Bootstrap Penalty Analysis

Alternatives to distributions and penalty analysis

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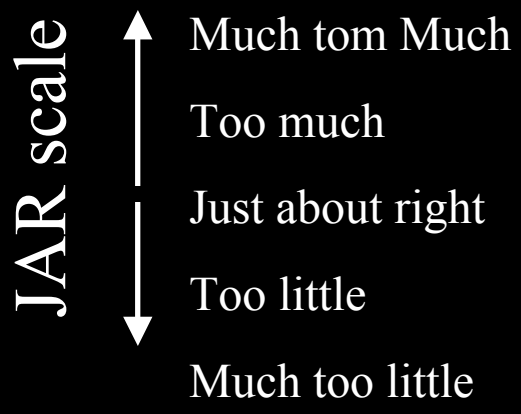
Introduction

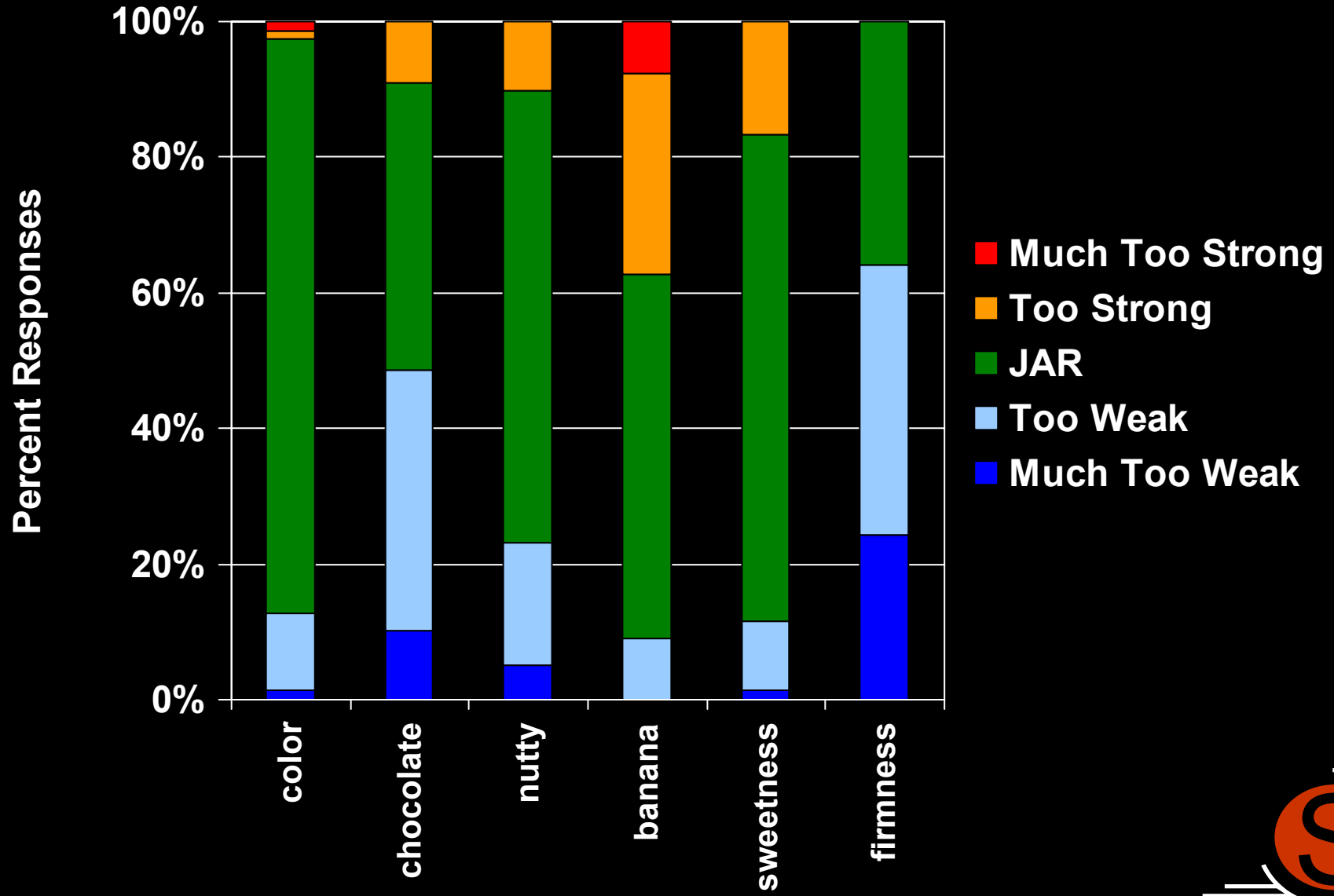
- Hedonic and JAR (just-about-right) scales are widely used together to provide directional information for product reformulation or optimization



Introduction

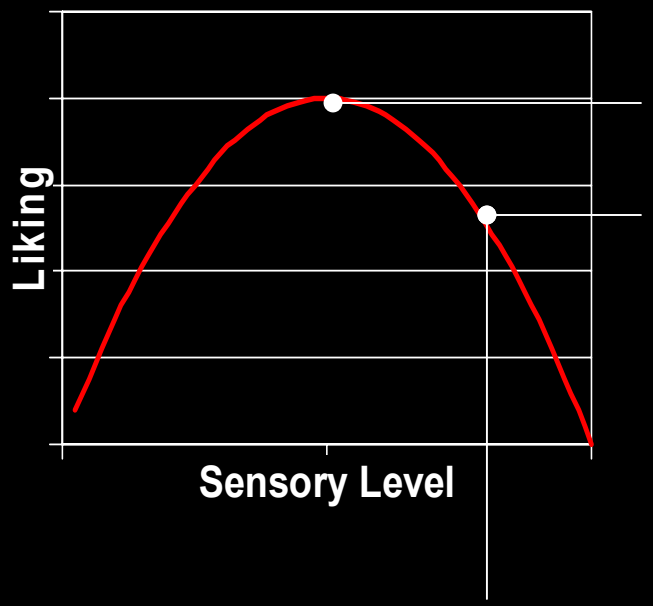
- Results from diagnostic attributes are not always actionable
  - What is the percentage of consumers required on the too little or too much side to consider an attribute to be at a inappropriate level?
  - If an attribute is not at its optimal level, does that have an impact on product liking?

