Using Novel Data for Vehicle Rating

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CAS Special Interest Seminar: Baltimore, October 2011

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Outline

1. Vehicle Characteristics vs. Series
2. Collecting and attaching data
3. Developing and Implementing Models
4. Some illustrative results

Vehicle Series

Working Definition: A vehicle series is an collection of vehicles that shares a number of characteristics in common and is used to aggregate loss experience.

- Different companies or organizations will partition the universe of vehicles in different ways, so the specific set of series will be similar across organizations but not identical.

Vehicle Series

- Common aggregations include:
  - Model year
  - Make
  - Model name
  - Additional attributes include:
    - Body Style &/or # of doors
    - # of drive wheels
    - Engine
    - Trim packages.

- Multiple price points (MSRPs) within series sharing common experience may lead to further refinement.

Vehicle Series

sounds simple but…:

- Model year (or range of model years).
  - ***When does the design change "significantly" enough to warrant a new series?***
- Make (manufacturer).
  - ***Chevy vs. GMC (~~Oldsmobile~~, ~~Pontiac~~, Buick, Cadillac)?***
- Model name (or aggregations like truck weight class).
  - ***VW Jetta / GTI / Fox / Golf?***
  - ***Ford Escape vs. Mazda Tribute?***
- Additional attributes, …
  - ***Irrelevant alternatives?***

…Credibility? …

Vehicle Characteristics

Alternate approach:

• Instead of defining a series, *link the loss experience* ***directly*** *to the characteristics of the vehicle*.

• Let a model *discover* the relationship between claims and the *relevant* aspects of a vehicle:

Model year	Price	Body style
# of doors	# of cylinders	# of drive wheels
Displacement	Horsepower	Torque
ESC	ALB	DRL
Curb weight	Wheelbase	***etc.***

Vehicle Characteristics

- *When does the design change "significantly" enough to warrant a new series?*
  - ***When / as much as the characteristics do.***
- *Chevy vs. GMC (~~Oldsmobile~~, ~~Pontiac~~, Buick, Cadillac)?*
  - ***The relevant differences are the characteristics, not the nameplate.***
- *VW Jetta / GTI / Fox / Golf?*
  - ***Design changes are considered, "branding" isn't.***
- *Ford Escape vs. Mazda Tribute?*
  - ***Share platform and common attributes, but some differences exist and are accounted for.***
- *Irrelevant alternatives?*
  - ***Not significant in models.***

Proxies vs. Characteristics

Proxies (working definition): attributes that are correlated with other relevant factors.

• Some of the relevant factors may be known, some may be readily available and others may not be easily measured or obtained.

• Proxies in models or series ratings may reflect or approximate the relationships inherent in the correlated factors, *but do so imperfectly*.

Proxies vs. Characteristics

Example: sedan with the same year, make and model.

Trim Level	Price (MSRP)	Horsepower	Braking Dist.
Base	$14K	120	X
Performance	$35K	276	0.8X

- Price captures the relationship between two performance measures that move in different directions.

Example: truck series from same make and year.

Truck Series	Price (MSRP)	Horsepower / Torque	Gross Weight
“15” (1/2 ton)	$21K	215 / 235	6,000
“25” (3/4 ton)	$28K	380 / 400	8,650
“35” (1 ton)	$36K	350 / 650	11,500

- Trucks are priced “by the pound” but also note that torque follows cost more closely than horsepower does.

Proxies vs. Characteristics

- Obtaining more detailed information (characteristics) can refine loss estimates that are approximated by proxies.
  - ✓ The proxy is still predictive in most cases
  - ✓ But, the magnitude of the effect is often dampened

- Other notable proxies:
  - ✓ Model year contains trends in engineering innovations
  - ✓ Model year is also correlated with price and miles driven

Collecting Data

In order to develop a model on vehicle characteristics, … **what data do we need?**

- Exposures and Losses at the specific exposure level.
- Other relevant rating factors (covariates):
  - Other applicable elements of the rating plan (Territory, Driver, etc.)
- Some vehicle specific characteristics (e.g. price, year, body style, # of cylinders, # of doors, etc.)

