Predicting Used Car Prices in Online Marketplaces

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The digital revolution is disrupting used-car retailing for the better, as a new wave of digital retailing representing more than just technology alone focuses a spotlight on the importance of the customer experience in the used-car buying process. Used cars provide excellent value for money to consumers who do not have the resources or inclination to invest in new vehicles. A 2019 study (Ellencweig et al., 2019) revealed that used-car buyers spend 40% more time researching online during the buying process than do new car buyers, who spend fewer than seven hours on average. Only a small percentage of used-car buyers rely solely on in-person salespeople at a dealer when purchasing a vehicle; the rest make decisions based on their own prior research.

Online marketplaces offer implicit trust between buyers and sellers, a highly desired customer requirement. Often, more used vehicle buyers are on tight budgets, and their average credit rating is lower, which limits their access to financing options, another reason why online marketplaces find favor with many. Facebook, Craigslist, eBay, Amazon, Alibaba are a few well-known traditional C2C or B2C marketplaces where buyers and sellers interact directly to complete a transaction. A platform like Facebook marketplace does not charge customers for advertising, but some others generate steady revenues by charging subscription fees either to list or view the used car classifieds. Research suggests that the value of a vehicle drops by about 50% after 5 years of initial ownership, and some vehicles are known to depreciate faster than others (Gorzalany, 2021). This paper aims to address the following research question, assuming advertising and subscription costs are not accounted in the final transaction:

1. What are the unique predictors of the price of a car on e-Bay classifieds, after controlling for registration year and region?
2. Is the final price moderated by factors like odometer, power, gear box or fuel type?

Methods

Subjects

This study draws from extant data from Kaggle, a data science community providing free, crowdsourced data. The original dataset consisted of 370,000 cases, scraped from e-Bay Kleinanzeigen, the German classifieds website in April 2016, and consisted of listings from all major postal regions. For this study, data from a sample of $N = 144$ listings were drawn from one of the postal regions (covering north-western parts of North Rhine-Westphalia, south-western parts of Lower Saxony) with the registration year of 2012. Various data points of the vehicle such as body style, mileage, accidental damage, brand, model, registration year, gear type, fuel type, horsepower rating, number of pictures, postal codes, among others were collected as part of the data scraping process.

Measures

The major outcome of this study is: price of a vehicle. Final selling price is assumed to be the same as listed price. Price is the final selling price of the vehicle, not controlled for inflation, and as listed on the original classified ad. For our sample, correlations for Power and Gear box are positive for price at 0.65 and 0.45 respectively ($ps < 0.01$).

Data Analysis Plan

Data were analyzed using multiple linear regression with standard predictor entry. Because the outcome (price) was heavily right skewed, log transformation was performed on this variable. Since data from only 2012 was used for analysis, there were no dependence issues due to vehicle registration year. Data from one region with postal codes between 40000 and 49999 were used in the analysis, removing dependence concerns due to region. However, since cases were drawn from different vehicle types, vehicle type was coded into a set of three predictors for

four categories, and explicitly controlled for (treated as fixed effects) to avoid non-independence of residuals. Normality and linearity were examined to ensure that linear regression model assumptions were tenable. Heteroscedastic standard error of residuals was used in the model to ensure that all linear regression assumptions were tenable. Brand and Fuel Type were binary coded as single predictor variables. For ease of interpretation, Vehicle Type, Brand, Fuel Type, Gear Box and Unrepaired Damage variables were effect coded, and Power and Odometer were standardized. The final model was:

$$\begin{aligned} \text{LN(Price)} = & b_0 + b_1*\text{Fuel Type} + b_2*\text{Power} + b_3*\text{Brand} + \\ & b_4*\text{Sedan} + b_5*\text{SUV} + b_6*\text{Compact} + \\ & b_7*\text{Gear Box} + b_8*\text{Unrepaired Damage} + b_9*\text{Odometer} + \\ & b_{10}*\text{Fuel Type}*\text{Gear Box} + b_{11}*\text{Sedan}*\text{Odometer} + \\ & b_{12}*\text{Fuel Type}*\text{Power}*\text{Gear Box} + b_{13}*\text{Fuel Type}*\text{Power}*\text{Odometer} \end{aligned}$$

In the model above, the natural logarithm (log) of price is equal to the conditional mean price (b_0), plus the unique effect of Vehicle Types Sedan, SUV, and Compact ($b_4 - b_6$), plus the unique effects of Fuel Type (b_1), Power (b_2), Brand (b_3), Gear Box (b_7), Unrepaired Damage (b_8), Odometer (b_9), and the unique effects of interactions Fuel Type*Gear Box, Sedan*Odometer, Fuel Type*Power*Gear Box, and Fuel Type*Power*Odometer ($b_{10} - b_{13}$).

