KU LEUVEN

An Actuarial Approach to Data-Driven Warranty Pricing

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FLANDERS MAKE

DRIVING INNOVATION IN MANUFACTURING

The Right-to-Repair demands pricing transparency

Right-To-Repair

New warranty rules
- Additional warranty time
- Full repair information
- …

Increase in warranty price

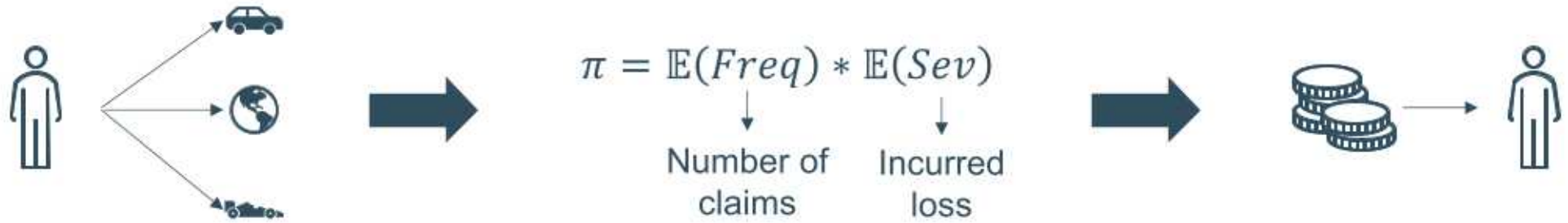
Unreliable

Transparent warranty pricing

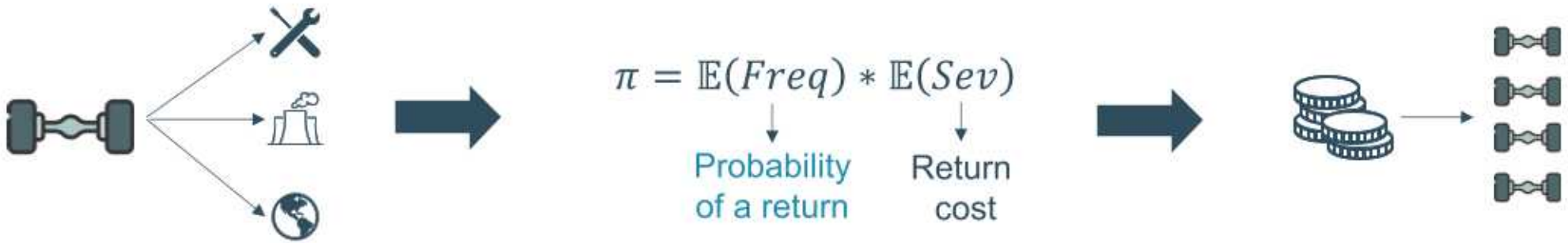
Methodology

We borrow ideas from non-life insurance

Insurance tariff plan



Warranty pricing



Warranty premiums are estimated using the product's return probability and cost

The warranty premium (π_i) for product i is defined by:

$$\pi_i = \mathbb{E}\left(\frac{N_i}{S_i}\right) * \mathbb{E}(C_i)$$

Probability of return

N_i: *returns of product i*

S_i: *sales of product i*

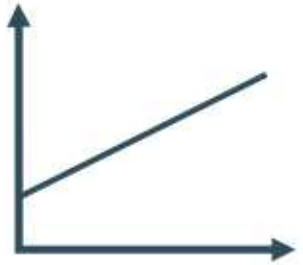
Average return cost

C_i: *return cost of product i*

We develop a surrogate model to capture machine learning accuracy with statistical transparency

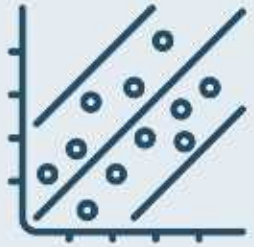
Gradient Boosting Machine (GBM)
Performance: +++
Explainability: +