What data do we want?

- As much detailed, *relevant* vehicle specific characteristic data as we can *reasonably* get our hands on.

Where does detailed vehicle data come from?

- *A lot of hard work!*
  - …and multiple public and proprietary sources.

Obtaining 3rd Party Data

Outline

1. Qualifying data sources
2. Match keys
3. String matching tools
4. Level of aggregation
5. Process and QC

* Thanks to Leila Mortazavi of ISO Innovative Analytics and the team.

Qualifying Data Sources

- Is the data (*potentially*) predictive of losses?
- Is the data accurate? Can it be accurately matched?
- Completeness: does the data cover:
    - Adequate history (older model years)?
    - Adequately large proportion of insured vehicles?
- Will the data continue to be available in the future?
- Is the data allowable for use?
- Do you have (or can you obtain) appropriate rights of use?
- Does the data contain enough novel information to justify its cost (both the price and the time and effort to use it)?

Match Keys

Some working definitions:

- "***Base***" dataset: containing exposures, losses, covariates and vehicle VIN for the specific risk.
  - The match keys should be *at least* as refined (disaggregated) as the 3rd party data.
- "***3rd Party***" dataset(s): Multiple sources.
  - Different match keys and levels of aggregation.

- ***Ideally*** (i.e. unrealistically) we would be able to match all of our 3rd party data to our base data by VIN or some common *decoded* VIN.
  - *What follows is a discussion of what to do when the ideal situation doesn't hold.*

Match Key Cascade

Conceptually, the process of matching 3rd party data to the base can be thought of as hierarchical or a "cascade".

1. Model year
2. Manufacturer (Make)
3. Model Name
4. Body Style
5. Doors
6. Drive Wheels
7. Tie breakers *(data source specific)*

- ➢ If an exact match is found, then merge / join to base.
- ➢ If not, then roll up to next higher levels of hierarchy and resolve ambiguous cases.
- ➢ Hierarchy may differ for various 3rd party sources.
- ➢ Some pre-processing (clean-up) of keys helps a lot.

Match Key Details

1. **Model Year**: matches are relatively easy
   - Some sources provide data in model year ranges (e.g. 2003-2007).
2. **Manufacturer** (Make): also relatively easy
   - Differences easily resolved (e.g. 'ACUR' ⇔ 'ACURA')
3. **Model Name**: not easy at all – a great deal of source specific detail and some idiosyncrasies.
   - Some sources have two fields (e.g. "model" and "sub model").
   - Model names in one source can be parsed to create tie breakers (or keys) with a defined field in another source e.g.:
     - Drive wheels: "4X4" vs. "4X2", "AWD"
     - Engine type: "TURBO", "HYBRID", "FLEX"
     - Engine cylinders or displacement: "(V6)", "(V8)" or "2.0", "3.2"
   - Other differences / idiosyncrasies not easily resolved.
     - Some tools to aid in matching or disambiguation of model names will be described in detail below.

Match Key Details

4. **Body Style** …
5. **…**and **doors**: keep an eye out for differences

Base Data	3rd Party Data	
Body Style	**Body**	**Doors**
SEDAN 4D	SEDAN	4
COUPE 2D	COUPE	2
HCHBK 3D	HATCHBK	2

6. **Drive wheels**: ‘2’ or ‘ ‘ vs. ‘4’ (or ‘AWD’ or ‘6’)
7. **Tie Breakers**:
   - Common fields that exist across the base and 3rd party source (or that can be parsed from name).
   - Will differ from source to source.
   - Sometimes measurements differ slightly among sources (rounding, definitions) – need to accommodate differences.

String Matching Tools (in SAS)

SAS functions and routines

see: SAS 9.2 Language Reference: Dictionary, 4th Ed.