Results

Correlations

Means, standard deviations, and zero-order correlations among all variables are given in Table 1. Only one vehicle type was correlated with the outcome (Compact), with $r = -0.27$, $p < 0.05$, indicating that this vehicle type was significantly lower in price than the average of other types. This vehicle type is also lower in power and odometer ($r_s = -0.33$ and -0.26 , $p_s < 0.05$ for

power and odometer). Power and gear box were also significantly correlated with price, with $r_s = 0.65$ and 0.45 , and $p_s < 0.05$, respectively. There was a direct positive relationship between power and price. Unrepaired damage and odometer were not correlated, and as such will both uniquely contribute to the model.

Regression Models

Price. As shown in Table 2, results from the final model with all predictors included indicated that the mean price across vehicle types, gear box, fuel type, brand, and unrepaired damage and vehicles with average levels of power and odometer were estimated to be 9.39 logs which translates to a predicted price of 11,968.10 USD. For every standard deviation increase in power, the mean price of a vehicle was estimated to increase by 0.29 logs (1.34 USD), holding all else constant. This value is significantly different from zero, meaning that power uniquely predicted price. For every standard deviation increase in odometer, there was an estimated 0.20 logs decrease in price (1.22 USD), holding all else constant, again, implying that odometer was uniquely predictive of price. For compact vehicle types, there was a predicted decrease of 0.25 logs in price (1.28 USD) compared to the average, whereas for SUVs, there was a predicted increase of 0.19 logs in price (1.21 USD) compared to average, holding all else constant. Both values were significantly different from zero. For automatic gear box styles, the predicted increase in price was 0.14 logs (1.15 USD) more than average, holding all else constant, and for repaired damages, the price was predicted to increase by 0.17 logs (1.19 USD) more than average, holding all else constant.

The model also included two-way and three-way interaction terms. A significant disordinal interaction between odometer and sedan vehicles was detected when we graphed across three levels of odometer ($-1\ SD$, mean, and $+1\ SD$) as shown in Figure 1. The effect of

odometer on price was being moderated or flipped for higher and lower values of odometer rating, by the sedan variable. We tested two three-way interactions and the results as described below. In the first, we tested Fuel type*Power*Gear box. A significant interaction was detected between Fuel type, power and gear box, and the nature of the interaction was understood by computing model-implied values for both groups of gear box for both types of fuel (petrol and others), across three levels of power rating ($-1\ SD$, mean, and $+1\ SD$). As shown in Figure 2 Panel A, the interaction is ordinal and shows that petrol laden vehicles with automatic gearbox and lower power rating were predicted to have a difference of 0.66 logs in price compared to similar vehicles with the sample average power rating (a difference of approximately 0.1 logs in price). For vehicles with higher power rating, there was a predicted difference of 0.34 logs in price compared to similar vehicles, favoring automatic gear box styles. As shown in Figure 2 Panel B, the interaction is disordinal and shows that vehicles with other fuel types, automatic gearbox and lower power rating were predicted to have a difference of 0.10 logs in price compared to similar vehicles with the sample average power rating (a difference of approximately 0.6 logs in price), favoring manual gear box styles. For vehicles with higher power rating, the effect was flipped, and there was a predicted difference of 0.22 logs in price compared to similar vehicles, favoring automatic gear box styles.

