320619892	.042300981	1.237697439	1.403542345
GRAD6570	1.482601187	.048601551	1.387327751	1.577874623
GRAD75	1.568350437	.055139968	1.460259767	1.676441107
GRAD80	1.709196662	.058792962	1.593945042	1.824448282
GRAD85	2.105767020	.074429014	1.959864107	2.251669933
GRAD90	2.022623004	.070794192	1.883845418	2.161400590
GRAD95	2.205217166	.082850743	2.042805170	2.367629163
GRAD100	2.414661907	.091435781	2.235420694	2.593903121
GRAD105	2.319117581	.094041692	2.134768009	2.503467153
GRAD110	2.242534333	.087738668	2.070540555	2.414528111
GRAD120	2.890347604	.110689742	2.673362924	3.107332283
COND1	.620085547	.066687927	.489357458	.750813637
COND2	.668282584	.032434913	.604700548	.731864620
COND4	1.204636621	.012214164	1.180693243	1.228580000
COND5	1.371841723	.016292107	1.339904367	1.403779078
COND6	1.481182903	.021903207	1.438246129	1.524119677
GUT	1.173896820	.027848337	1.119305831	1.228487809
MAJORREN	1.094628119	.015139929	1.064949374	1.124306864
REMOD	1.034334168	.010045905	1.014641218	1.054027118
COSMETIC	1.012494211	.042041784	.930079862	1.094908561
PGD_EXP	-.061416816	.023845513	-.108161084	-.014672547
DETGAR_R	46.514572497	10.719795602	25.500597938	67.528547057
POOLRATE	78325.627496	9795.3586840	59123.823113	97527.431880
XF_FACT	.766029785	.074323505	.620333700	.911725871

Ratio Statistics for ESP_1 / TASP

Sales	7292
Median	1.006
Weighted Mean	.999
Minimum	.553
Maximum	2.064
Std. Deviation	.157
Price Related Differential	1.022
Coefficient of Dispersion	.114

Exhibit 6 - Final Predict Algorithm

```
*NBHDSUB FACTORS.
RECODE NBHDSUB (' 1A'=1.016)(' 1B'=1.041)(' 1C'=1.045)(' 2A'=0.343)(' 2B'=0.390)(' 3'=0.329)(' 4A'=0.907)
(' 4B'=0.850)(' 4C'=0.887)(' 5A'=0.378)(' 5B'=0.322)  INTO  NSUB_FAC.

COMPUTE LSIZ_EXP=-.785.
IF (SIZEGRP2=1)LSIZ_EXP=-.546.
IF (SIZEGRP3=1)LSIZ_EXP=-.384.
IF (SIZEGRP4=1)LSIZ_EXP=-.313.

*LAND VALUE.
COMPUTE LSIZFACT=(LOT_SIZE/STD_SIZE)**LSIZ_EXP.
COMPUTE LV=(BASLRATE+XLRATE1+XLRATE2)*LANDFAC1*LANDFAC2*LOT_SIZE*LSIZFACT.

*BASE RATES.
RECODE USE (11=92.51)(12=116.67)(13=91.03)(23=55.29)(24=94.73)(ELSE=92.51) INTO BAS_RATE.

*ADDITIONS TO BASE RATES ("A" CODES).
RECODE EXT (10,14,15,18=3.95)(11,17=9.38)(20=6.67)(21,22=1.98)(23,24=4.69)(ELSE=0) INTO EXT_ADJ.
RECODE ROOF (3,15=.68)(4=.79)(5,6,7=.50)(8=-.43)(9,12=1.88)(10=2.93)(11=2.86)(ELSE=0) INTO
ROOFRATE.
COMPUTE ROOF_ADJ=ROOF*ROOFRATE.
RECODE FLOOR (0=2.50)(1=2.63)(2=2.17)(3=6.06)(4=8.53)(5=8.30)(6=7.17)(7=8.15)(8=1.64) (9=2.86)(10=.75)
(11=4.67)(ELSE=0) INTO FLOORADJ.
RECODE HEAT (2=.55)(3=-1.27)(4=-.29)(5=-.20)(6=1.42)(ELSE=0) INTO HEAT_ADJ.
RECODE AIRCOND ('Y'=1.80)('N'=0)(ELSE=0) INTO COOL_ADJ.

*BUILDING SIZE FACTOR.
COMPUTE BASESIZE=1800.
IF (USE=23)BASESIZE=3000.
COMPUTE BSIZERAT=1.
IF (USE NE 23) BSIZERAT=EFF_AREA/BASESIZE.
COMPUTE BSIZEFAC=1.
IF (USE NE 23) BSIZEFAC=BSIZERAT**-.113.

*ADJUSTED RATE.
COMPUTE ADJ_RATE=(BAS_RATE+EXT_ADJ+ROOF_ADJ+FLOORADJ+HEAT_ADJ+COOL_ADJ
  +1.91*ROW_END)*BSIZEFAC.

*BATHS.
COMPUTE HBATHS2=HBATHS.
IF (HBATHS>2)HBATHS2=2.

*GRADE FACTORS.
RECODE GRADE (10,15=.50)(20=.85)(25,30=1)(35,40=1.10)(45,50=1.17)(55,60=1.25)(65,70=1.35)(75=1.45)
 (80=1.60) (85,90=1.85)(95,100=2.10)(105,110,115=2.35)(120 THRU HI=2.65) INTO GRADEFAC.

*RCN.
COMPUTE CALC_RCN=(ADJ_RATE*EFF_AREA+15000*(BATHS-1)+10000*HBATHS2+5300*FP+35.95
  *LINPORCH + 30*FBP + 20*FBB + 20*BGR)*GRADEFAC.
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*EFFECTIVE AGE AND DEPRECIATION.
*EFFECTIVE AGE CAPPED AT 75.
COMPUTE AGE=SYEAR-YRBLT.
COMPUTE AGE75=AGE.
IF (AGE75<0)AGE75=0.
IF (AGE>75)AGE75=75.
RECODE B_STYL(2=.95)(3=.90)(4=.80)(ELSE=1) INTO BATH_FAC.
RECODE K_STYL(2=.90)(3=.80)(4=.60)(ELSE=1) INTO KIT_FAC.
RECODE GRADE (10,15=1.20)(20=1.10)(25,30=1)(35,40=.95)(45,50=.90)(55,60=.85)(65,70=.75)(75,80=.65)
  (85,90=.55)(95 THRU HI=.50) INTO GRAD_FAC.
COMPUTE EFFAGE=RND(AGE75*BATH_FAC*KIT_FAC*GRAD_FAC).
COMPUTE DEPREC=1-(1-(SQRT(EFFAGE))/15)**.20.
COMPUTE PCTGOOD=1-DEPREC.

*CONDITION FACTORS.
RECODE I_COND(1=.50)(2=.70)(3=1)(4=1.15)(5=1.30)(6=1.35) INTO ICONDFAC.
RECODE E_COND(1=.50)(2=.70)(3=1)(4=1.15)(5=1.30)(6=1.35) INTO ECONDFAC.
RECODE O_COND(1=.50)(2=.70)(3=1)(4=1.15)(5=1.30)(6=1.35) INTO OCONDFAC.
COMPUTE COND_FAC = ICONDFAC**(1/3)*ECONDFAC**(1/3)*OCONDFAC**(1/3).

*RENOVATION FACTORS.
COMPUTE REM_AGE=SYEAR-REM_YR.
COMPUTE REM_PCT=1-REM_AGE/20.
IF (REM_AGE>20)REM_PCT=0.
COMPUTE GUT_PCT=0.
IF (REN_GUT=1)GUT_PCT=REM_PCT.
COMPUTE MAJR_PCT=0.
IF (REN_MAJR=1)MAJR_PCT=REM_PCT.
COMPUTE REMD_PCT=0.
IF (REN_REMD=1)REMD_PCT=REM_PCT.
COMPUTE COSM_PCT=0.
IF (REN_COSM=1)COSM_PCT=REM_PCT.
COMPUTE RENO_FAC=1+.20*GUT_PCT+.10*MAJR_PCT+.08*REMD_PCT+.03*COSM_PCT.

*EXTRA FEATURES AND OUTBUILDINGS.
COMPUTE XFOB_VAL=53.03*DETGARZ + 46000*POOL + XF_OTH + OUTB_OTH.

*TOTAL VALUE.
COMPUTE CALC_TV=LV+CALC_RCN*PCTGOOD*COND_FAC*RENO_FAC*NSUB_FAC+XFOB_VAL.
```