- SPEDIS: Spelling Distance [asymmetric]
  - Syntax: SPEDIS(query, keyword)
  - Performs a series of operations to convert “keyword” ➔ “query”
    - Assigns a cost to each operation, e.g.

Operation	Cost	Description
truncate	50	Delete a letter from the end
append	35	Add a letter to the end

  - Sums costs and divides by length(query) – rounds to nearest integer.
  - SPEDIS(string 1, string 2) not always equal to SPEDIS(string 2, string 1).

String Matching Tools (in SAS)

- COMPGED: Generalized Edit Distance
  - Similar to SPEDIS
    - Different operations & costs
    - More options
    - Doesn’t adjust for length
  - CALL COMPCOST: Use to modify (or ignore) operation costs in COMPGED
- COMPLEV: Levenshtein Edit Distance
- COMPARE: Position of leftmost character by which two strings differ
- SOUNDEX: Sounds Like
  - SOUNDEX(Couger) = SOUNDEX(Cougar)
- Also see: FIND, INDEX, etc.

Other software exists for evaluating string matches (e.g. Python).

String Matching Example

Base Model Name: "CAYENNESAWD"

3rd Party Model Names: "CAYENNETURBO"

"CAYENNE"

"CAYENNES"

Is the "best" match as obvious to the algorithm?

SPEDIS (CAYENNESAWD, CAYENNETURBO)

- Cost to convert CAYENNETURBO -> CAYENNESAWD
  - ***replace*** "TURB" with "SAWD" (cost to replace 4 = 100 x 4)
  - ***truncate*** "O" from the end (cost to truncate 1 = 50)
- **total cost = 40** = (400 + 50) / 11

SPEDIS (CAYENNESAWD, CAYENNE)

- Cost to convert CAYENNE -> CAYENNESAWD
  - ***append*** "SAWD" to end (cost to append 4 = 35 x 4)
- **total cost = 12** = 140 / 11

SPEDIS (CAYENNESAWD, CAYENNES)

- Cost to convert CAYENNES -> CAYENNESAWD
  - ***append*** "AWD" to end (cost to append 3 = 35 x 3)
- **total cost = 9** = 105 / 11

String Matching Example

Alternately, the Base Model Name: "CAYENNESAWD" could have been pre-processed to extract the "AWD" (into a tie breaker field):

- New Base MN: "CAYENNES", New Drive Wheels = "4" (or "A")

➢ then the SPEDIS example would be clear:

SPEDIS (CAYENNES, CAYENNETURBO)

- Cost to convert CAYENNETURBO -> CAYENNES
  - ***replace*** "T" with "S" (cost to replace 1 = 100)
  - ***truncate*** "URBO" from the end (cost to truncate 4 x 50 = 200)
- **total cost = 27** = (100 + 200) / 11

SPEDIS (CAYENNES, CAYENNE)

- Cost to convert CAYENNE -> CAYENNES
  - ***append*** "S" to end (cost to append 1 = 35)
- **total cost = 3** = 35 / 11

SPEDIS (CAYENNES, CAYENNES)

- Cost to convert CAYENNES -> CAYENNES
- **total cost = 0**

Matching Summary

- “Cascade” approach automates the discovery of exact matches and allows efforts to focus on disambiguation.
- A lot of pre-processing of fields is required to align them.
- String matching tools can aid in the process:
  - Each function has different aspects (costs, features and options).
  - Use multiple functions, and resolve disagreement (special cases).
- There is still a large manual effort.
  - EDA (Exploratory Data Analysis), data queries (group by, unique, …).
- Every different source requires unique solution details.
- The process needs to be replicable, in order to accommodate the introduction of new model years.

Aggregation in Data Sources

- Base data source should be as *disaggregate* as possible.
  - Merging / joining one row from a 3rd party source to multiple rows in the base is acceptable (and common).
  - Multiple rows in a 3rd party source matching a single row in the base is more *problematic*.
    - Are the differences in the rows of the 3rd party data source relevant (i.e. are they in fields that are not of interest / used in the model)?