For the second three-way interaction, we tested Fuel type*Power*Odometer. The interaction was significant, and the nature of the interaction was understood by separating power into high and low values, and then computing model-implied values of log of price for both groups of fuel (petrol and others). Values were computed across three levels of odometer rating ($-1\ SD$, mean, and $+1\ SD$). As shown in Figure 3 Panel A, the interaction is disordinal and shows that vehicles with high power rating and lower odometer rating were predicted to have a

difference of 0.26 logs in price favoring petrol laden vehicles, compared to similar vehicles with the sample average odometer rating (no difference in price). For vehicles with higher odometer rating, there was a predicted difference of 0.26 logs in price compared to similar vehicles, favoring other fuel laden vehicles. As shown in Figure 3 Panel B, the interaction was again disordinal, and depicts vehicles with lower power ratings. Vehicles having a lower odometer rating were predicted to have a difference of 0.26 logs in price favoring other fuel laden vehicles, compared to similar vehicles with the sample average odometer rating (no difference in price). For vehicles with higher odometer rating, the effect was flipped, and there was again a predicted difference of 0.26 logs in price compared to similar vehicles, this time favoring petrol laden vehicles.

Conclusion

Results revealed that odometer and power ratings were among some of the unique predictors of vehicle prices on e-Bay (effect sizes of $sr^2 = 0.11$ and 0.07 , respectively). Unrepaired damages were also uniquely predictive of prices, as one would expect. What was more interesting was how vehicle types affected prices – compact cars and sedans were significantly predictive of prices, more so than any other types of vehicles. Sedans moderated odometer rating effect on prices, and full moderation was observed. Gear box styles and fuel types together moderated the effect of power on prices, and we observed partial moderation for petrol vehicles and full moderation for other fuel types. The effect size for this interaction was small $sr^2 = 0.03$. Power rating and fuel type moderated the effect of odometer on price, and we observed full moderation for both low and high values of power rating. The effect size for this interaction was small $sr^2 = 0.02$. While there was no correlation between brand and gear box styles, only gear box was uniquely predictive of price (small effect size of $sr^2 = 0.04$). The power

level for this study was >99% and adequate and the recommended N:p ratio of 15:1 was met.

However, this study has a limitation: the results of the study are specific to the characteristics of vehicles used in Germany, as e-Bay classified listings were local to that region. Future research could find a way to examine actual sale prices of vehicle listed in the classified ads, rather than simply the listed price, as some these transactions are often subject to negotiations between buyers and sellers. Most importantly, the data was missing information on the number of pictures per listing, which is well known to attract the attention of buyers to improve chances of a sale.

References

- Ellencweig, B., Ezratty, S., Fleming, D., & Miller, I. (2019, June 6). Used cars, new platforms: Accelerating sales in a digitally disrupted market. *McKinsey & Company*.
<https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/used-cars-new-platforms-accelerating-sales-in-a-digitally-disrupted-market>
- Gorzelany, J. (2021, January 11). Burning Money: Vehicles That Depreciate The Fastest, and Those That Hold Onto Their Values Best. *Forbes*.
<https://www.forbes.com/sites/jimgorzelany/2019/11/07/burning-money-vehicles-that-depreciate-the-fastest-and-those-that-hold-onto-their-values-best/?sh=264d43ef5f4a>

Table 1.

Descriptives and Zero-Order Correlations

Measure	<i>M</i>	<i>(SD)</i>	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
<i>Outcomes</i>												
1. LN(Price)	16785.60	(15885.10)	--									
<i>Predictors</i>												
2. Power	139.11	(77.07)	0.65 **	--								
3. Odometer	81388.89	(42014.17)	-0.12	.01	--							
4. Gear Box	0.28	(0.45)	0.45 **	.57 **	.02	--						
5. Fuel Type	0.41	(0.49)	-0.06	-.05	-.57 **	-.18 *	--					
6. Compact	0.20	(0.40)	-0.27 **	-.33 **	-.26 **	-.28 **	.43 **	--				
7. Sedan	0.21	(0.41)	.00	.14	-.02	.06	.03	-.26 **	--			
8. SUV	0.19	(0.39)	.09	.02	-.03	.05	-.22 **	-.24 **	-.25 **	--		
9. Unrepaired Damage	0.96	(0.20)	0.05	.04	.08	-.02	-.04	-.07	.11	.01	--	
10. Brand	0.23	(0.42)	-0.09	-.09	.22 **	-.12	-.19 *	-.19 *	-.04	-.05	.03	--

Note. $N=144$. *Dummy coding:* Compact=1, Others=0; Sedan=1, Others=0; SUV=1, Others=0; Gear Box(Automatic=1, Others=0); Fuel Type(Petrol=1, Others=0); Unrepaired Damage(No=1, Others=0); Brand(Volkswagen=1, Others=0)

* $p < .05$, ** $p < .01$, *** $p < .001$.

