### **DEFICIENCIES OF PRICE-WEIGHTED REGRESSION MODEL (A.K.A."PROBIT")**

### **NOTES FOR THIS REPORT**

### Key findings

- Townships are divided into two or three markets (models) based on price alone
- This is a fundamental flaw that ignores location and introduces unneeded complexity and lack of transparency in the rest of the process (pages 5-7)
- Breaks down in the late stages ("micro phase") and produces flawed data
- It is inconsistent with the theory and practice of mass appraisal (pages 1-4)
- Side-by-side properties can be valued by different models which leads to an inherent bias in the valuation process (pages 15-18)
- Introduces sampling bias, i.e., sales sample does not match subject property profile (pages 17-18)
- Likelihood that it is inconsistent with national and international standards of mass appraisal
- Therefore not suitable as a primary mass appraisal valuation method

# **Evaluation of Price Weighted Regression aka Probit Method**

### Introduction

This report contains an evaluation of the "Probit Method" based on an examination of its description in materials provided by the CCAO. It is intended to inform decision makers as to the suitability of its use as a mass appraisal tool in the real property tax setting. The reader will be able to note that the majority of this document presents facts about mass appraisal and the Probit Method as compared to an industry standard method. As is usual in cases like this, there is judgment in which facts to present. The goal was to present the facts in an "apples-to-apples" comparison of the two methods evaluated. The conclusions drawn are fact-based, but do reflect opinions of the author as well.

# **This Report Contains**

Best Practices in Mass Appraisal for the Property Tax

Methodology Used for the Evaluation

A brief outline of the Probit Method

A Closer look at Price-Based Segmentation

Implication of Spatial Distribution of Market Segments

Sales Sample vs Subject Property Characteristics

Method Comparison

Conclusions

Selected References

# Best Practices in Mass Appraisal for the Property Tax

# **Summary of Mass Appraisal Process**

A succinct summary of the mass appraisal process for residential properties contains the following elements:

- 1. Adequate numbers of qualified staff to fulfill various roles within the valuation process:
  - a. Data collection
  - b. Sales verification
  - c. Market modeling
  - d. Value Review (appraisal)
- 2. An accurate and comprehensive database of property characteristics
- 3. A "sales history" database capturing the property's characteristics at the time of sale
- 4. An integrated system that includes data maintenance and valuation functionality
- 5. Delineated neighborhoods
- 6. Delineated neighborhood groups
- 7. Delineated market segments consistent with appraisal theory and which recognize local market conditions

Most common method of market segmentation

- 8. Production of values estimates using multivariate statistical methods that are:
  - a. Explainable
  - b. Defensible
  - c. Transparent
  - d. Repeatable
- 9. A value review process in which the computer generated value estimates are examined and either accepted or modified based on the reviewers knowledge of the market area under consideration

### Standards Governing the Conduct of Mass Appraisal

The mass appraisal process in the United States is governed by two principal standards. The first of which is the Uniform Standards of Professional Appraisal Practice or USPAP. In particular Standard 6 is relevant. A portion of that standard is given in Figure 1 below. In particular attention is drawn to item 2 "defining market area of consistent behavior that applies to properties". The second standard is entitled Standard on Mass Appraisal of Real Property, published in 2013 by the International Association of Assessing Officers. Figure 2 provides important information regarding the use of geographic areas for submarkets.

STANDARD (
STANDARD 6: MASS APPRAISAL, DEVELOPMENT AND REPORTING
In developing a mass appraisal, an appraiser must be aware of, understand, and correctly employ thos recognized methods and techniques necessary to produce and communicate credible mass appraisals.
Comment: STANDARD 6 applies to all mass appraisals of real or personal property regardless of the purpose or use of such appraisals. 53 STANDARD 6 is directed toward the substantive aspects of developing and communicating credible analyses, opinions, and conclusions in the mass appraisal of properties. Mass appraisals can be prepared with or
without computer assistance. The reporting and jurisdictional exceptions applicable to public
mass appraisals prepared for ad valorem taxation do not apply to mass appraisals prepared for
other purposes.
A mass appraisal includes:
<ol> <li>identifying properties to be appraised;</li> </ol>
<ol><li>defining market area of consistent behavior that applies to properties;</li></ol>
<ol> <li>identifying characteristics (supply and demand) that affect the creation of value in that market area;</li> </ol>
<ol> <li>developing a model structure that reflects the relationship among the characteristics affecting value in the market area;</li> </ol>
5) calibrating the model structure to determine the contribution of the individual
characteristics affecting value;
6) applying the conclusions reflected in the model to the characteristics of the
property(ies) being appraised; and
7) reviewing the mass appraisal results.
The JURISDICTIONAL EXCEPTION RULE may apply to several sections of STANDARD
6 because ad valorem tax administration is subject to various state, county, and municipal
laws.