Diagnostic results



Introduction

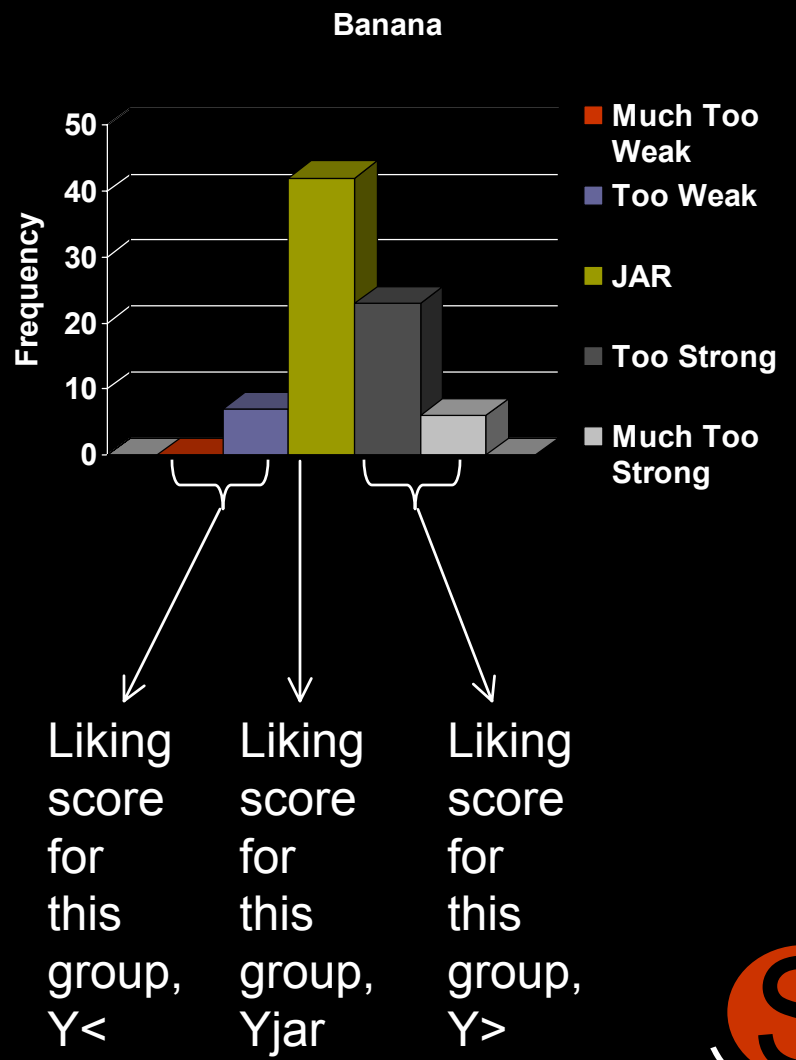
- Simple graphical method for assessing the cost associated with having an attribute not at its optimum level
  - A graphical technique, understandable to managers
  - Ignoring correlations among attributes
  - Not a regression method



Penalty Analysis

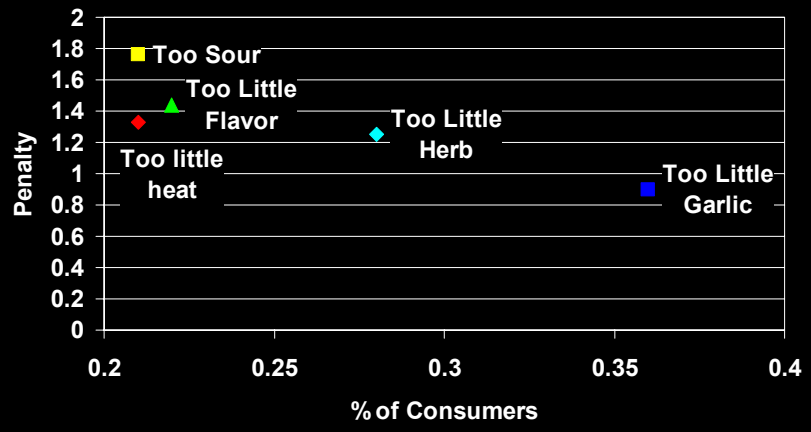
- Consumers are split is 3 groups (TL, JAR, TM)
- Penalties not calculated if proportion of consumers is less than 20%