Using 3rd Party Data

Process and Quality Control

- Initial matching process is very large:
    - > 25 model years.
    - > 100K distinct vehicles.
- Annual updates need to be executed quickly.
    - About 4,000 distinct vehicle make / model / trims per year.
    - Some percentage are new model introductions, some models are significantly redesigned , and some features are added / introduced or made standard equipment.
- A robust process with built in QC is required for the production process.

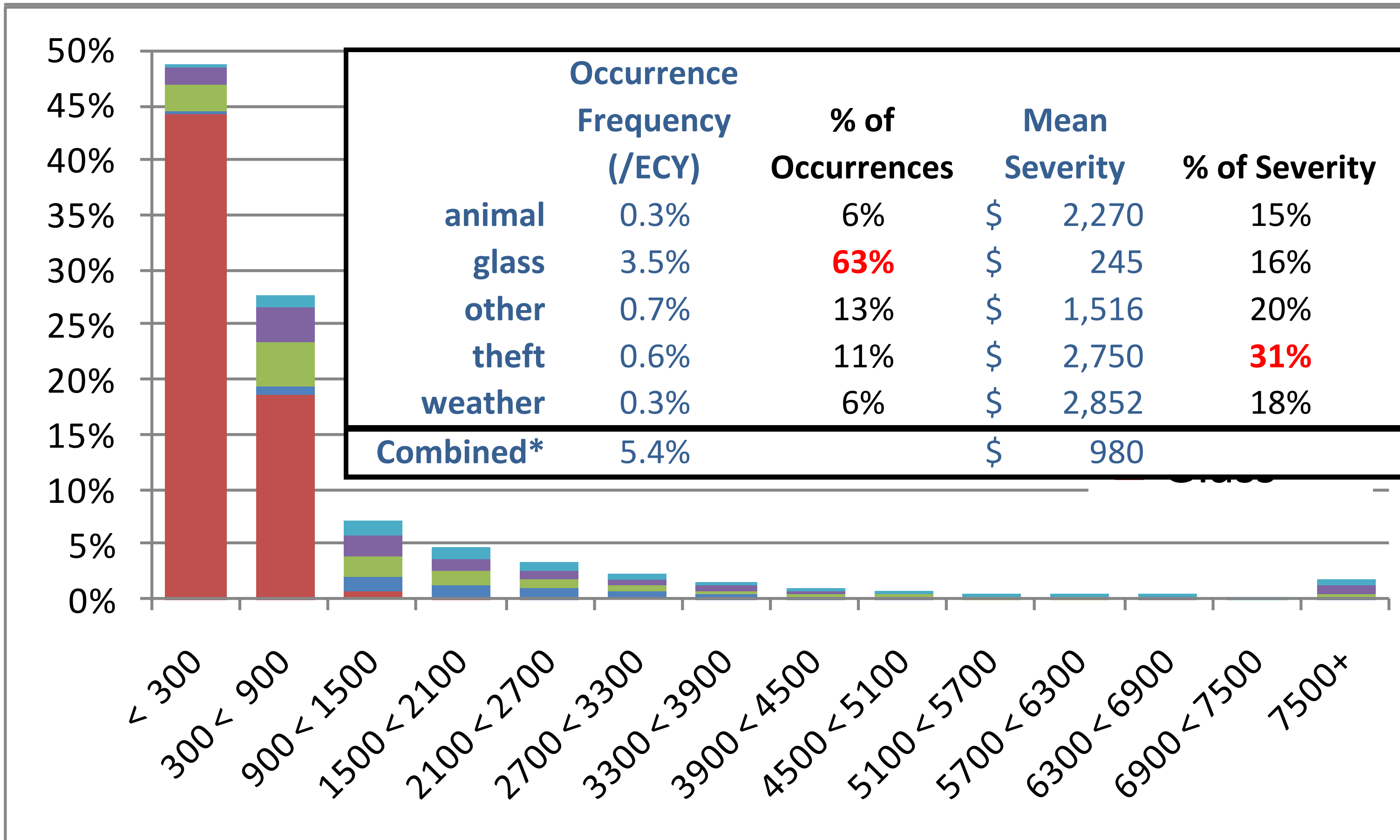
Developing Models

- When developing models from characteristics:
  - The variable selection task becomes challenging.