Figure 1 USPAP Standard 6 Overview

USPAP Standards favor spatially aware market segmentation

Values are not "computer

they become appraisals

generated"; humans review computer estimates before

Valuation models are developed for defined property groups. For residential properties, geographic stratification is appropriate when the value of property attributes varies significantly among areas and each area is large enough to provide adequate sales. It is particularly effective when housing types and styles are relatively uniform within areas. Separate models are developed for each market area (also known as economic or model areas). Subareas or neighborhoods can serve as variables in the models and can also be used in land value tables and selection of comparable sales. (see Mass Appraisal of Real Property [Gloudemans 1999, 118-120] or Fundamentals of Mass Appraisal [Gloudemans and Almy 2011, 139-143] for guidelines on stratification.) Smaller jurisdictions may find it sufficient to develop a single residential model.

IAAO Standards favor spatially aware market segmentation

Figure 2 Selection from IAAO Standard on Mass Appraisal

### Sample Journal Reference to Housing Submarkets

The literature is rich with information on the topic of housing submarkets as related to mass appraisal models. The author of this document devoted considerable research time to the topic of detecting and using submarkets in mass appraisal. The section "References Related to Market Segmentation" at the end of this document provides the opportunity review some of the research conducted prior to the author's submission of his doctoral dissertation. A particularly relevant selection of reference article related to housing submarkets is given in Figure 3. The authors clearly favor submarket defined based on spatial dependence.

<sup>&</sup>lt;sup>1</sup> Chapter 5 of *Discovering and Applying Location Influence Patterns in the Mass Valuation of Domestic Real Property*, Richard A. Borst, B.E.S., M.S., Faculty of Engineering of the University of Ulster, Submitted for the degree of Doctor of Technology, March 2007

### 6. Conclusions

We start with the premise that the evaluation of alternative definitions of submarkets depends on the purpose for which the submarkets are constructed. If the purpose is to group close substitutes, then we argue that attention should be paid primarily to the characteristics of properties. On the other hand, if the aim is mass appraisal, then a focus on hedonic prices is warranted. In the latter case, the objective is to segment the market in a way that allows for accurate estimates of house values.

Using a sample of sales transactions from Auckland, New Zealand, we have demonstrated that housing submarkets defined as small geographical areas have more practical utility than submarkets defined using statistical techniques that disregard spatial contiguity. Adjusting for spatial dependence results in better predictions in most cases, although the degree of improvement depends on the level of spatial aggregation in the model. Not only do submarkets matter, but geography is what makes them matter. "Location, location, location" is not just a tired dictum. Moreover, our conclusions underscore the value of the practical knowledge of appraisers.

The broader implication of our results is that established neighborhood or other urban boundaries probably define suitable submarkets for mass appraisal purposes. In other words, it is probably not useful to employ elaborate statistical methods to define submarkets. However, such techniques may be useful in combining small geographical areas into larger areas for more basic research on the internal structure of cities. For example, such an approach could be employed to shed light on neighborhood patterns and dynamics.

Figure 3 Journal Article Citation<sup>2</sup>

Researchers favor spatially aware market segmentation

<sup>&</sup>lt;sup>2</sup> Bourassa, Steven C., Hoesli, Martin, Peng, Vincent S., 2003, *Do Housing Submarkets Really Matter?*, Journal of Housing Economics 12:1,12-28

### **Methodology Employed in the Evaluation**

Several datasets were provided by CCAO for use in evaluating the Probit Method. The process involved developing models by industry standard methods and by the Probit Method, hereafter called "Probit".

