1 Problem Statement

The used car market is a large and strategically important market for car manufacturers. The overall size of the used car market in terms of total sales volume, number of establishments and employees was, respectively, $104,604 million, 227,765, and 1,706,001 in 2011 (Barnes, 2011). Furthermore, the second-hand market is closely connected to the new car business. Trading-in used cars in new car retail sales and handling lease returns, repossessions and fleet returns from car rental companies necessitate car manufacturers to engage in the used car market.

Car makers face several challenges in the second-hand market. The depth crisis in the European Union, the general problem of overcapacity, increasing competition from Asian manufacturers, and the trend toward more eco-friendly cars are only a few factors that add to the difficulty of selling used vehicles in the second-hand market and decrease sales margins. Therefore, car makers require sophisticated decision support systems to sustain the profitability of the used car business. A core component of such systems is a prediction model that estimates resale prices on the basis of car attributes and other factors (Du et al., 2009; Jerenz, 2008). Although a statistical modeling of resale prices has been considered in previous work (e.g., Purohit, 1992), only very few studies have explicitly attempted to predict resale prices with maximal accuracy to support decision making. As a consequence, answers to the following questions are unclear: i) to which degree are resale prices predictable, ii) what is the relative accuracy of different prediction methods and are some methods particularly effective, iii) given that market research agencies have specialized in residual value estimation, is it sensible for car makers to invest into an in-house resale price forecasting system? The objective of this paper is to provide empirical answers to these questions.
2 Contributions
The paper contributes to the theory and practice of resale price modeling in the following ways. First, using real-world sales data from a leading German car manufacturer, a large-scale empirical benchmarking study is undertaken to contrast the predictive power of alternative prediction methods. The resale price forecasting task exhibits specific characteristics such as high dimensionality. It is therefore important to explore how different methods cope with such challenges and to identify particularly appropriate techniques. For example, our benchmark is, to the best of our knowledge, the first empirical study of forecast combination – one of the most successful modeling strategies in other domains – in the automotive industry.

Second, the paper explores the predictive value of private information (PI) that is only available to used car makers/vendors. From an economic perspective, investing into an internal forecasting system is sensible only if this allows car makers to predict resale prices more accurately than external market research agencies. Informational advantages are the most important asset car makers can use to achieve this goal. It is thus important to clarify whether employing PI in prediction models leads to more accurate forecasts.

Third, the study sheds light upon the specificity of resale price forecasting models. Prediction models can be devised at different levels of granularity. For example, one can build a single model for all vehicles under study (low specificity). Alternatively, individual prediction models for different car models can be built (high specificity). A high specificity modeling approach may improve predictive accuracy, but at the cost of multiplying the total number of prediction models. This increases the costs for model building, monitoring and maintenance. Examining the trade-off between accuracy and specificity helps to provide recommendations how the forecasting task should be approached in corporate practice and to contribute toward an economic assessment of internal resale price forecast systems.

Results and Implications
Our empirical results suggest that the Ensemble Selection (ES) methodology (Caruana et al., 2006) performs best in resale price forecasting. Using this approach, the mean absolute error (MAE) of forecasts is only 3.97. This level of accuracy suggests that resale prices are well predictable. Figure 1 depicts the performance of eighteen other prediction methods relative to ES. That is, it shows the pairwise difference in MAE between a competing method and ES (dotted bar). Figure 1 also shows a critical difference (solid bar). Whenever, the observed
difference in MAE exceeds the critical difference, it can be concluded that ES performs significantly better than the corresponding competitor (1% level). The main implications of Figure 1 are that Random Forest (RF) performs as good as ES – the performance difference between the two is insignificant – and that all other methods are significantly inferior to ES and RF; see (Hastie et al., 2009) for a comprehensive discussion of all prediction methods.

![Figure 1: Pairwise (observed and critical) difference in MAE between a prediction method and the overall best method (Ensemble Selection).](image)

A second experiment explores how the accuracy of resale price forecasts changes when prediction methods receive only publicly available information as input. This mimics the way in which market research agencies develop residual value estimates. We find that taking PI into account increases forecast accuracy by about 4.5% on average. A two-way repeated measures ANOVA confirms that this difference is significant ($p$-value<0.000). Furthermore, ANOVA suggests that the value of PI depends on the prediction method. Most methods benefit from PI, whereas linear regression methods perform worse when incorporating PI into a prediction model. This tendency can be explained with the sensitivity of linear regression methods toward high dimensional data.

A third experiment provides evidence that prediction model specificity does not have an overall (i.e., main) effect on forecast accuracy. However, ANOVA reveals a significant interaction between the experimental factors model specificity and prediction method. Linear
regression methods perform better when prediction models are geared toward individual car models (high specificity approach). We suggest that this is because high specificity allows these methods to account for heterogeneity, which is a well-known issue in regression modeling. More advanced nonlinear methods, on the other hand, benefit from a low specificity approach. Heterogeneity is not a major problem for these methods because they can account for complex interaction among covariates. Moreover, they benefit from the larger data samples that follow from a low specificity setup.

In summary, our results suggest that the methods most widely used in resale price modeling are least effective. In particular, linear regression methods predict significantly less accurately than advanced methods such as RF and ES. Furthermore, advanced methods are able to extract useful predictive information from PI and are robust toward high dimensionality. This allows car makers to improve upon the accuracy of external residual value estimates through an internal forecasting support system. Finally, advanced methods need only a single prediction model to forecast resale prices for different car models. This reduces costs associated with model building, monitoring and maintenance and thus further increases the attractiveness of an in-house forecasting approach.

References