Table 2.

Model Results for LN(Price)

	R^2_{total}	R^2_{adjusted}	$F(17,126)$	p	b	(SE)	$t(134)$	p	sr^2
<i>LN(Price)</i>	0.81	0.78	30.80	<0.001					
Intercept					9.39 ***	(0.08)	119.38	< 0.001	
Fuel Type					-0.09	(0.06)	-1.55	0.05	0.01
Power					0.29 ***	(0.11)	2.68	<0.001	0.07
Brand					0.02	(0.03)	0.74	0.444	0.01
Sedan					-0.07	(0.07)	-1.04	0.135	0.01
SUV					0.19 ***	(0.08)	2.46	<0.001	0.04
Compact					-0.25 ***	(0.07)	-3.38	<0.001	0.04
Gear Box					0.14 ***	(0.06)	2.45	<0.001	0.04
Unrepaired Damage					0.17 **	(0.06)	2.83	0.004	0.05
Odometer					-0.20 ***	(0.05)	-3.81	<0.001	0.11
Fuel Type x Gear Box					0.11 **	(0.06)	2.01	0.004	0.01
Sedan x Odometer					0.09 **	(0.04)	2.26	0.008	0.06
Fuel Type x Power x Gear Box					-0.08 *	(0.07)	-1.24	0.028	0.03
Fuel Type x Power x Odometer					-0.13 **	(0.11)	-1.23	0.006	0.02

Note. $N=144$. Fuel Type effect coded with 1=Petrol, -1=Others; Brand effect coded with 1=Volkswagen, -1=Others; Gear Box effect coded with 1=Automatic, -1=Manual; Unrepaired Damage effect coded with 1=No, -1=Yes; Vehicle Type effect coded with all others except Compact, Sedan and SUV as reference group; Power and Odometer standardized.

* $p < .05$, ** $p < .01$, *** $p < .001$.

Figure 1. Predicted LN(Price) for vehicle type, by odometer rating

Figure 2. Predicted LN(price) for gear box styles, by power rating and fuel type

Figure 3. Predicted LN(price) for varying power, by odometer rating and fuel type

Appendix

CORRELATIONS

```

/VARIABLES=price powerPS odometer gb_auto ft_petrol vt_compact vt_sedan
vt_suv nd_no brand_vw
/PRINT=TWOTAIL NOSIG FULL
/STATISTICS DESCRIPTIVES
/MISSING=PAIRWISE.

```

Descriptive Statistics

	Mean	Std. Deviation	N
price	16785.6319	15885.09037	144
powerPS	139.11	77.070	144
odometer	81388.8889	42014.16862	144
gb_auto	.2847	.45286	144
ft_petrol	.4097	.49350	144
vt_compact	.2014	.40244	144
vt_sedan	.2083	.40753	144
vt_suv	.1875	.39167	144
nd_no	.9583	.20052	144
brand_vw	.2292	.42176	144