Penalty=Yjar-Y<or>

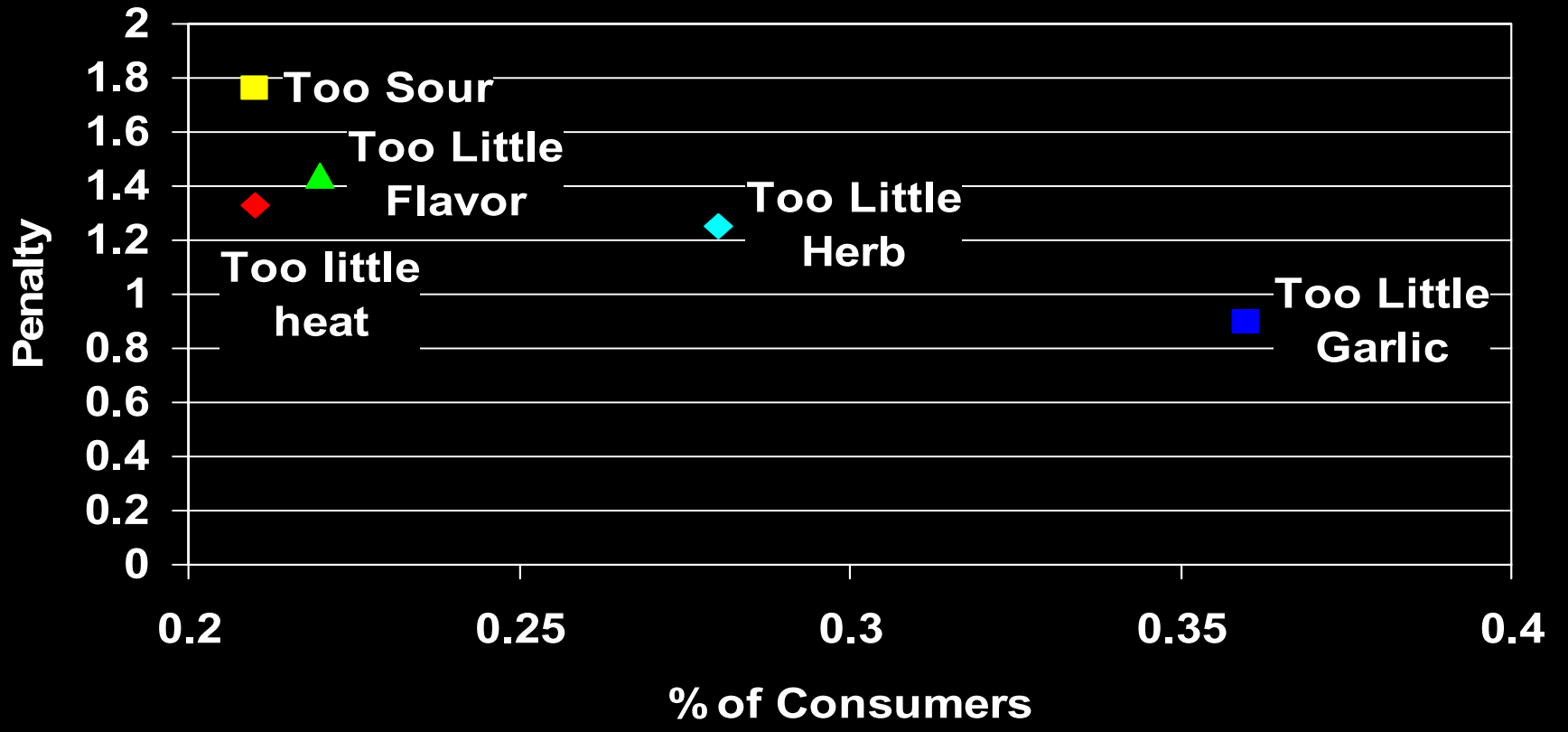


Penalty Analysis

- The major limitations of penalty analysis are:
  - The fact that categories below and above JAR level are collapsed (i.e. because n is often not large enough within a single category)
  - Collinearities between variables are being ignored.
  - Does not allow the application of preference mapping concepts since it is not a regression method



Penalty Analysis

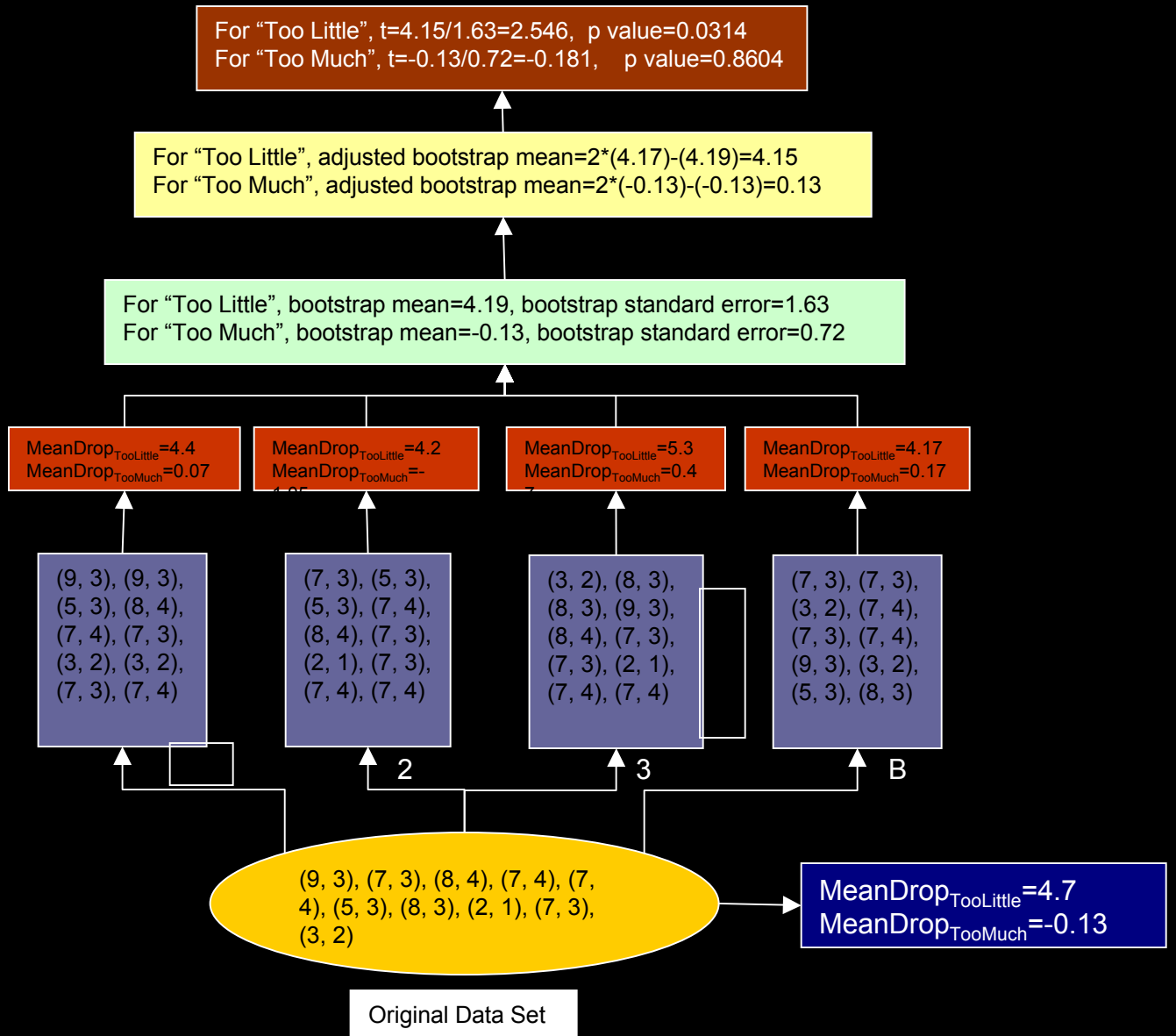


- Are penalties significantly different from 0? This is of importance to determine which attributes should be modified.

Objective

- Apply bootstrap (and Jacknife) re-sampling to penalty calculations to allow statistical testing (h_0: Y_{jar}-Y_{TL}or$_{TM}$=0) of the penalties or mean drops.