+



Generalized Linear Model (GLM)
Performance: +
Explainability: +++

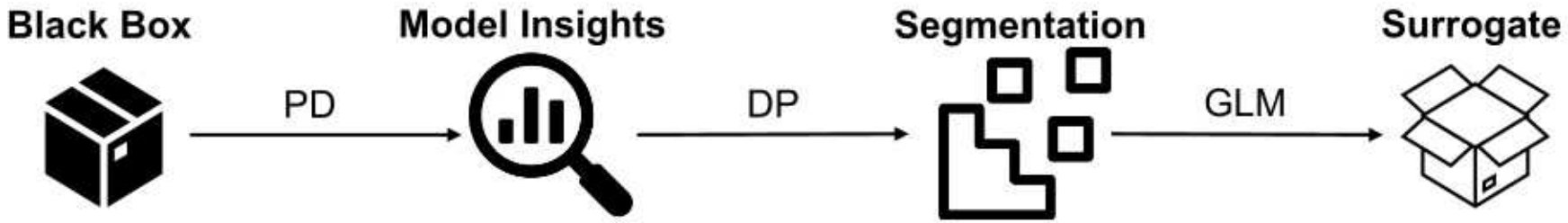
≈



Surrogate Model

Performance: ++
Explainability: +++

Construction of a surrogate model



1. The partial dependencies are computed for all features, and key feature interactions are identified using Friedman's H-statistic.
2. A dynamic programming algorithm clusters feature levels by minimizing within-group variation in PD effects.
3. A GLM is fitted using the new segmentation

Heckaerts, R., Antonio K., Cote, M. (2022). When stakes are high: Balancing accuracy and transparency with Model-Agnostic Interpretable Data-Driven suRRogates

We model return probability and cost using binomial–logit and gamma–log

$\mathbb{E}\left(\frac{N_i}{S_i}\right)$	**Probability of return** N_i: *returns of product i* S_i: *sales of product i*

$\mathbb{E}(C_i)$	**Average return cost** C_i: *return cost of product i*

Binomial with logit-link

$$Y \sim Binomial(n, p)$$

$$\hat{p} = \frac{1}{1 + \exp(-f(\boldsymbol{x}))}$$

Gamma with log-link

$$Y \sim Gamma(\mu, \phi)$$

$$\hat{Y} = \mu = \exp(f(\boldsymbol{x}))$$

Results

A case study with an automotive parts supplier

Company Context

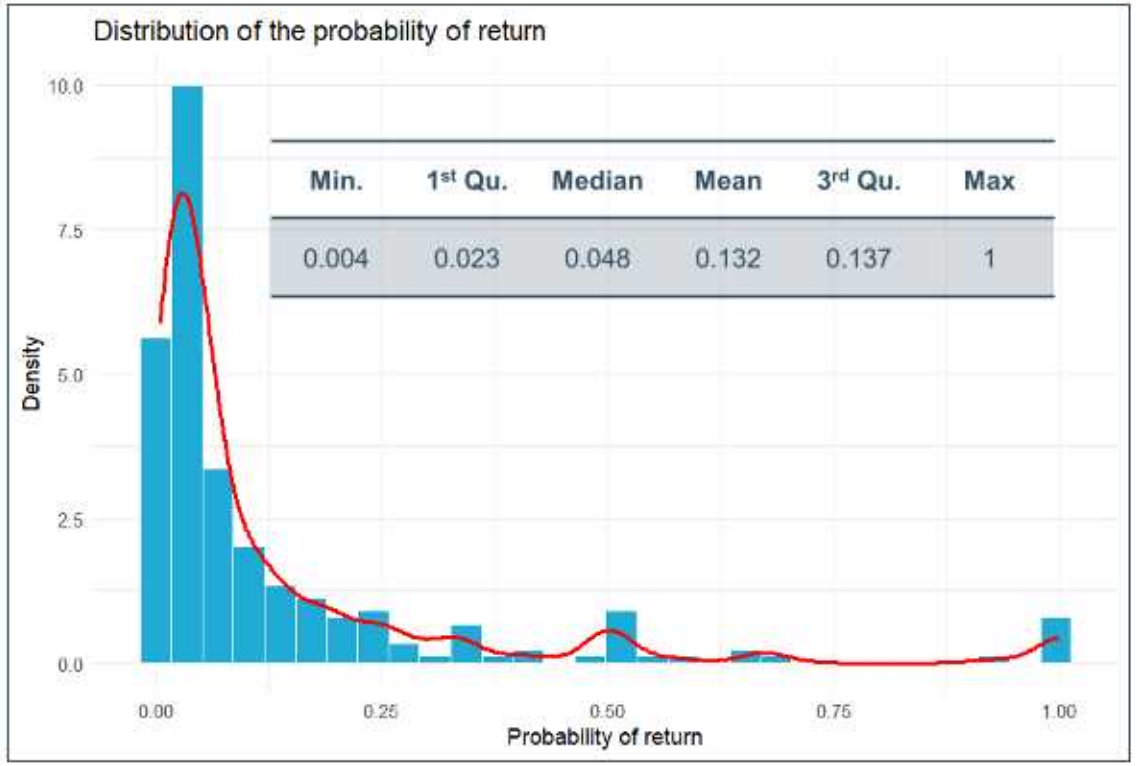
- Automotive parts supplier (B2B)
- Axles, Transmissions, Gearboxes, …