The industry standard method was one in which models were developed on clusters of similar properties in contiguous or near contiguous areas. The clustering methodology started with block as the basic unit to be assembled into groups of blocks and ultimately clusters. To facilitate comparison to Probit, three clusters were defined in the evaluation datasets.

Both linear additive and log linear models were calibrated using ordinary least squares multiple regression analysis (MRA) to determine which performed better. After calibrating the models, comparable sales valuation methodology was used to produce comparative value estimates.

The evaluation used an "apples-to-apples" comparison of Probit to industry standard methodology. That is, the same data, and the same variables were used in the method comparisons.

The steps involved in Probit were replicated and the results were used for comparison to the industry standard method.

### What is the Probit Method?

The Probit Method has been documented elsewhere by its developers. In brief it has the following features:

- 1. It seeks to reduce regressivity in market value estimates
- 2. Key to the approach is segmenting the market based on price, usually three segments based on the 33.3rd and 66.7<sup>th</sup> percentile of price. Two examples are shown below in Table 1

	Orland		
Breaks	Price Seg	Number In	Percent In
<=\$65,000	1	1,117	34%
>\$65,000 and <= \$287,000	2	1,112	33%
>287000	3	1,098	33%
	<b>Grand Total</b>	3,327	100%
	Thornton		
Breaks	Price Seg	Number In	Percent In
<=\$37,000	1	2,325	17%
>\$37,000 and <=\$92,000	2	4,658	34%
>\$92,500	3	6,915	50%
	<b>Grand Total</b>	13,898	100%

Two examples of price-based segmentation

Table 1

3. Price weighted models are developed for each segment using the available sales and property characteristic data. The sales are weighted according to the scheme below:

	Weig	ht given to	Sale
Sale in Seg	W1	W2	W3
1	1.00	0.25	0.25
2	0.25	1.00	0.25
3	0.25	0.25	1.00

"Probit" price weighting scheme by segment

**Table 2 Sale Weighting Scheme** 

4. Since unsold properties cannot be segmented on price, a model is developed to assign the probability of belonging to a particular segment to each subject. A weighted value estimate (PWR Est) is computed for each subject according a scheme where regression models for each segment are applied based on the probability of being associated with that segment model:

		Example Subje	ect Property	
		Α	В	A*B
				Weighted
		Probability of	Segment	Contribution
		belonging to	Model Value	to PWR
Segment		Segment	Estimate	Estimate
	1	0.04	\$210,000	\$8,400
	2	0.90	\$220,000	\$198,000
	3	0.06	\$200,000	\$12,000
PWR Est				\$218,400

Example Probit Value Estimate

**Table 3 Probit Estimate** 

5. There are other aspect to the method involving variables definition and model structure which, although interesting, are not critical to this analysis.

# A Closer Look at the Price-Based Market Segmentation

### Segmenting on Price when Price Estimation is the Goal

It is either a case where it is too obvious for mention, or too subtle for notice, but segmenting the market based on sale price when sale price estimation is the goal will necessarily lead to better performance statistics on the sales sample. To understand why this is so, consider a simple experiment of this nature:

- 1. Develop an estimate of Value using the average sale price for the town in question
- 2. Develop an estimate of value using the average of sale price by price segment
- 3. Compare the results using appropriate sales ratio methods

The table below shows that the Coefficient of Dispersion and Price Related Differential are dramatically improved by this simple step. The fundamental problem is we don't know to which segment a subject belongs, the same concern as was expressed by the developers of the Probit Method.

Orland Ratio Statistics							
Method	Count	Median	Mean	Wgt Mean	COD	PRD	
Overall Average	3104	1.092	1.130	1.000	26.729	1.130	
Average by Segment	3104	1.012	1.030	1.000	12.838	1.030	

Table 4

The experiment can be carried a bit further. The models described are linear additive. Calibration is of the following:

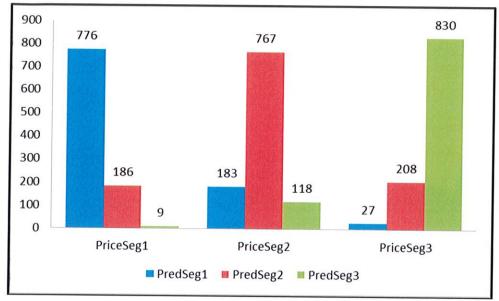
- 1. A single (no segment) model
- 2. An independent model for each segment
- 3. Three price weighted models using the weights as described in Table 2
- 4. Three models based on characteristics-based market segmentation (industry standard method)

Segmenting on price leads to obvious, but inconsequential improvement in predictive performance because Subjects do not belong to a known price segment

		Si	ngle M	lodel (1)			
PriceSeg	Count	Median	Mean	Wgt. Mean	COD	PRD	PRB
1	971	1.08	1.09	1.08	11.38	1.01	-0.075
2	1068	1.01	1.01	1.01	9.93	1.00	0.545
3	1065	0.97	0.97	0.96	10.09	1.01	0.049
Combined	3104	1.01	1.02	1.00	11.16	1.02	-0.067
<del> </del>							
				n Price Segr		· <u>′</u>	T -
PriceSeg				Wgt. Mean		PRD	PRB
1	971	0.99	-	1.00			
2	1068		-				
3	1065	1.01	1.01	1.00	9.07		-0.067
Combined	3104	1.00	1.01	1.00	8.13	1.01	-0.034
				<del></del>			
			Ī	els based on			$\overline{}$
PriceSeg				Wgt. Mean		PRD	PRB
1	971	1.07	1.07	1.06			
2	1068	1.01	1.01	1.01	10.02	1.00	
3	1065	0.97	0.97	0.97	10.17		
Combined	3104	1.01	1.02	1.00	10.95	1.02	-0.047
				n Logical Clu			
				Wgt. Mean			PRB
1	1032	1.01	1.02	1.00	11.76		
2	1537	1.01	1.02	1.00	10.52		-0.120
3	535	1.01	1.01	1.00	9.59	1.01	-0.043
Combined	3104	1.01	1.02				

**Table 5 Method Comparison** 

The model based on three separate segments (2) shows superior statistics in comparison to the baseline (1). However, it is not useable for valuation of subjects for the reasons previously mentioned. The probit method (3) was constructed by the method described by its developers. That is, a model was developed based on property characteristics that assign each subject three probabilities, one for each market segment. The efficacy of the segment prediction model developed for the Orland data is captured in Figure 4 which shows for each actual price segment the number of times it was assigned to each of three possible predicted segments. Table 6 contains the same information shown in Figure 4.



Probit Segment Prediction as applied to sales

Figure 4

		Pred Seg		
Price Seg	PredSeg1	PredSeg2	PredSeg3	Mean Seg
PriceSeg1	776	186	9	1.21
PriceSeg2	183	767	118	1.94
PriceSeg3	27	208	830	2.75

Table 6

The final model (4) is one based on three logically defined market segments, and happens to be the best performer of among the three that could actually be applied to subjects.

### **Segment Location vs Cluster Location**

Two sequences of images are presented to illustrate the nature of the price segmentation in spatial terms. The first sequence of three shows:

- 1. The price segments for sales only on a portion of Orland Figure 5
- 2. The predicted segments for subjects in same spatial extent Figure 6
- The characteristics based clusters for the same spatial extent Figure 7

The second set of three images shows the same information for the full extent of the Orland dataset in Figure 8, Figure 9 and Figure 10.

It is clear, from Figure 6 in particular, that the predicted market segment for subject properties varies considerably within confined areas of a township. What this means is that side-by-side properties are being valued by a different predominant segment model. The implications of this are taken up in the next section, Implication of Spatial Distribution of Market Segments. Contrast this with the spatially homogenous Clusters based on location and property characteristics as evidenced in Figure 7 and Figure 10, where it is evident that side-by-side properties will be valued with the same model. Additionally, in the case of the Orland dataset, the Cluster-based segmentation had better overall performance statistics as compared to Probit.

