HEDONIC PRICING OF VEHICLE CHARACTERISTICS, SAFETY AND EQUIPMENT IN THE UK CAR MARKET

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Overview

Recently, increased attention has been paid to the car market by researchers, governments, reporters and the general public, as the market is entering a unique stage of transformation and development, where the focus on environmentally friendly vehicles is greater than ever. UK has one of the largest car markets in the world, with a growing share of alternative fuel vehicles (AFVs), and a great importance to the UK economy. However, extensive insight into the vehicle characteristics and features that influence prices and sales in the UK car market is lacking. To provide such insight, this research paper manually constructs a novel, extensive and unique dataset for the entire UK car market, for the period between 2008 and 2019. This dataset represents over 99% of the UK car market and includes a wide-range of information on car characteristics, attributes, equipment, prices and sales. The main goals of the paper include: finding the key car characteristics that influence market prices, comparing these characteristics between conventional vehicles (CVs) and AFVs, constructing quality constant hedonic price indices, and finding the most important car characteristics for AFV consumers. To answer these research questions, a full hedonic pricing model is applied, using the adaptive Lasso technique, ordinary least squares, weighted least squares, quantile, weighted quantile, and penalized weighted quantile regressions.

Methods

The research paper constructs and uses a completely new dataset, providing a unique and contemporary insight into the UK car market. The entire dataset was manually collected from a wide range of sources, both physical and online. This extensive information includes a wide range of car physical characteristics, safety features, equipment, sale figures and prices, for almost all of the car models in the UK car market, for the time period 2008-2019. As such the dataset contains 3017 observations, 67 different vehicle characteristics, 144 different variables constructed from these characteristics and therefore, more than 450 000 unique data points. All the data has been standardized to mean 0 and standard deviation 1, to allow for a direct comparison between coefficients of various variables.

The main model applied to the data is the hedonic pricing model. A hedonic model is used to derive implicit prices of various attributes that make up a composite good. A composite good (e.g. house or car) is a heterogeneous good that can be described as a bundle of different characteristics that consumers derive utility from, such that:

$$\boldsymbol{P}(\boldsymbol{Z}) = \boldsymbol{P}(\boldsymbol{z_1}, \boldsymbol{z_2}, \dots, \boldsymbol{z_n}) \tag{1}$$

where $P(Z)$ is the market price of car Z,
n is the total number of measurable characteristics z_i, such that $Z = (z_1, z_2, \dots, z_n)$.

The utility is not derived from the composite good itself, but rather from the good's many different characteristics. Since the prices for each individual characteristic are not independently observed, hedonic pricing regressions attempt to estimate them. As such, the hedonic technique can be applied to any composite good to find the marginal effect of the attributes on the good's overall price. After using the heteroskedasticity robust RESET test to identify that the optimal functional form is semi-logarithmic, the hedonic model applied to the data is:

$$\ln P_j = \beta_0 + \sum_{t=1}^{T} \beta_t d_{j,t} + \sum_{i=1}^{I} \beta_i z_{j,i} + \epsilon_j, \qquad j = 1,2, \dots, n \tag{2}$$

where P_j is the price of car model j,
$d_{j,t}$ is a dummy variable equal to 1 if car model j was in the market in the year t,
$z_{j,i}$ is the value of vehicle characteristic i for the car model j,
β_i and β_t are the coefficients for characteristic i and time dummy t respectively,
ϵ_j is the error term,
T is the number of time periods, n is the number of car models, and I is the number of car characteristics.

Before any regressions can be run, the issue of too many characteristics (and therefore variables) needs to be solved. As stated above, there are altogether 144 variables available for regression, and such large number can lead to several problems, such as multicollinearity between characteristics, overfitting, or parameter estimation issues and thus subsequent problems in interpretation. Therefore, to improve the estimation with such large number of variables, it is important to only include those variables that are important and relevant on economic grounds and that do not suffer from high levels of multicollinearity. For this purpose, I apply the adaptive Lasso methodology:

$$\hat{\beta}_n^{AL} = \arg\min_{\beta} \sum_{j=1}^{n} \left(y_j - x_j\beta\right)^2 + \lambda_n \sum_{i=1}^{I} \lambda_{n,i}|\beta_i| \tag{3}$$

where $\lambda_n > 0$ is the tuning parameter,
$\lambda_{n,i} = \frac{1}{(|\hat{\beta}_{n,i}|)^{\gamma}}$ *is the adaptive weights vector,*
$\hat{\beta}_{n,i}$ *is an initial estimate of the coefficients,*
γ *is a positive constant for adjustment of the adaptive weights vector, set between $\frac{1}{3}$ and $\frac{10}{3}$.*

Following the identification of key variables, the ordinary least squares, weighted least squares, quantile, and weighted quantile regressions are applied, in order to answer the main goals of the study. An example of the weighted quantile regression used can be expressed as:

$$\hat{\beta}_{q_w} = \arg\min_{\beta_q \in \mathbb{R}} \sum_{j=1}^{n} w_j\left(x_j, q\right)\rho_q\left(y_j - x_j'\beta_q\right) \tag{4}$$

where $\hat{\beta}_{q_w}$ is the vector of coefficient estimates,
q is the quantile that is going to be estimated, with $q \in (0,1)$,
n is the number of observations,
ρ_q is the loss function,
$w_j(x_j, q)$ is any uniformly bounded positive weight function.

Furthermore, a number of robustness tests were applied, such as variance inflation factor (VIF) analysis, omitted variables tests, and heteroskedasticity tests, to ensure greater confidence in the results.

Results

The results of the research show that the key drivers of car prices in the UK are vehicle performance, and size/massiveness. The effect is found to get stronger as vehicles get more expensive. In terms of equipment, these are automatic air conditioning, full electric mirrors, automatic wipers, rear-view camera and an infotainment display, but the effect gets weaker as car prices increase. Comparing the effects between CVs and AFVs, AFV prices are significantly more sensitive to changes in features than CV prices, especially to changes in performance, emissions and extra equipment. Analysis of the hedonic price indices show that about 65% of the increase in car prices between 2008 and 2019 in the UK car market was caused by improvements in vehicle quality, which cause the car prices to rise by about 2% per year.

Conclusions

The results acquired from the research and the subsequent analysis can offer useful information to various parties. For example, the characteristics that influence vehicle prices are of interest to car dealers and manufacturers, who aim to optimize their pricing strategies and offer competitive prices to the buyers, while increasing their sales in the UK. Confirming which vehicle characteristics and attributes are the most important to the UK AFV buyers is also of great use to the UK government, manufacturers and marketers, who look to encourage the adoption of environmentally friendly and more energy efficient vehicles. A possible recommendation to manufacturers is to focus their research and development on improvements in performance and maximum range (such as batteries), as these significantly affect car prices, and are also key to AFV buyers. Since AFV consumers are also found to value vehicles' greater positive effect on the environment, both the manufacturers and the government should also support cleaner AFVs (such as better hybrids), and promote them through marketing and advertising campaigns, in order to encourage higher sales and reach the promises and goals of reducing climate change.

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