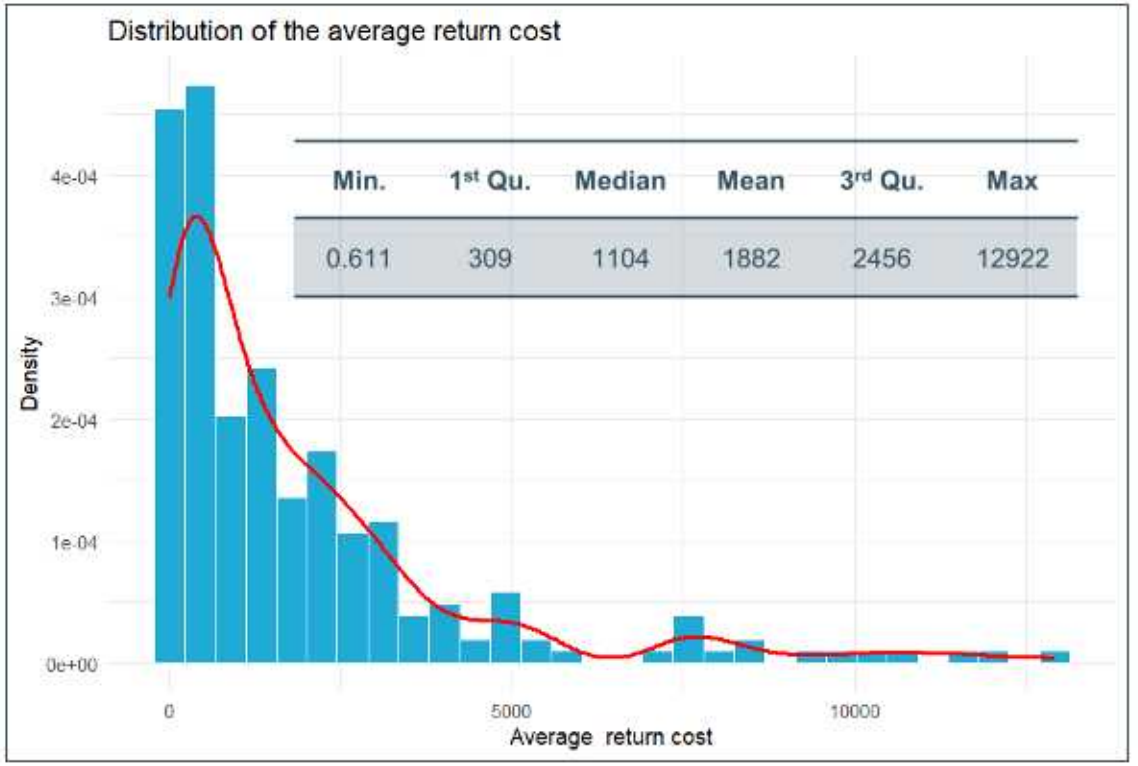
Data Overview

- 8.000 sales
- 2.400 returns
- 800 unique products
- Sold in 2012, returned over the next 3 years