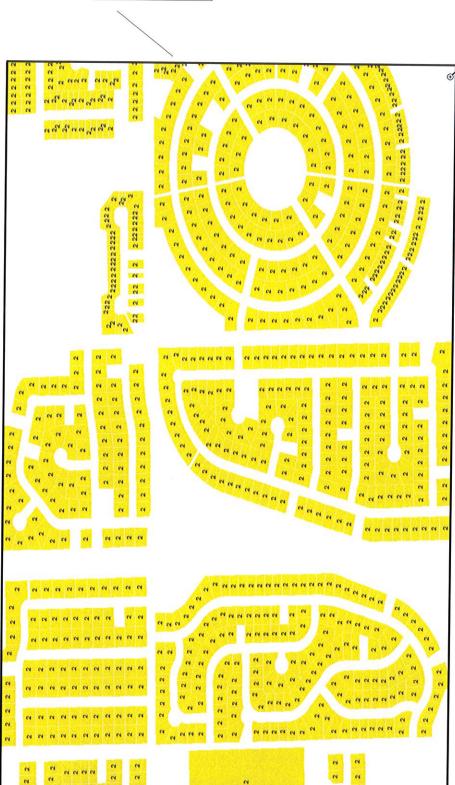


Figure 5 Price Segment for Sales - Selected Area

Predicted Subject segments have inconsistent spatial

pattern

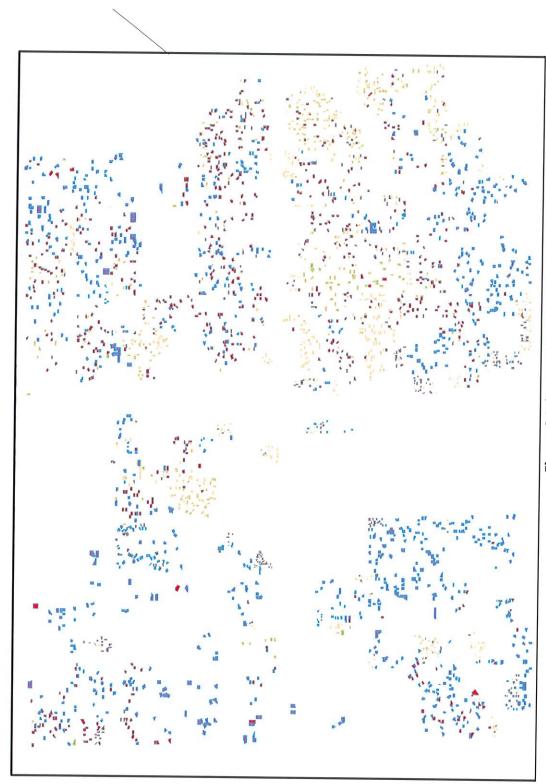
Figure 6 Predicted Segment - Selected Area



Characteristicsbased segments

have spatial contiguity

Figure 7 Cluster – Selected Area



Comingled pricebased segments have little spatial

pattern

Figure 8 Price Segment for Sales – Full Extent

Comingled estimated market segments have inconsistent spatial pattern

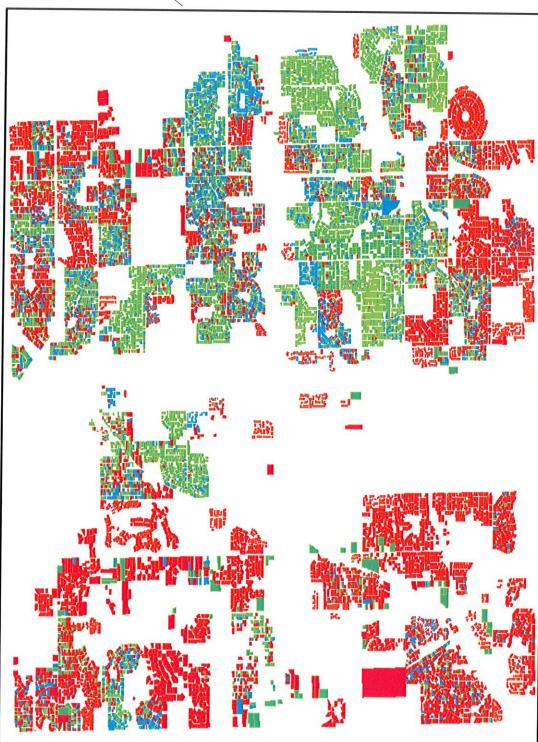
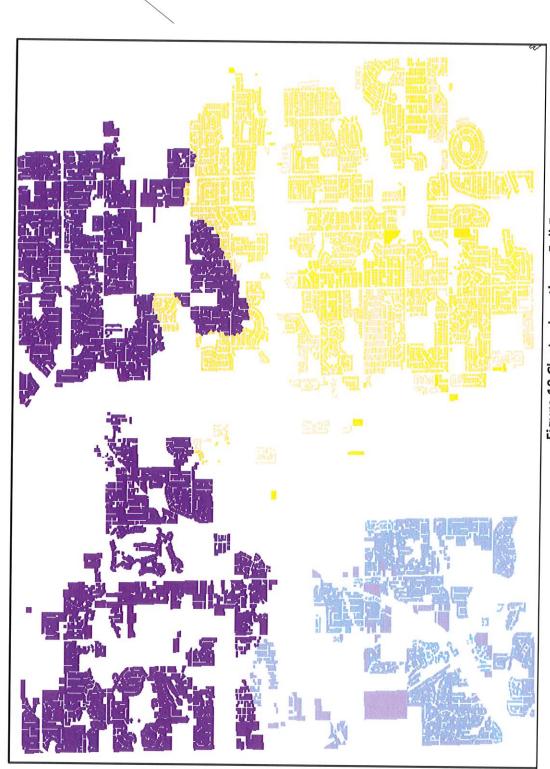