  - Need to adequately control for covariates (other elements of risk) like garaging address, driver, policy, etc.
  - Different characteristics may be associated with the likelihood (frequency) and the magnitude (severity) of losses, including antagonistic relationships (+/-).
  - Within a multi-peril coverage like comprehensive, different vehicle characteristics may be related to different perils.
    - The aspects of a vehicle that make it attractive to a thief may not matter to a deer.

Comprehensive Perils

By Peril - Frequency and Severity Distributions

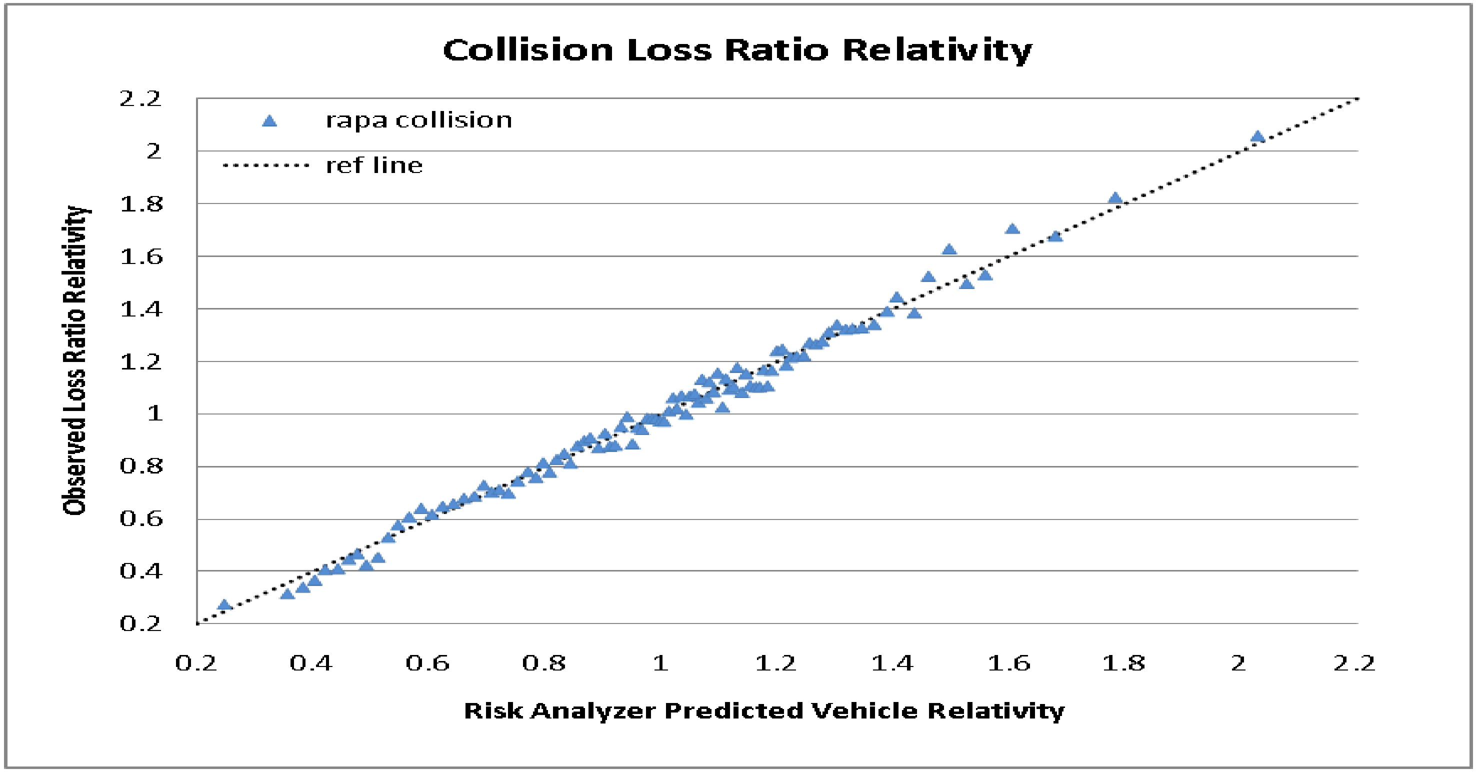
Comprehensive Losses – Severity Distribution