Descriptive statistics of probability of return and average return cost

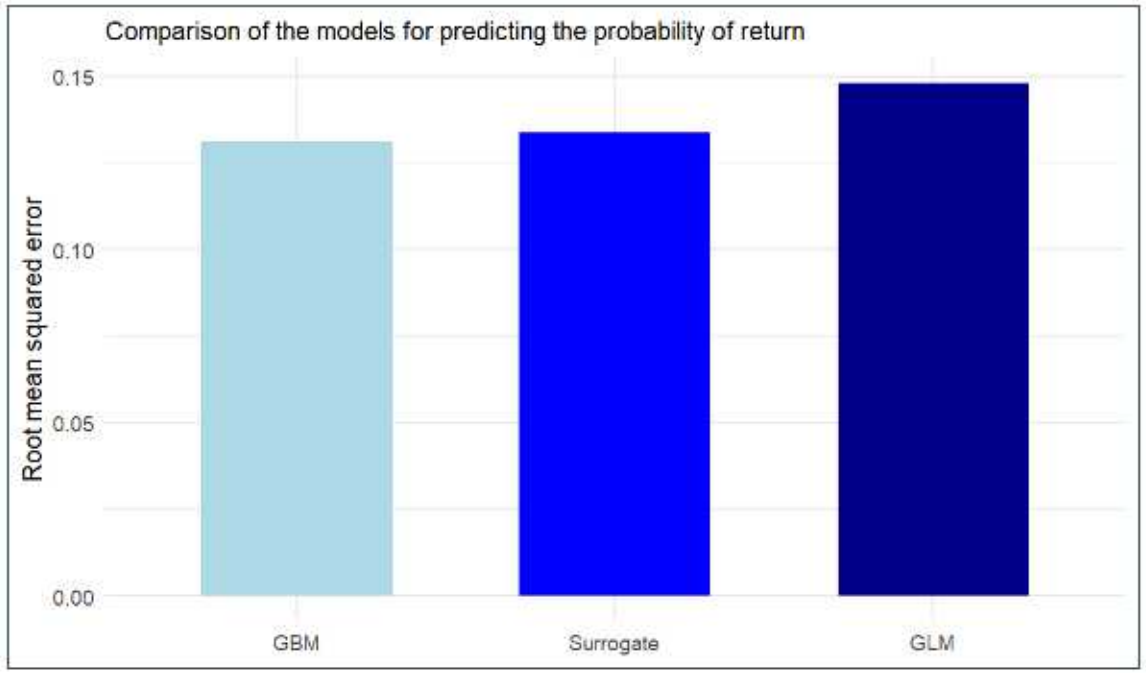
≈70% of products are not returned within the warranty timeframe