Figure 9 Predicted Segment – Full Extent



Coherent market

segmentation based on geography and market factors

Figure 10 Cluster Location - Full Extent

# Implication of Spatial Distribution of Market Segments

To illustrate the spatial nature of the price-based market segmentation the following process was used:

Each subject property was assigned the three probabilities predicted by the probit method. However, instead of valuing the subject property's characteristics, a constant house was valued at each location. This method eliminates variations in property characteristics and focuses only on the value created by variations in the probit methodology. Two cases are shown for comparison. The first is Orland in which results predicted by the probit method and the industry standard method were both statistically within standards of performance promulgated by the IAAO.

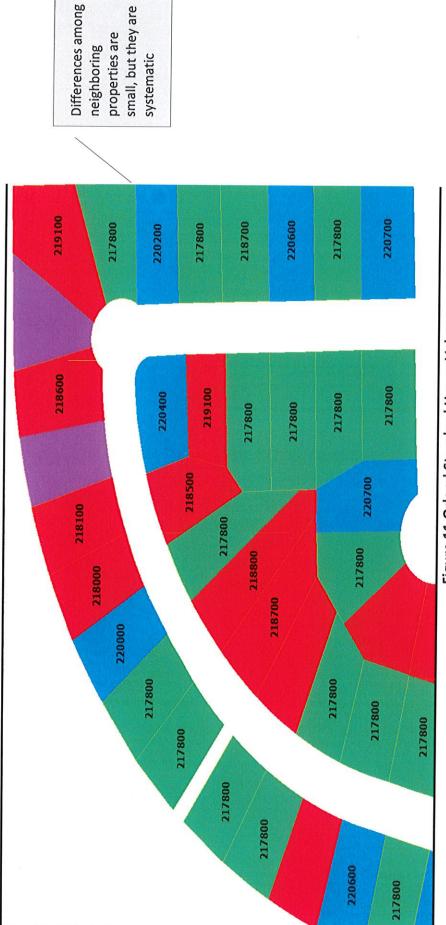
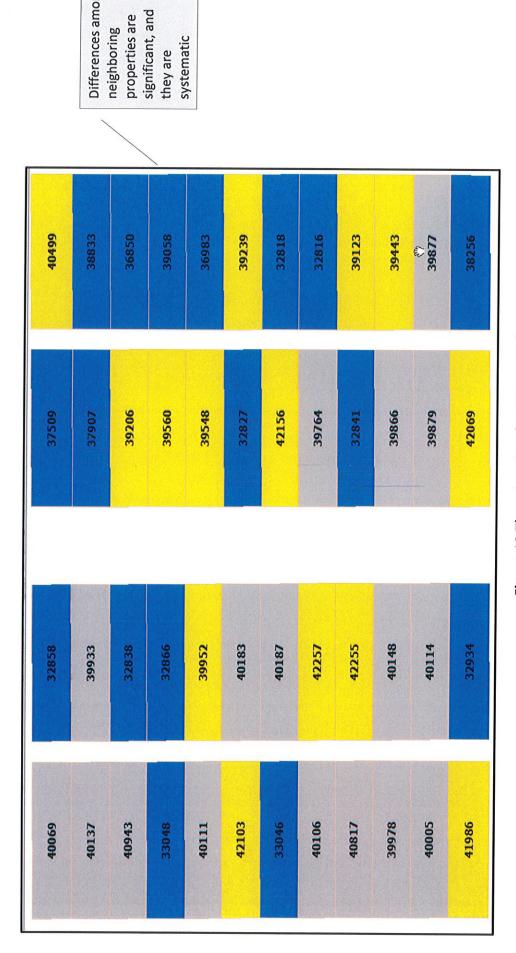