FIG. 2.
SCHEME FOR BOOTSTRAPPING PENALTY ANALYSIS WITH BOOTSTRAP REPLICATIONS OF B=10,000



Bootstrap

$$S^*_{i\,TL} = \overline{X}^*_{JAR} - \overline{X}^*_{TL}$$

$$S^*_{i\,TM} = \overline{X}^*_{JAR} - \overline{X}^*_{TM}$$

Estimated bootstrap mean

$$\bar{s}^*_{b\,TL} = \frac{\sum_{i=1}^{B} s^*_{i\,TL}}{B}$$

$$\bar{s}^*_{b\,TM} = \frac{\sum_{i=1}^{B} s^*_{i\,TM}}{B}$$

Standard error

$$\hat{se}_{b\,TL} = \sqrt{\frac{\sum_{i=1}^{B}\left(s^*_{i\,TL} - \bar{s}^*_{b\,TL}\right)^2}{(B-1)}}$$

$$\hat{se}_{b\,TM} = \sqrt{\frac{\sum_{i=1}^{B}\left(s^*_{i\,TM} - \bar{s}^*_{b\,TM}\right)^2}{(B-1)}}$$

Means adjusted for bias

$$\bar{s}_{b\,TL} = 2S_{n\,TL} - \bar{s}^*_{b\,TL}$$

$$\bar{s}_{b\,TM} = 2S_{n\,TM} - \bar{s}^*_{b\,TM}$$

Confidence interval

$$\bar{s}_{b\,TL} \pm t_{\alpha'/2,\,n-1}\,\hat{se}_{b\,TL}$$

$$\bar{s}_{b\,TM} \pm t_{\alpha'/2,\,n-1}\,\hat{se}_{b\,TM}$$

TABLE 1.
PERCENT OF CONSUMERS AND SUM OF OVERALL LIKING SCORES FOR SALTINESS FOR PRODUCT A ON A 5-POINT JAR SCALE

JAR scale	Frequency	Percent (%) of consumers	Sum of overall liking scores
1	5	3.18	10
2	18	11.46	87
3	93	59.24	633
4	32	20.38	159
5	9	5.73	36
Total	157	100.00	

TABLE 2.
PERCENT OF CONSUMERS, MEAN OF OVERALL LIKING SCORES AND MEAN DROPS FOR SALTINESS FOR PRODUCT A ON A COLLAPSED 3-POINT JAR SCALE*

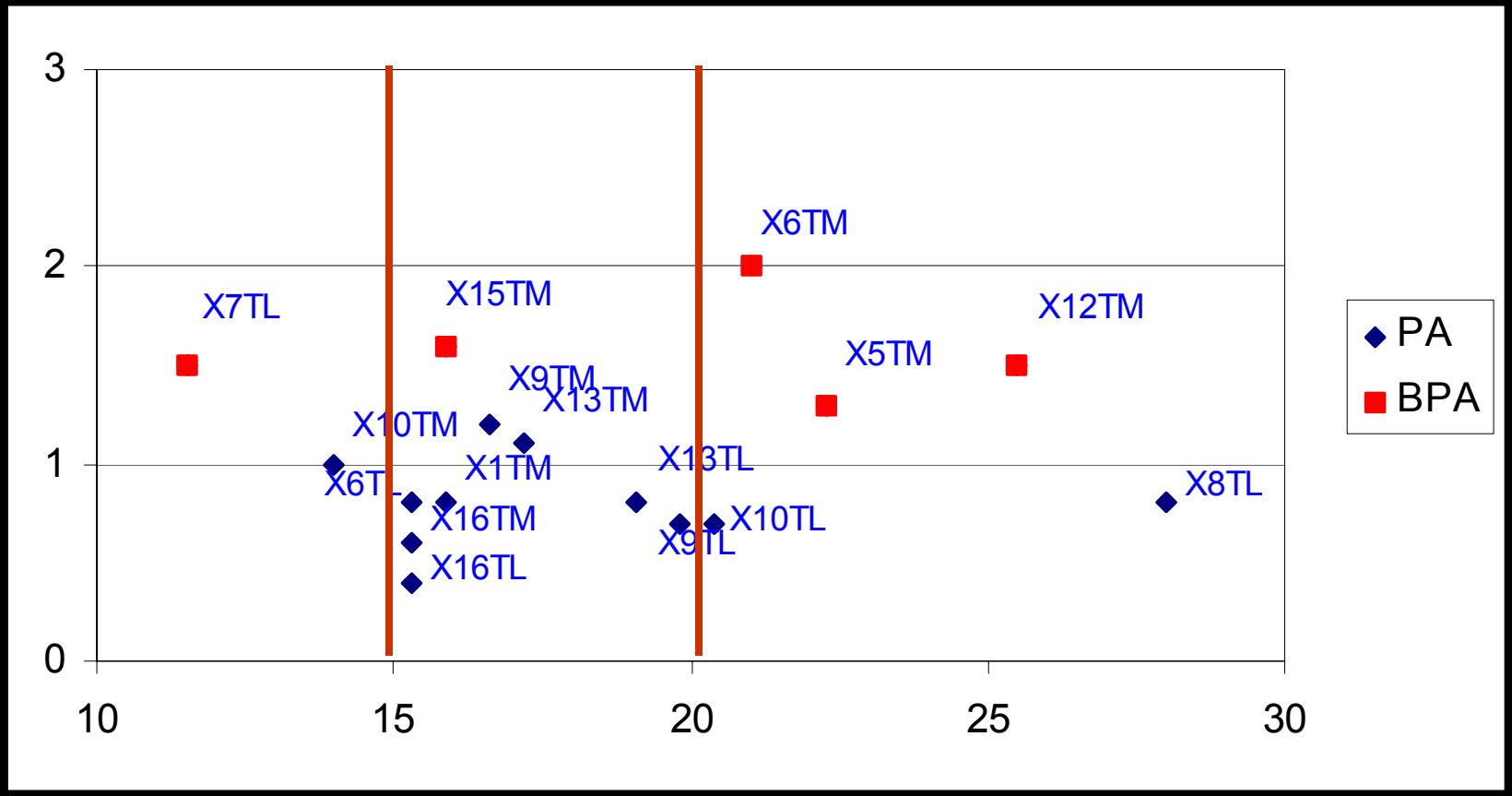
Collapsed JAR scale	JAR scale	Percent (%) of consumers	Mean of liking scores	Mean drop
Too Little	1, 2	14.65	4.22=(10+87)/(5+18)	2.59=6.81-4.22
JAR	3	59.24	6.81=633/93	
Too Much	4, 5	26.11	4.76=(159+36)/(32+9)	2.05=6.81-4.76