Correlations

		price	powerPS	odometer	gb_auto	ft_petrol	vt_compact	vt_sedan	vt_suv	nd_no	brand_vw
price	Pearson Correlation	1	.647**	-.120	.445**	-.060	-.265**	-.004	.091	.052	-.093
	Sig. (2-tailed)		.000	.151	.000	.477	.001	.967	.277	.539	.266
	N	144	144	144	144	144	144	144	144	144	144
powerPS	Pearson Correlation	.647**	1	.007	.565**	-.047	-.327**	.144	.022	.037	-.094
	Sig. (2-tailed)	.000		.933	.000	.577	.000	.086	.796	.660	.263
	N	144	144	144	144	144	144	144	144	144	144
odometer	Pearson Correlation	-.120	.007	1	.018	-.574**	-.263**	-.021	-.029	.082	.221**
	Sig. (2-tailed)	.151	.933		.834	.000	.001	.802	.733	.331	.008
	N	144	144	144	144	144	144	144	144	144	144
gb_auto	Pearson Correlation	.445**	.565**	.018	1	-.181*	-.278**	.055	.052	-.022	-.124
	Sig. (2-tailed)	.000	.000	.834		.030	.001	.511	.538	.789	.138
	N	144	144	144	144	144	144	144	144	144	144
ft_petrol	Pearson Correlation	-.060	-.047	-.574**	-.181*	1	.427**	.025	-.219**	-.038	-.185*
	Sig. (2-tailed)	.477	.577	.000	.030		.000	.770	.008	.649	.026
	N	144	144	144	144	144	144	144	144	144	144
vt_compact	Pearson Correlation	-.265**	-.327**	-.263**	-.278**	.427**	1	-.258**	-.241**	-.069	-.191*
	Sig. (2-tailed)	.001	.000	.001	.001	.000		.002	.004	.414	.022
	N	144	144	144	144	144	144	144	144	144	144
vt_sedan	Pearson Correlation	-.004	.144	-.021	.055	.025	-.258**	1	-.246**	.107	-.036
	Sig. (2-tailed)	.967	.086	.802	.511	.770	.002		.003	.202	.672
	N	144	144	144	144	144	144	144	144	144	144
vt_suv	Pearson Correlation	.091	.022	-.029	.052	-.219**	-.241**	-.246**	1	.011	-.050
	Sig. (2-tailed)	.277	.796	.733	.538	.008	.004	.003		.895	.550
	N	144	144	144	144	144	144	144	144	144	144
nd_no	Pearson Correlation	.052	.037	.082	-.022	-.038	-.069	.107	.011	1	.031
	Sig. (2-tailed)	.539	.660	.331	.789	.649	.414	.202	.895		.712
	N	144	144	144	144	144	144	144	144	144	144
brand_vw	Pearson Correlation	-.093	-.094	.221**	-.124	-.185*	-.191*	-.036	-.050	.031	1
	Sig. (2-tailed)	.266	.263	.008	.138	.026	.022	.672	.550	.712	
	N	144	144	144	144	144	144	144	144	144	144

** . Correlation is significant at the 0.01 level (2-tailed).

* . Correlation is significant at the 0.05 level (2-tailed).

REGRESSION

```

/DESCRIPTIVES MEAN STDDEV CORR SIG N
/MISSING LISTWISE
/STATISTICS COEFF OUTS R ANOVA CHANGE ZPP
/CRITERIA=PIN(.05) POUT(.10)
/NOORIGIN
/DEPENDENT price
/METHOD=ENTER powerPS odometer vt_compact vt_sedan vt_suv gb_auto ft_petrol
brand_vw nd_no
/SCATTERPLOT=(*ZRESID ,*ZPRED)
/RESIDUALS HISTOGRAM(ZRESID) .

```


Variables Entered/Removed^a

Model	Variables Entered	Variables Removed	Method
1	nd_no, vt_suv, powerPS, odometer, brand_vw, vt_sedan, gb_auto, vt_compact, ft_petrol ^b	.	Enter

a. Dependent Variable: price

b. All requested variables entered.

Model Summary^b

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	Change Statistics			Sig. F Change
						F Change	df1	df2	
1	.688 ^a	.473	.438	11912.18028	.473	13.366	9	134	.000

a. Predictors: (Constant), nd_no, vt_suv, powerPS, odometer, brand_vw, vt_sedan, gb_auto, vt_compact, ft_petrol

b. Dependent Variable: price

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.707E+10	9	1896606279	13.366	.000 ^b
	Residual	1.901E+10	134	141900039.1		
	Total	3.608E+10	143			

a. Dependent Variable: price

b. Predictors: (Constant), nd_no, vt_suv, powerPS, odometer, brand_vw, vt_sedan, gb_auto, vt_compact, ft_petrol

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations		
		B	Std. Error	Beta			Zero-order	Partial	Part
1	(Constant)	5320.191	6244.512		.852	.396			
	powerPS	119.043	16.369	.578	7.273	.000	.647	.532	.456
	odometer	-.079	.030	-.210	-2.635	.009	-.120	-.222	-.165
	vt_compact	-4155.451	3223.622	-.105	-1.289	.200	-.265	-.111	-.081
	vt_sedan	-5061.533	2744.383	-.130	-1.844	.067	-.004	-.157	-.116
	vt_suv	-490.382	2888.943	-.012	-.170	.865	.091	-.015	-.011
	gb_auto	2849.922	2766.587	.081	1.030	.305	.445	.089	.065
	ft_petrol	-3090.217	2757.810	-.096	-1.121	.264	-.060	-.096	-.070
	brand_vw	-1031.909	2526.677	-.027	-.408	.684	-.093	-.035	-.026
	nd_no	4215.665	5027.890	.053	.838	.403	.052	.072	.053