Exhibit 7 - Example of “Cost” Calculations

*******************Building Calc **********************
Account Number = 0893   0803
Use Code = 011
Cost Rate Group = R11
Model ID: R06

Base Rate: 92.51
Size Adjustment: 1.097
Effective Area: 792
Adjusted Base Rate = (92.51 + 14.22) * 1.097
Adjusted Base Rate: 117.08
RCN = ((117.08 * 792) + 21769) * 1.17
RCN: 133961

**************Base Rate Adjustments********************
AIR CONDITIONING Y (Yes) = 1.8 + BaseRate
EXTERIOR WALL 14 (Common Brick) = 3.95 + BaseRate
FLOOR COVER 3 (Wood Floor) = 6.06 + BaseRate
ROOF COVER 6 (Metal- Sms) = .5 + BaseRate
ROW END ADJUSTMENT 6 (Row End) = 1.91 + BaseRate

**************Flat Value Additions**********************
HALF BATHS = 10000 + RCN
FIREPLACES = 5300 + RCN
BASIC FINISHED BASEMENT = 5300 + RCN
COVERED OPEN PORCH = 1169 + RCN

**************Factor Adjustments***********************
GRADE 50 (V Good Quality) = 1.17 x RCN

**************Effective Age Adjustments*****************
EFF AGE GRADE 50 (V Good Quality) = .9 * Age
****

Actual Year Built: 1912
Effective Age = 75 * .9
Effective Age: 67
Percent Good = 86
RCNLD: 115210

********************Land Calc ***********************
Land Use Code = 011
Base Nbhd = 39
Base SubNbhd = K
SubNbhd Standard Size = 1500
SubNbhd BasePrice = 177.1
SubNbhd Size Adjustment = LG1
SizeRatio = 818 / 1500 * 10000 = 5453.333
SizeAdj = 1.723 + ((1.599 - 1.723) / (5500 - 5000) * (5453.333 - 5000)) = 1.6105
SubNbhd pricing base unit value = 285.22
LandVal = 285.22 * 818
LandVal(Rounded) = 233310