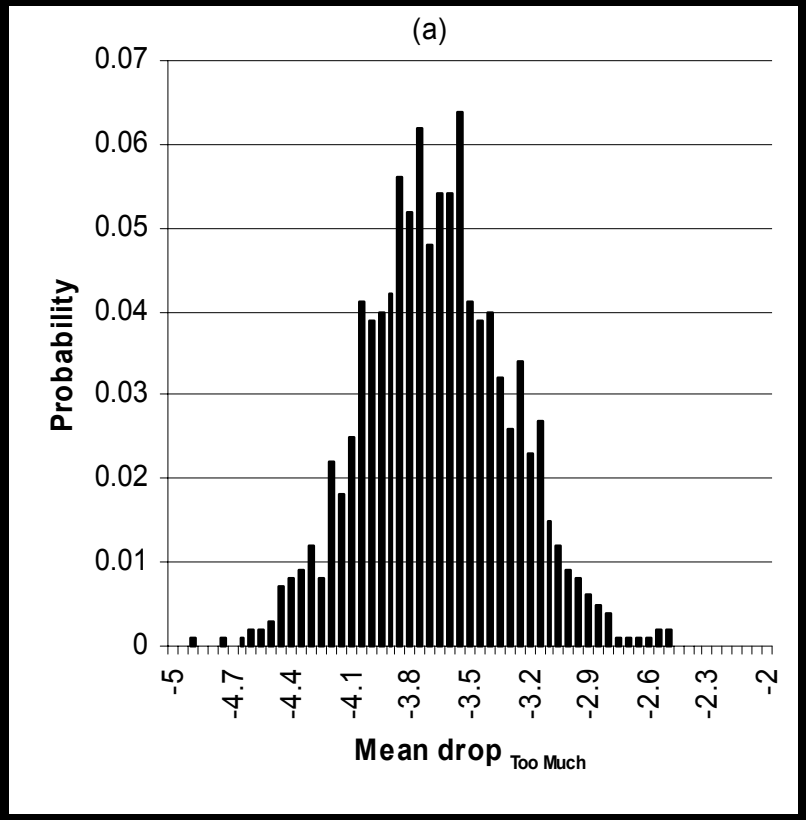
* Calculations are based on TABLE 1.

TABLE 3.
TOTAL MEAN DROPS, AVERAGED MEAN DROPS AND OBSERVED MEANS OF OVERALL LIKING FOR ELEVEN PRODUCTS (A, B, …, K)

X	A	B	C	D	E	F	G	H	I	J	K
Total mean drop	69.4	36.7	30	43.2	43.2	44.4	44.4	36.3	50.2	59.3	63.3
Product mean drop	2.2	1.1	0.9	1.4	1.4	1.4	1.4	1.1	1.6	1.9	2.0
Standard deviation	0.72	0.47	0.44	0.55	0.54	0.61	0.59	0.57	0.58	0.87	0.72
95% lower confidence limit	1.9	1.0	0.8	1.2	1.2	1.2	1.2	0.9	1.4	1.6	1.7
95% upper confidence limit	2.4	1.3	1.1	1.6	1.6	1.6	1.6	1.4	1.8	2.2	2.2
Observed mean of overall liking	5.9	7.3	7.3	7.4	6.8	7.3	7.3	7.4	7.1	6.3	6.1
JAR mean	8.1	8.4	8.2	8.8	8.2	8.7	8.7	8.5	8.7	8.2	8.1