a. Dependent Variable: price

Residuals Statistics^a

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	-2472.4006	70919.6484	16785.6319	10925.51275	144
Residual	-25405.68164	117808.7031	.00000	11531.23009	144
Std. Predicted Value	-1.763	4.955	.000	1.000	144
Std. Residual	-2.133	9.890	.000	.968	144

a. Dependent Variable: price

```
install.packages("foreign")  
install.packages("psych")  
install.packages("car")
```

```
install.packages("moments")
install.packages("sandwich")
install.packages("lmtest")
library(foreign)
library(psych)
library(car)
library(moments)
library(sandwich)
library(lmtest)

options(scipen = 100)
options(digits = 2)

# 2012 pin code 4~ ----
autos_2012 <- read.csv(file = "autos_2012_pin4.csv", header = TRUE, sep =
",")

autos_2012 <- data.frame(
  "price" = autos_2012$price,
  "vehicleType" = autos_2012$vehicleType,
  "gearbox" = autos_2012$gearbox,
  "powerPS" = autos_2012$powerPS,
  "odometer" = autos_2012$odometer,
  "fuelType" = autos_2012$fuelType,
  "brand" = autos_2012$brand,
  "notRepairedDamage" = autos_2012$notRepairedDamage)

# Start recoding

# recode vehicleType
autos_2012$vehicleTypeCompactEFF <- car::recode(autos_2012$vehicleType, '
"kleinwagen"=1; "suv"=0; "limousine"=0; else=-1 ')
autos_2012$vehicleTypeSuvEFF <- car::recode(autos_2012$vehicleType, '
"kleinwagen"=0; "suv"=1; "limousine"=0; else=-1 ')
autos_2012$vehicleTypeSedanEFF <- car::recode(autos_2012$vehicleType, '
"kleinwagen"=0; "suv"=0; "limousine"=1; else=-1 ')

# recode gearbox
autos_2012$gearboxAutoEFF <- car::recode(autos_2012$gearbox, ' "automatik"=1;
else=-1')

# recode fuelType
autos_2012$fuelTypePetrolEFF <- car::recode(autos_2012$fuelType, '
"benzin"=1; else=-1')

# recode notRepairedDamage
autos_2012$notRepairedDamageNoEFF <-
car::recode(autos_2012$notRepairedDamage, ' "nein"=1; else=-1 ')

# recode brand
autos_2012$brandVolkswagenEFF <- car::recode(autos_2012$brand, '
"volkswagen"=1; else=-1')

# Z-score power
```

```
autos_2012$ZpowerPS <- scale(autos_2012$powerPS, center = TRUE, scale = TRUE)
```

```
# Z-score odometer
```

```
autos_2012$Zodometer <- scale(autos_2012$odometer, center = TRUE, scale = TRUE)
```

```
# Linear model standard entry
```

```
# with all three interactions ----
```

```
m16 <- lm(price_log ~ fuelTypePetrolEFF + ZpowerPS + brandVolkswagenEFF +
  vehicleTypeSedanEFF + vehicleTypeSuvEFF + vehicleTypeCompactEFF +
  gearboxAutoEFF + notRepairedDamageNoEFF + Zodometer +
  gearboxAutoEFF*ZpowerPS*fuelTypePetrolEFF +
  Zodometer*fuelTypePetrolEFF*ZpowerPS +
  vehicleTypeSedanEFF*Zodometer + fuelTypePetrolEFF*gearboxAutoEFF,
  data = autos_2012)
```

```
summary(m16)
```

```
*** OUTPUT BEGIN ***
```

```
Call:
```

```
lm(formula = price_log ~ fuelTypePetrolEFF + ZpowerPS + brandVolkswagenEFF +
  vehicleTypeSedanEFF + vehicleTypeSuvEFF + vehicleTypeCompactEFF +
  gearboxAutoEFF + notRepairedDamageNoEFF + Zodometer + gearboxAutoEFF *
  ZpowerPS * fuelTypePetrolEFF + Zodometer * fuelTypePetrolEFF *
  ZpowerPS + vehicleTypeSedanEFF * Zodometer + fuelTypePetrolEFF *
  gearboxAutoEFF, data = autos_2012)
```

```
Residuals:
```

```
      Min       1Q   Median       3Q      Max
-0.6729 -0.1720 -0.0035  0.1241  1.0766
```

```
Coefficients:
```