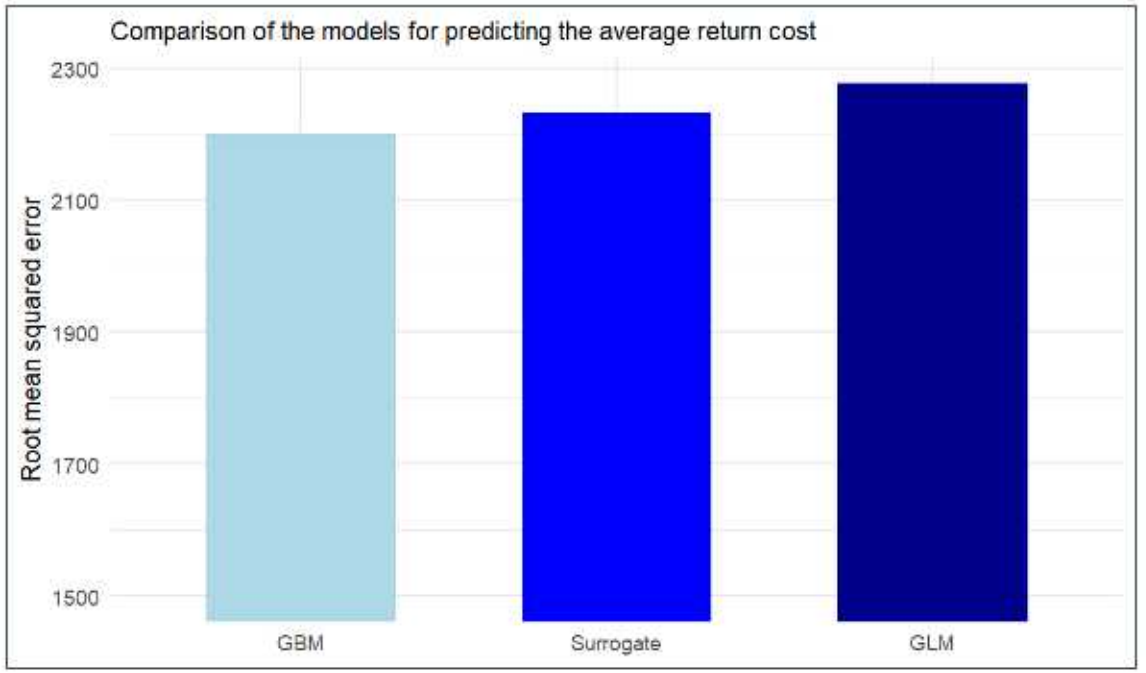


The surrogate model outperforms the GLM and nearly matches the GBM

Probability of return

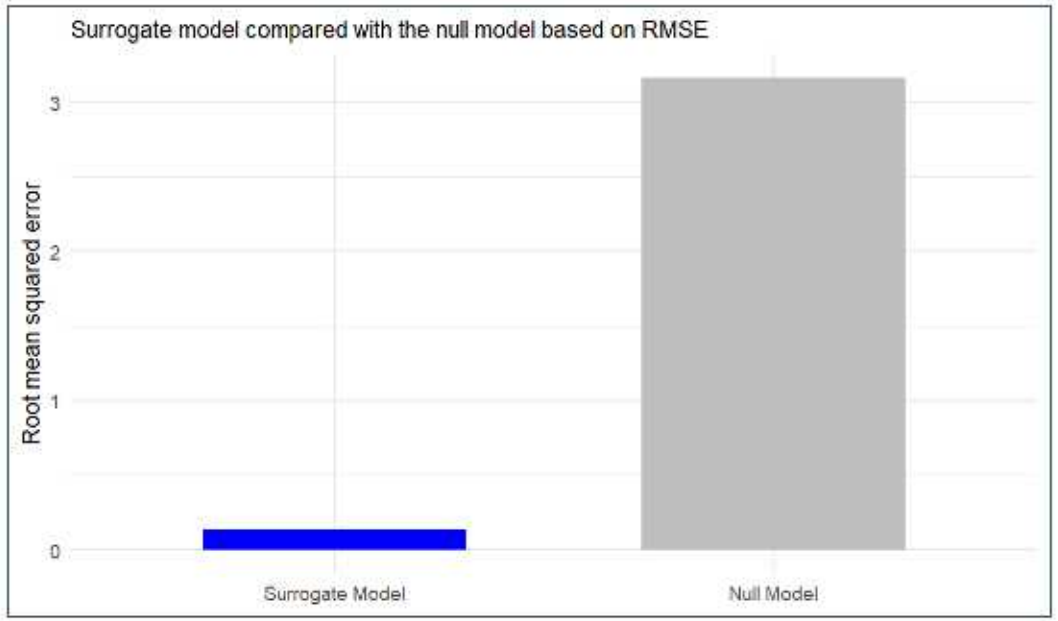