FIG. 2
PENALTY AND BOOTSTRAP PENALTY ANALYSES FOR PRODUCT C





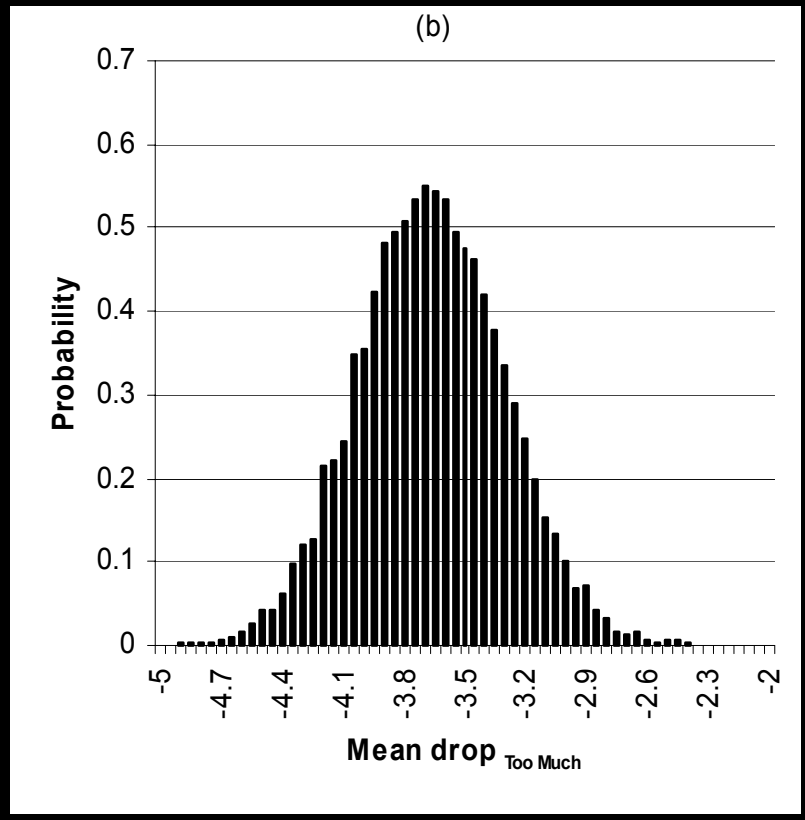
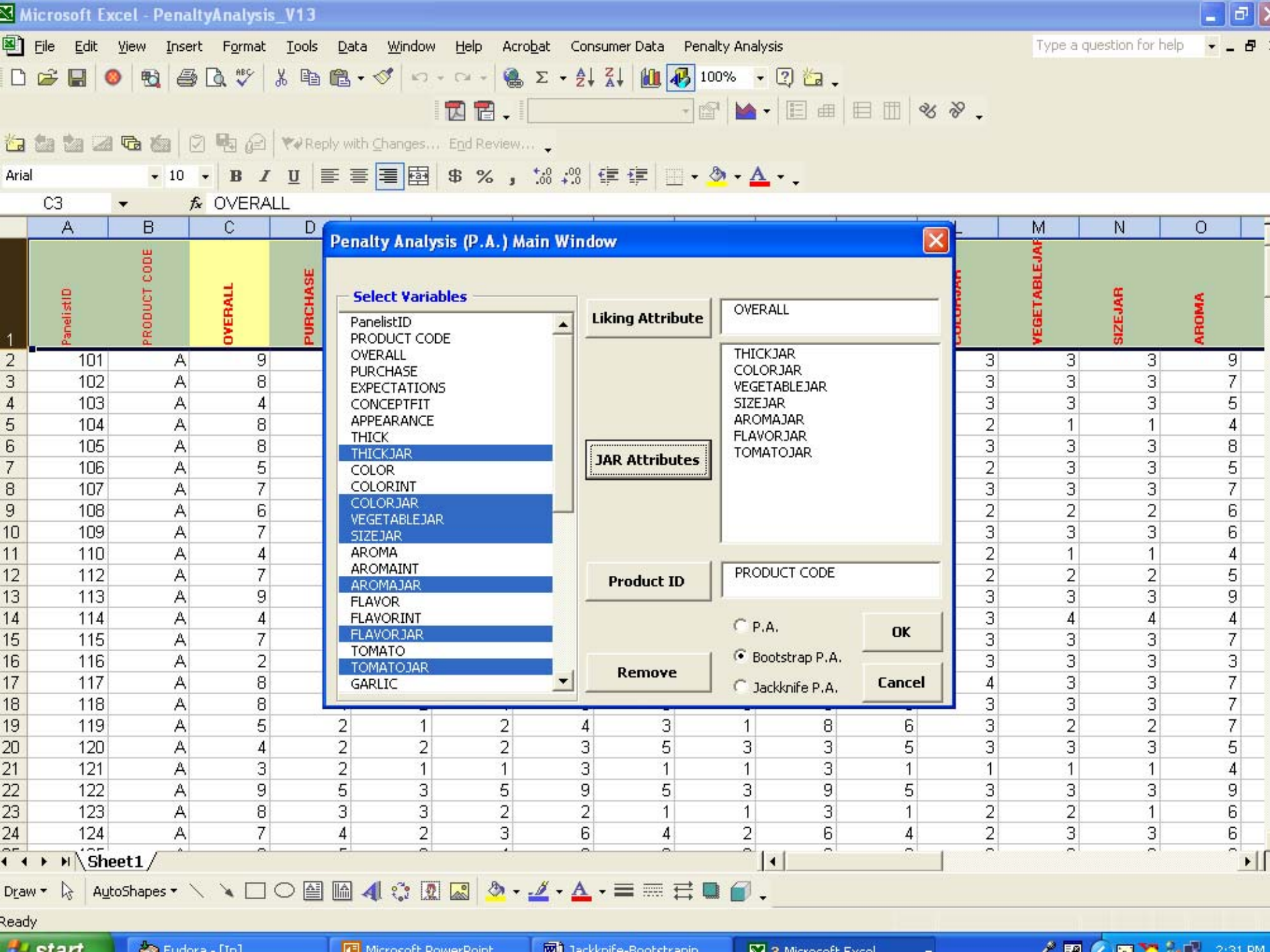
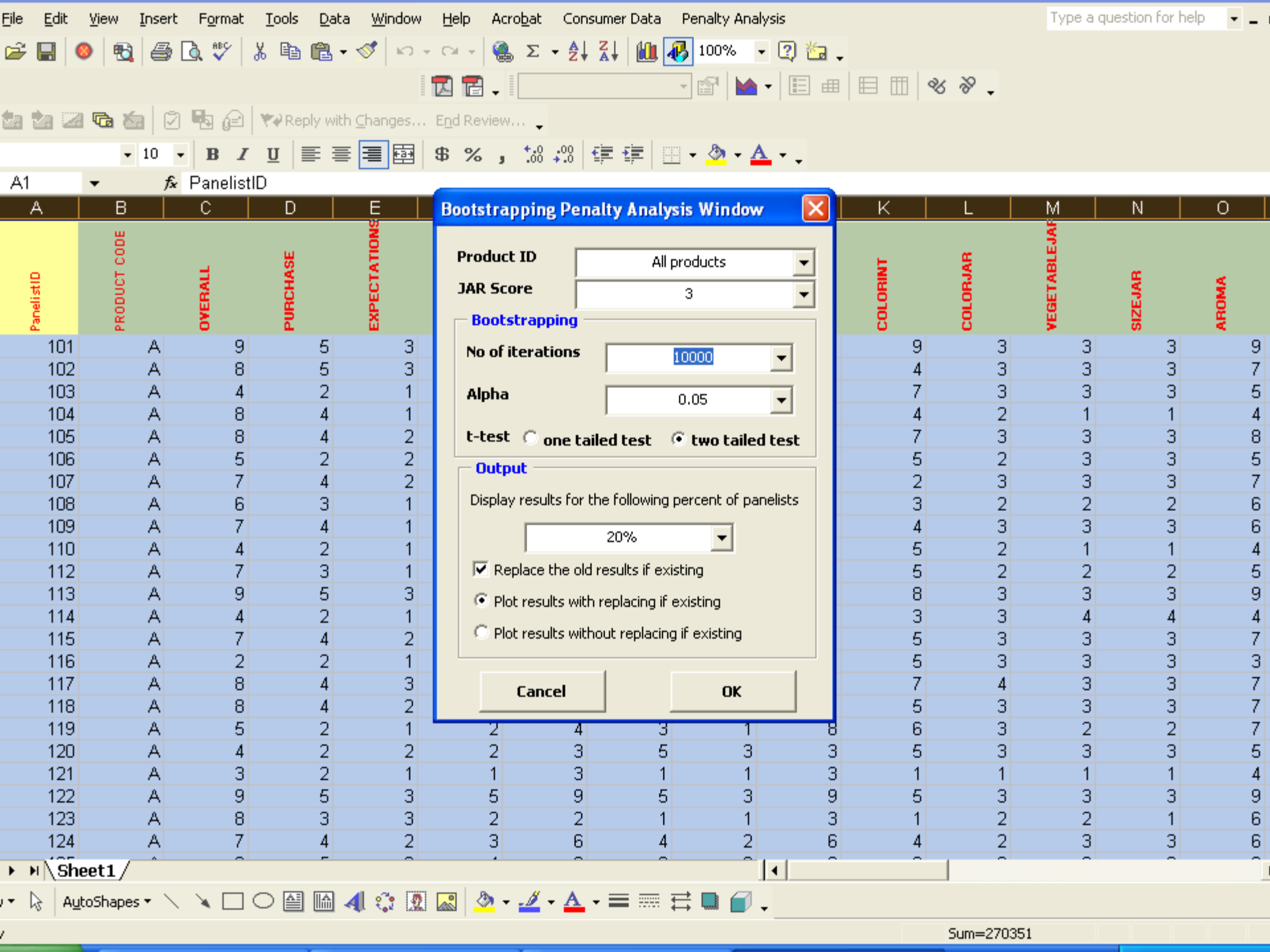


FIG. 3.
HISTOGRAM OF THE MEAN DROPS FOR "TOO MUCH" FLAVOR FOR PRODUCT A: (a) BOOTSTRAP REPLICATIONS OF 1000 AND BOOTSTRAP REPLICATIONS OF 10,000

How to compute Bootstrap Penalties?