Figure 11 Orland Standard House Values



Differences among

neighboring

systematic they are

Figure 12 Thornton Standard House Values

## **Price-Based Segments do Not Mirror Subject Characteristics**

Another question about the methodologies being compared is how well the sales sample selection represents the subject's property characteristics. This is important because it goes to the question of are the models developed on the same types of properties or not?

The models can be sown to have good statistical performance, but are they being applied to similar properties? Table 7 presents selected statistics for the sales and subject properties by Price Segment for the Sales and Predicted Segment for the subjects – the Probit method. The two columns to the right show Delta%, a percent difference between the sales and the subjects for each characteristic. Acknowledging that the sales may not be representative of the subjects overall, a second column Adj% takes into account the inherent differences between the sales sample and the subjects. Table 8 shows the same information for the Cluster approach. Finally, Table 9 shows the comparison between the two methods.

	Sale	S			Subjec	cts			
PriceSeg	Variable	Count	Mean	PredSeg	Variable	Count	Mean	Delta%	Adj%
1	saleamt	971	180,310	1	saleamt	0			
_	land size	971	6,755		land size	8604	10,242	34.0	23.8
	age	971	38	v l	age	8604	42	9.2	5.5
	build size	971	1,425		build size	8604	1,405	-1.4	-4.7
	Bath Fixt	971	7.6		Bath Fixt	8604	7.4	-2.7	-2.7
2	saleamt	1068	249,992	2	saleamt	0			
	land size	1068	8,515		land size	5075	11,073	23.1	12.8
	age	1068	31		age	5075	32	1.7	-2.0
	build size	1068	1,785		build size	5075	2,275	21.6	18.3
	Bath Fixt	1068	8.8		Bath Fixt	5075	9.6	8.6	8.5
3	saleamt	1065	388,584	3	saleamt	0			
	land size	1065	12,572		land size	9177	10,251	-22.6	-32.9
	age	1065	24		age	9177	23	-4.4	-8.0
	build size	1065	2,884		build size	9177	2,700	-6.8	-10.1
	Bath Fixt	1065	10.5		Bath Fixt	9177	10.1	-3.2	-3.2
All	saleamt	3104	275,746	All	saleamt	0			
	land size	3104	9,357		land size	22856	10,430	10.3	
	age	3104	31		age	22856	32	3.7	
	build size	3104	2,049		build siz€	22856	2,118	3.3	
	Bath Fixt	3104	9.0		Bath Fixt_	22856	9.0	0.0	

**Table 7 Probit** 

	Sal	es			Subje	ects			
CLUST	Variable	Count	Mean	CLUST	Variable		Mean	Delta%	Adj%
1	saleamt	1032	300,591	1	l saleamt	0			,
	land size	1032	11,268		land size	7775	12,585	10.5	0.2
	age	1032	34		age	7775	35	1.9	
5	build size	1032	2,175		build size	7775	2,291	5.0	
	Bath Fixt	1032	9.2		Bath Fixt	7775	9.3	1.1	1.1
2	saleamt	1537	238,702	2	saleamt	0			
	land size	1537	8,170		land size	11716	9,046	9.7	-0.6
	age	1537	32		age	11716	33	2.5	-1.1
	build size	1537	1,814		build size	11716	1,872	3.1	-0.2
	Bath Fixt	1537	8.5		Bath Fixt	11716	8.5	-0.1	-0.1
3	saleamt	535	334,242	3	saleamt	0			
	land size	535	9,077		land size	3365	10,269	11.6	1.3
	age	535	21		age	3365	22	6.8	3.1
	build size	535	2,483		build size	3365	2,577	3.7	0.4
	Bath Fixt	535	9.9		Bath Fixt	3365	9.9	0.1	0.1
ΔII	saleamt	3104	275,746	AII	saleamt	0	-		
	land size	3104	9,357		land size	22856	10,430	10.3	
	age	3104	31		age	22856	32	3.7	
	build size	3104	2,049		build size	22856	2,118	3.3	
	Bath Fixt	3104	9.0		Bath Fixt	22856	9.0	0.0	