Average return cost

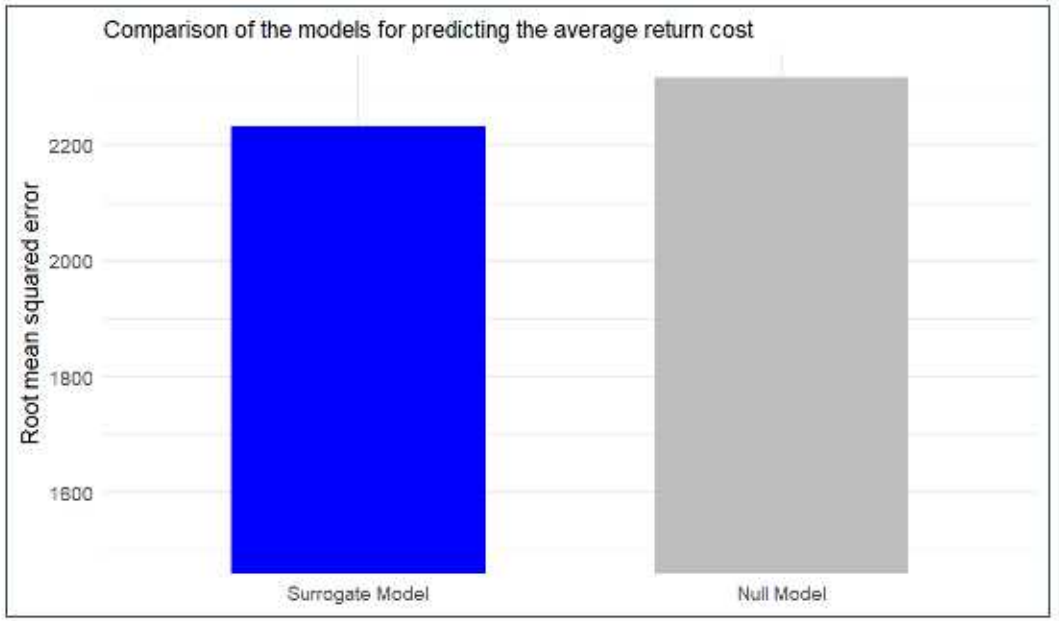


Predictor features improve return probability accuracy without affecting average return cost