	Occurrence Frequency (/ECY)	% of Occurrences	Mean Severity	% of Severity	99th %tile Severity
animal	0.3%	6%	$ 2,270	15%	9,000
glass	3.5%	**63%**	$ 245	16%	967
other	0.7%	13%	$ 1,516	20%	9,388
theft	0.6%	11%	$ 2,750	**31%**	23,580
weather	0.3%	6%	$ 2,852	18%	18,901
Combined*	5.4%		$ 980		

Some illustrative results

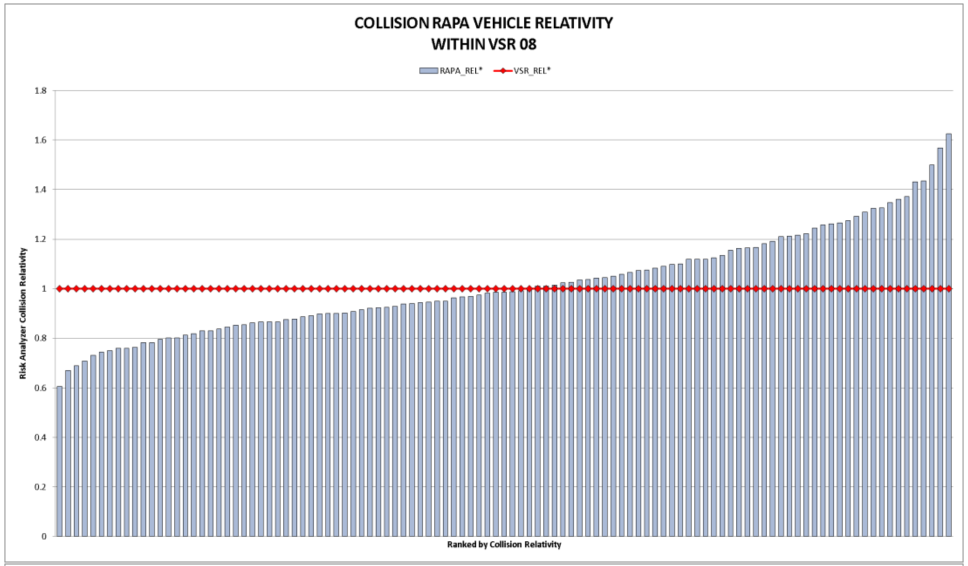
Collision Model Validation
Predicted Vs Actual