- An add-on to Excel is available upon request jfmeull@uark.edu
- Need Microsoft Excel 2002 or higher


Microsoft Excel - PenaltyAnalysis_V13
File Edit View Insert Format Tools Data Window Help Acrobat Consumer Data Penalty Analysis
Penalty Analysis (P.A.) Main Window
Select Variables
PanelistID
PRODUCT CODE
OVERALL
PURCHASE
EXPECTATIONS
CONCEPTFIT
APPEARANCE
THICK
THICKJAR
COLOR
COLORINT
COLORJAR
VEGETABLEJAR
SIZEJAR
AROMA
AROMAINT
AROMAJAR
FLAVOR
FLAVORINT
FLAVORJAR
TOMATO
TOMATOJAR
GARLIC
Liking Attribute
OVERALL
JAR Attributes
THICKJAR
COLORJAR
VEGETABLEJAR
SIZEJAR
AROMAJAR
FLAVORJAR
TOMATOJAR
Product ID
PRODUCT CODE
Remove
P.A.
Bootstrap P.A.
Jackknife P.A.
OK
Cancel
Sheet1
Ready


File Edit View Insert Format Tools Data Window Help Acrobat Consumer Data Penalty Analysis
Type a question for help
100%
Reply with Changes... End Review...
A1
PanelistID
Bootstrapping Penalty Analysis Window
Product ID
All products
JAR Score
3
Bootstrapping
No of iterations
10000
Alpha
0.05
t-test
one tailed test
two tailed test
Output
Display results for the following percent of panelists
20%
Replace the old results if existing
Plot results with replacing if existing
Plot results without replacing if existing
Cancel
OK
PanelistID
PRODUCT CODE
OVERALL
PURCHASE
EXPECTATIONS
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VEGETABLEJAR
SIZEJAR
AROMA
Sheet1
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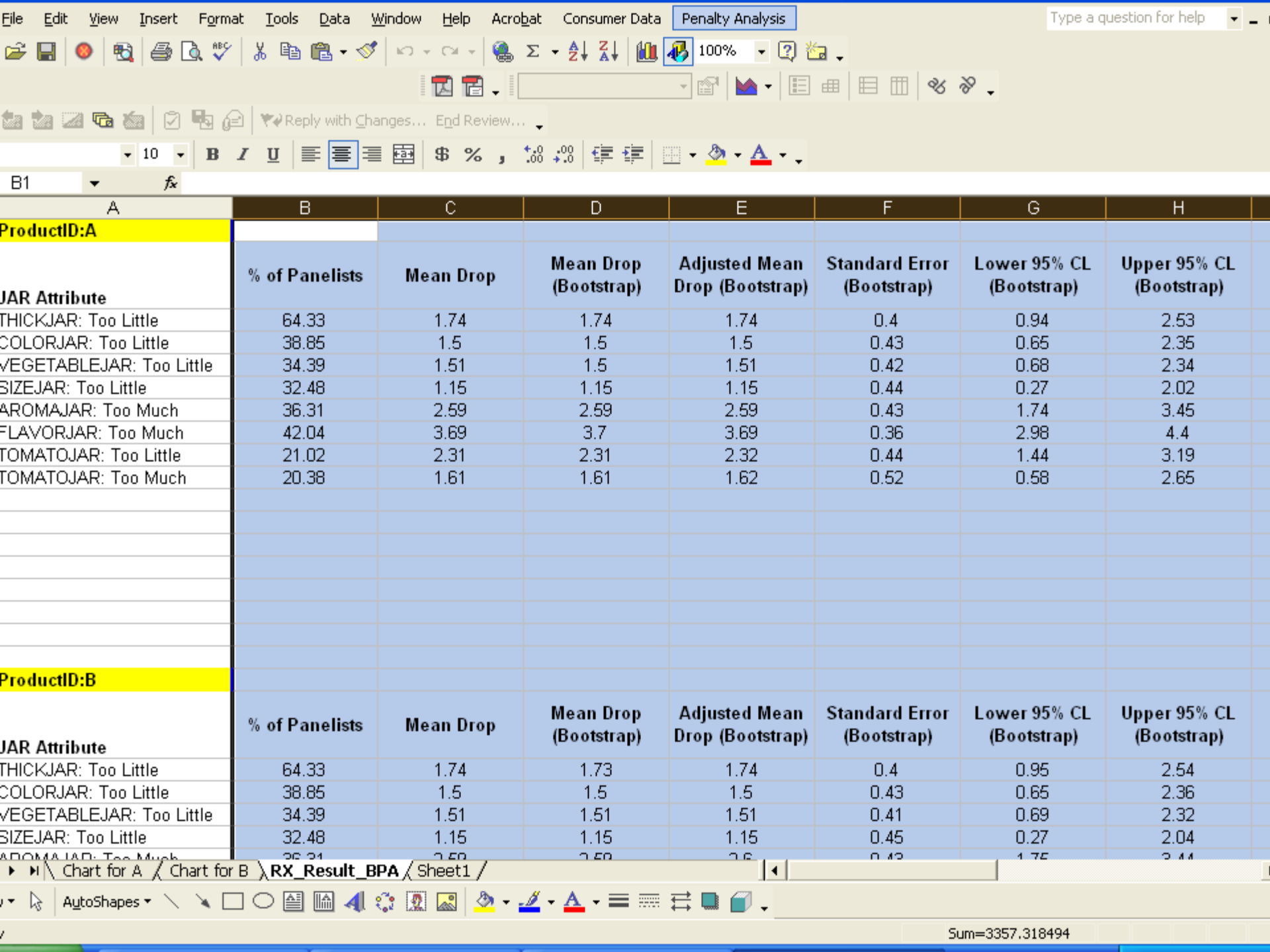

File Edit View Insert Format Tools Data Window Help Acrobat Consumer Data Penalty Analysis

Type a question for help

100%

Reply with Changes... End Review...