**Table 8 Cluster** 

		Pro	bit		Clu	ster
_	PredSeg	Delta%	Adj%	CLUST	Delta%	Adj%
saleamt	1			1	L	
land size		34.0	23.8		10.5	0.2
age		9.2	5.5	_	1.9	
build size		-1.4	-4.7		5.0	1.8
Bath Fixt	-	-2.7	-2.7		1.1	1.1
saleamt	2			2		
land size		23.1	12.8		9.7	-0.6
age		1.7	-2.0		2.5	-1.1
build size		21.6	18.3		3.1	-0.2
Bath Fixt		8.6	8.5		-0.1	-0.1
saleamt	3			3	- 11 ==	
land size		-22.6	-32.9		11.6	1.3
age		-4.4	-8.0		6.8	3.1
build size		-6.8	-10.1		3.7	0.4
Bath Fixt		-3.2	-3.2		0.1	0.1

The clustering method sales samples are much closer in characteristics to the subjects than are the Probit segments

### **Table 9 Comparison**

# **Method Comparison**

Two datasets illustrate the bottom line comparison between industry standard and Probit methods. The Orland dataset yielded good statistical performance while the Thornton dataset posed a challenge to obtaining good performance. Nonetheless, the two cases allow some generalizations to be made.

On the question of model structure, the linear additive model was better than the log linear model in Orland, while the log linear model was better in Thornton.

ORLAND Model	Count	Media	n Mean	WtMean	COD	cov	PRD	PRB
Linear Additive	310	04 1.00	06 1.01	1.000	9.874	12.446	1.014	-0.042
logLinear	310	04 1.00	00 1.00	0.992	10.081	12.781	1.016	-0.052
THORTON Model	Count	Median	Mean	Wtd Mean	COD	cov	PRD	PRB
Log Linear	5461	0.99	1.07	0.96	32.05	37.15	1.11	-0.12
Linear Additive	5465	1.02	1.13	1.00	34.22	38.92	1.13	-0.09

Linear vs. log linear model structure is data dependent and should be examined on a case by case basis

On the question of overall performance, the industry standard method was better in Orland while in Thornton the two models performed virtually the same.

ORLAND Model	Count	Median	Mean	WtMean	COD	cov	PRD	PRB
Industry Standard	3104	1.006	1.015	1.002	9.421	12.142	1.013	-0.038
ProbitMethod	3104	1.001	1.009	0.995	9.952	12.661	1.014	-0.039
THORTON Model	Count	Median	Mean V	Ntd Mean	COD	cov	PRD	PRB
<b>THORTON Model</b> Probit	Count 5465	Median 0.99	Mean V	Vtd Mean 0.97	COD 31.31	<b>COV</b> 36.48	PRD 1.09	PRB -0.08

The industry standard method was better in Orland while in Thornton the two models performed virtually the same

### **Conclusions**

The distinguishing feature of the Probit Method is that it segments the market based on price alone. The preceding material illustrates the following:

- Based on the scope of this study (report) there are no advantages offered by Probit when compared to industry standard methods
- There is no theoretical justification for segmenting on price
- The method shows bias in side-by-side value estimate comparisons
- Sales samples do not compare well to the corresponding subjects when compared to traditional market based clustering
- Method requires a background in mathematics and statistics to understand
- Value defensibility is an issue with a process as complex as this
- More defensible methods abound in the literature and in working jurisdictions around the country, North America and other parts of the industrial world

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