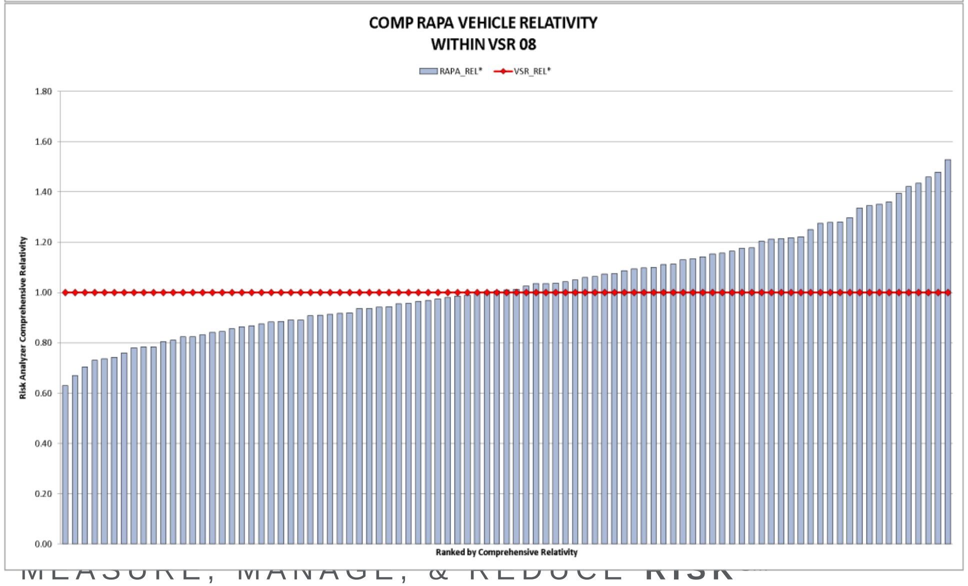
The vehicle model produces highly accurate predictions in line with the observed losses

Note: results against a holdout test dataset

Segmentation within VSR SYMBOL 08



Collision Coverage



Comprehensive Coverage

Predictive Modeling using Vehicle Characteristics provides significant segmentation within VSR Symbols

Example 1:Differentiation within series

2007 Ford Explorer Limited

Selected Attributes				RAPA Symbols/Relativities				VSR Symbols/Relativities		
Cyl	Horse-power	Curb-weight	Price New	COL SYM	COL REL	COM SYM	COM REL	SYM	COL REL	COM REL
6	210	4615	$34,070	LN	-	LJ	-	'12'	-	-
8	292	4615	$35,365	LP	+2%	LT	+19%	'12'	Same	Same

RAPA	➢RAPA Vehicle Module is able to pick up differences among several different styles of a common line, and differentiate the risks.
VSR	➢The VSR Symbol Set sometimes groups different model trims within a series together under a common VSR symbol.

Example 2: Performance Matters

2007 Honda Accord

Selected Attributes				RAPA Symbols/Relativities				VSR Symbols/Relativities		
Model Trim	Horse power	Engine Size	Cyl	COL SYM	COL REL	COM SYM	COM REL	SYM	COL REL	COM REL
EX	166	2.4L	4	HU	-	HT	-	'13'	-	-
SE	244	3.0L	6	HV	+5%	HV	+7%	'13'	Same	Same

COMP	➢The relativity for the EX model in RAPA is about 7% higher, compared to a 0% differential in VSR.

COLL	➢The relativity increase for the EX model in RAPA is about 5%, compared to a 0% differential in VSR.

Example 3: Redesigned Vehicle Series

Toyota Camry 4-Door SE

Selected Attributes			RAPA Symbols/Relativities				VSR Symbols/Relativities		
Model Year	Accel Rate	Price New	COL SYM	COL REL	COM SYM	COM REL	SYM	COL REL	COM REL
2006	X	$19,925	FR	-	FM	-	'11'	-	-
2007	1.6X	$18,270	EW	+15%	ER	+8%	'10'	-5%	-9%

COMP	➢The 2007 redesign produces an 8% ***increase*** in relativity over the prior version in RAPA. ➢Contrast with a 9% ***decrease*** in relativity in VSR

COLL	➢The 2007 redesign produces an 15% ***increase*** in relativity over the prior version in RAPA. ➢Contrast with a 5% ***decrease*** in relativity in VSR

Summary

- Vehicle series rating and vehicle characteristic driven modeling
- Techniques and challenges: vehicle data for modeling and results
- Questions?