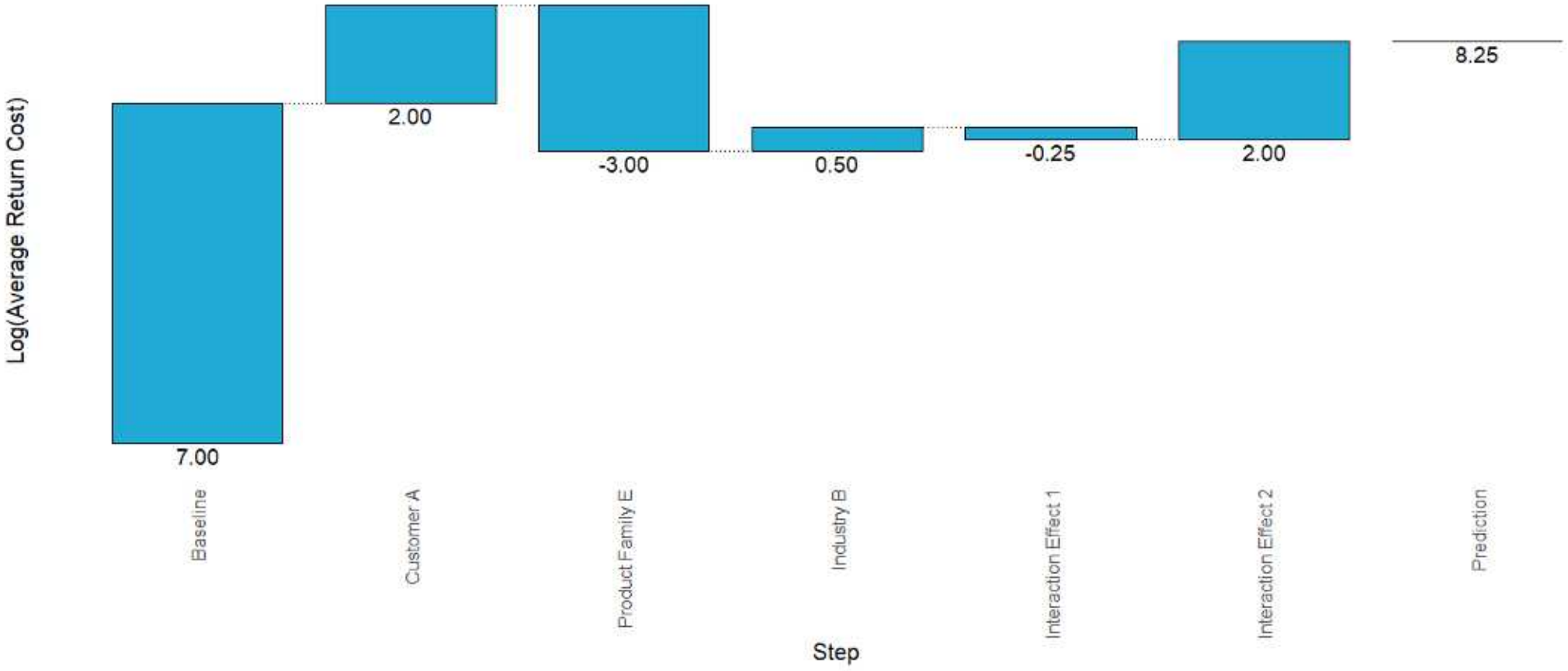
Including explanatory features for the probability of return significantly improves the model's performance



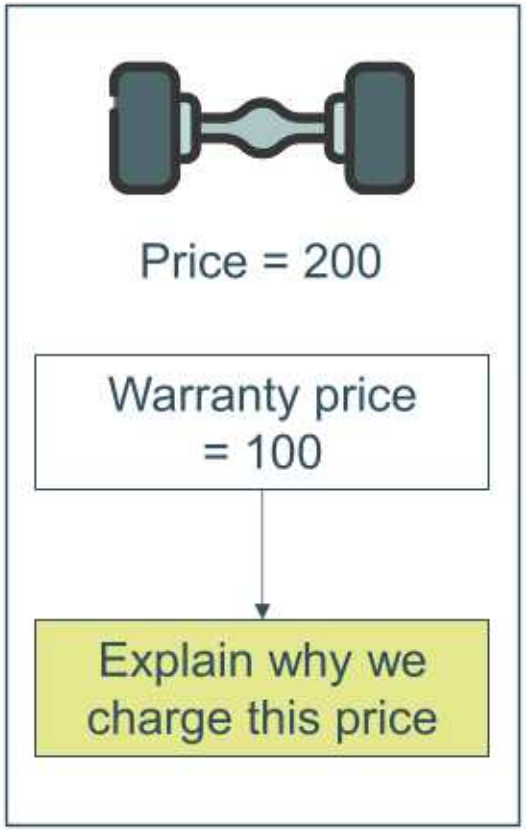
The explanatory features used for the average return cost predictions do not have a significant impact on the model's performance