10

B1

A	B	C	D	E	F	G	H
ProductID:A							
JAR Attribute	**% of Panelists**	**Mean Drop**	**Mean Drop (Bootstrap)**	**Adjusted Mean Drop (Bootstrap)**	**Standard Error (Bootstrap)**	**Lower 95% CL (Bootstrap)**	**Upper 95% CL (Bootstrap)**
THICKJAR: Too Little	64.33	1.74	1.74	1.74	0.4	0.94	2.53
COLORJAR: Too Little	38.85	1.5	1.5	1.5	0.43	0.65	2.35
VEGETABLEJAR: Too Little	34.39	1.51	1.5	1.51	0.42	0.68	2.34
SIZEJAR: Too Little	32.48	1.15	1.15	1.15	0.44	0.27	2.02
AROMAJAR: Too Much	36.31	2.59	2.59	2.59	0.43	1.74	3.45
FLAVORJAR: Too Much	42.04	3.69	3.7	3.69	0.36	2.98	4.4
TOMATOJAR: Too Little	21.02	2.31	2.31	2.32	0.44	1.44	3.19
TOMATOJAR: Too Much	20.38	1.61	1.61	1.62	0.52	0.58	2.65
ProductID:B							
JAR Attribute	**% of Panelists**	**Mean Drop**	**Mean Drop (Bootstrap)**	**Adjusted Mean Drop (Bootstrap)**	**Standard Error (Bootstrap)**	**Lower 95% CL (Bootstrap)**	**Upper 95% CL (Bootstrap)**
THICKJAR: Too Little	64.33	1.74	1.73	1.74	0.4	0.95	2.54
COLORJAR: Too Little	38.85	1.5	1.5	1.5	0.43	0.65	2.36
VEGETABLEJAR: Too Little	34.39	1.51	1.51	1.51	0.41	0.69	2.32
SIZEJAR: Too Little	32.48	1.15	1.15	1.15	0.45	0.27	2.04

Chart for A | Chart for B | RX_Result_BPA | Sheet1

AutoShapes

Sum=3357.318494

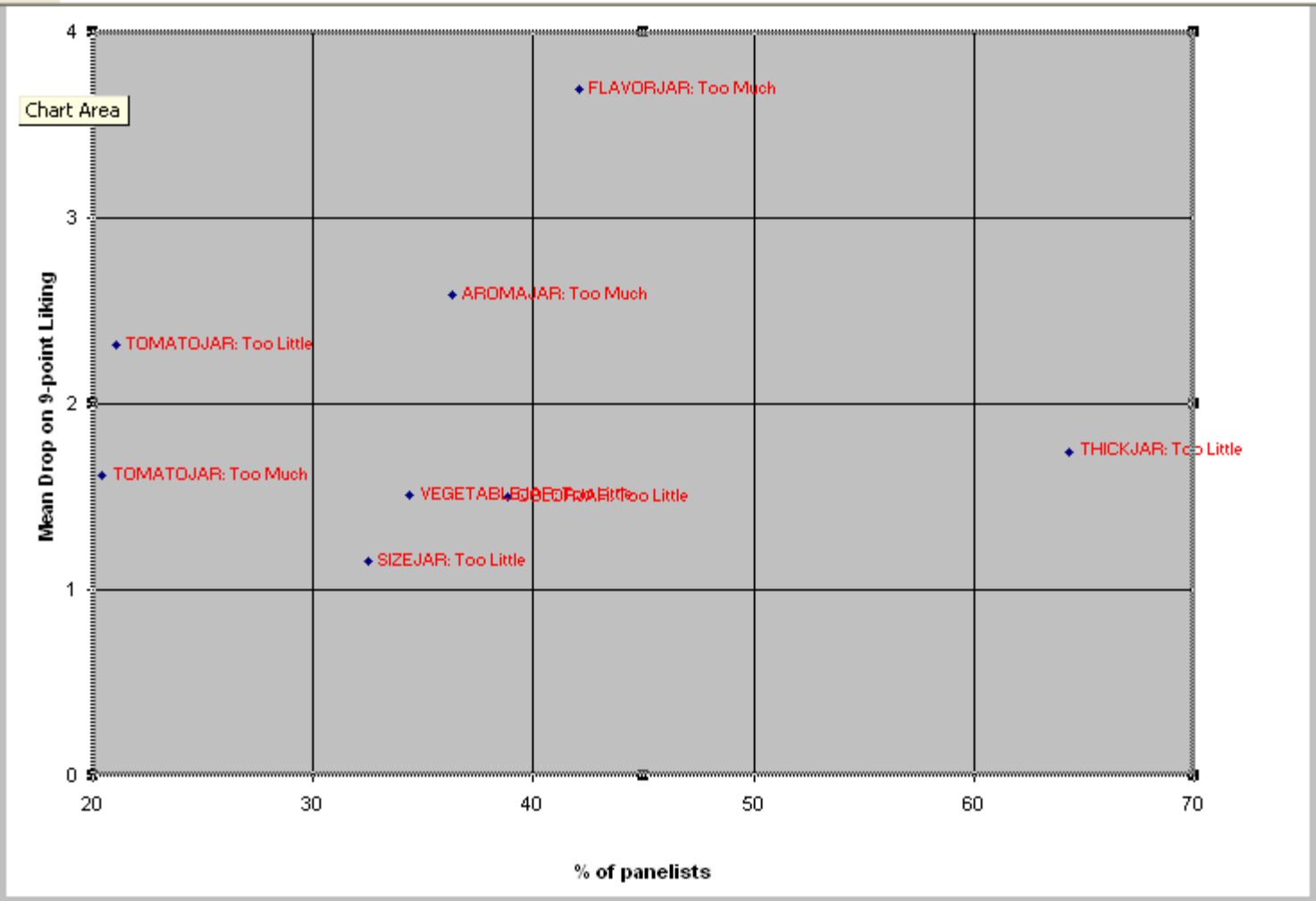
Chart Area
FLAVORJAR: Too Much
AROMAJAR: Too Much
TOMATOJAR: Too Little
THICKJAR: Too Little
TOMATOJAR: Too Much
VEGETABLEJAR: Too Little
SIZEJAR: Too Little
Mean Drop on 9-point Liking
% of panelists
0
1
2
3
4
20
30
40
50
60
70

Conclusions

- Testing the significance of penalties constitutes an improvement
- However, the method is still flawed from the point of view that collinearities are ignored
- Penalties do not add up!
- The integration of PLS and penalty concepts will provide more realistic estimations of product improvements

Thanks to Richard Popper for providing the data and for useful insight on penalty analysis