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	9.3955	0.0743	126.49	< 0.0000000000000002 ***
fuelTypePetrolEFF	-0.0850	0.0430	-1.98	0.05037 .
ZpowerPS	0.2911	0.0494	5.90	0.000000032 ***
brandVolkswagenEFF	0.0238	0.0304	0.78	0.43577
vehicleTypeSedanEFF	-0.0685	0.0456	-1.50	0.13497
vehicleTypeSuvEFF	0.1901	0.0477	3.99	0.00011 ***
vehicleTypeCompactEFF	-0.2472	0.0539	-4.59	0.000010738 ***
gearboxAutoEFF	0.1357	0.0383	3.54	0.00056 ***
notRepairedDamageNoEFF	0.1710	0.0578	2.96	0.00370 **
Zodometer	-0.1981	0.0365	-5.43	0.000000282 ***
ZpowerPS:gearboxAutoEFF	0.0302	0.0373	0.81	0.41900
fuelTypePetrolEFF:gearboxAutoEFF	0.1137	0.0390	2.92	0.00421 **
fuelTypePetrolEFF:ZpowerPS	-0.0748	0.0485	-1.54	0.12570
fuelTypePetrolEFF:Zodometer	-0.0556	0.0370	-1.50	0.13604
ZpowerPS:Zodometer	0.0506	0.0491	1.03	0.30433
vehicleTypeSedanEFF:Zodometer	0.0885	0.0332	2.67	0.00862 **
fuelTypePetrolEFF:ZpowerPS:gearboxAutoEFF	-0.0815	0.0367	-2.22	0.02825 *
fuelTypePetrolEFF:ZpowerPS:Zodometer	-0.1335	0.0479	-2.79	0.00616 **

```
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 0.27 on 126 degrees of freedom
```

```
Multiple R-squared:  0.806,    Adjusted R-squared:  0.779
```

```
F-statistic: 30.7 on 17 and 126 DF,  p-value: <0.0000000000000002
```

*** OUTPUT END ***

```
# Model 16 log Price with HC3 ----
m17 <- coeftest(m16, vcov = vcovHC(m16, type="HC3"))
m17
```

*** OUTPUT BEGIN ***

t test of coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	9.3955	0.0789	119.14	< 0.0000000000000002 ***
fuelTypePetrolEFF	-0.0850	0.0550	-1.55	0.12468
ZpowerPS	0.2911	0.1088	2.68	0.00843 **
brandVolkswagenEFF	0.0238	0.0315	0.76	0.45147
vehicleTypeSedanEFF	-0.0685	0.0661	-1.04	0.30136
vehicleTypeSuvEFF	0.1901	0.0770	2.47	0.01491 *
vehicleTypeCompactEFF	-0.2472	0.0734	-3.37	0.00100 **
gearboxAutoEFF	0.1357	0.0554	2.45	0.01563 *
notRepairedDamageNoEFF	0.1710	0.0607	2.81	0.00566 **
Zodometer	-0.1981	0.0522	-3.79	0.00023 ***
ZpowerPS:gearboxAutoEFF	0.0302	0.0707	0.43	0.66961
fuelTypePetrolEFF:gearboxAutoEFF	0.1137	0.0566	2.01	0.04648 *
fuelTypePetrolEFF:ZpowerPS	-0.0748	0.1044	-0.72	0.47515
fuelTypePetrolEFF:Zodometer	-0.0556	0.0548	-1.01	0.31253
ZpowerPS:Zodometer	0.0506	0.1111	0.46	0.64955
vehicleTypeSedanEFF:Zodometer	0.0885	0.0392	2.26	0.02575 *
fuelTypePetrolEFF:ZpowerPS:gearboxAutoEFF	-0.0815	0.0659	-1.24	0.21847
fuelTypePetrolEFF:ZpowerPS:Zodometer	-0.1335	0.1093	-1.22	0.22392

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

*** OUTPUT END ***