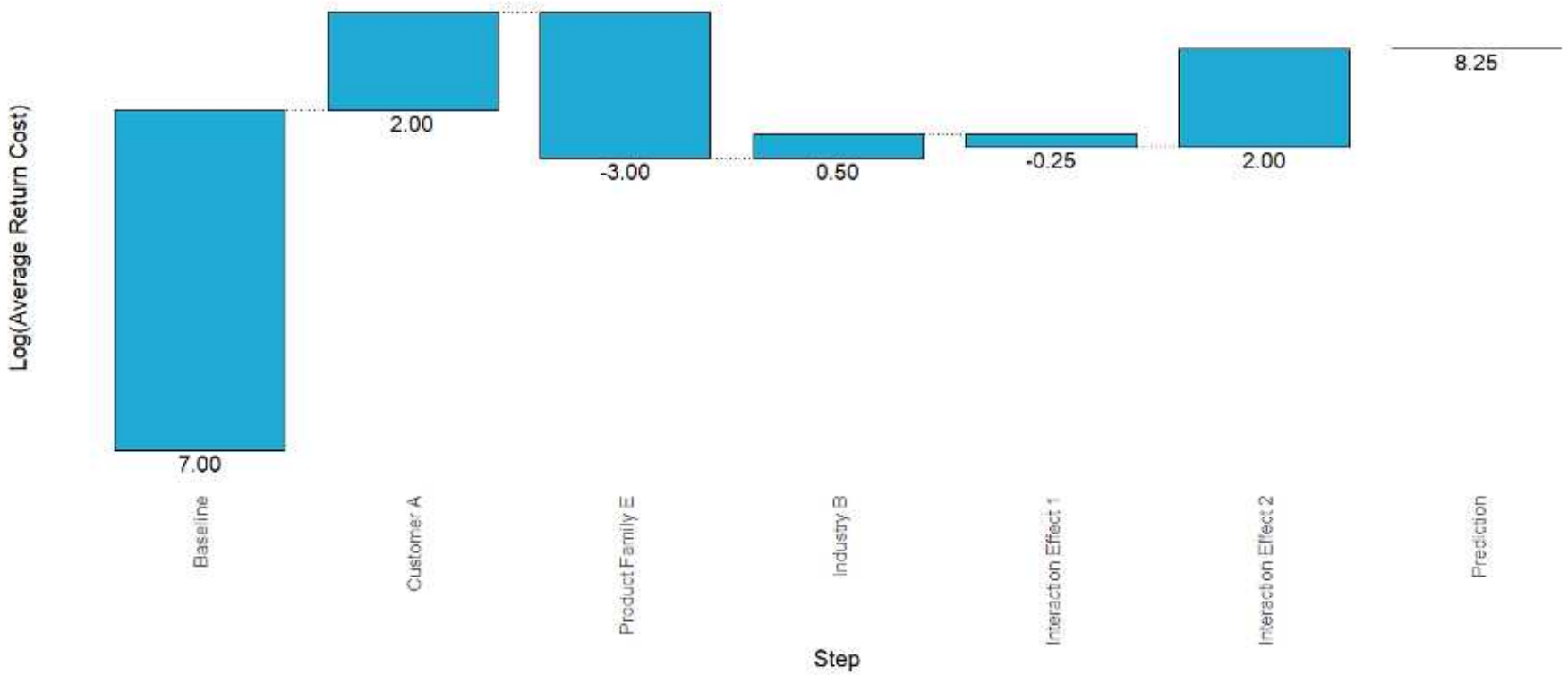


Transparent predictions are provided by showing how each variable influences the result



Using the waterfall plot, the OEM can explain why it charges the warranty premium

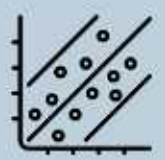




Discussion and next steps

Main Insights

Transparent warranty premium prediction models can help minimize the impact of the right to repair on manufacturers.



The warranty premium can be predicted transparently by using surrogate models.

Surrogate models outperform traditional generalized linear models (GLMs) and nearly match the performance of machine learning.

Next steps

- Feature engineer for average cost model
- Safety premium prediction
- Test model on multiple product categories