Part 1a Summary

To maximize profits, firms ensure that their marginal cost (MC) is equal to their marginal revenue (MR). The profit equation is $\Pi = p_j * q_j - C(q_j)$, and the equilibrium condition and first order condition of profit maximization is $MR_j = MC_j$. The relationship between price and marginal cost can be written as $p_j = MC_j + markup$. The Lerner Index quantifies how much a firm can mark up its price over marginal cost and it shows market power. Combining the equilibrium conditions, we get that the Lerner Index is defined as $L_j = \frac{p_j - MC_j}{p_j}$. A higher Lerner Index indicates greater market power, whereas a lower Lerner Index suggests that there is more competitive pressure and firms don't have as much freedom to mark up prices as much.

Part 1b Summary

Using the estimated coefficient for price from Question b from problem set 1, $\alpha = -0.030604$. This reflects the average price sensitivity across the dataset. I calculated the market size and market share, and was then able to find the Lerner Index for every car-market-year observation in the data.

Part 1b Code

```
library(tidyverse)
rm(list=ls())
data <- read_csv("C:/Users/eugen/OneDrive/Desktop/cars.csv")

alpha <- -0.030604

data <- data %>%
  mutate(market_size = pop/4) %>%
  mutate(sj = qu/(market_size)) %>%
  mutate(scaledeurpr = eurpr/1000) %>%
  mutate(lerner_index = -1 / ( alpha * (1-sj) * scaledeurpr))
```

Part 1c Summary

In the previous part, I calculated the Lerner Index for every car-market-year observation in the data using alpha and the market share. Then, I group the data by country/market, so that I am able to find the mean Lerner Index for each country using the mean function. A higher mean Lerner Index in a country shows that firms in that country have greater market power and can set prices significantly above marginal costs. Ultimately, this may mean that there is less competition and it could be a more oligopolistic market structure.

Part 1c Code

```
meansummary <- data %>%
  group_by(ma, ye) %>%
  summarize(mean_lerner_index = mean(lerner_index, na.rm = TRUE))
  arrange(desc(mean_lerner_index))

view(meansummary)
```

	ma	mean_lerner_index
1	Belgium	6.357921
2	Italy	6.259411
3	Germany	6.145442
4	France	5.860344
5	UK	5.410263

Part 1d Summary

Previously, I calculated the Lerner Index for every car-market-year observation and the mean Lerner Index for each country. The first step here is to sum the total sales for each car manufacturer across all markets and years. By grouping by brand, I was able to find the total quantity sold for each car manufacturer. After sorting it, we find that the brands with the top five total sales were fiat, renault, ford, opei, and VW, with their respective total quantities shown in the table. Finally, I could take Lerner Index values from before, and calculate the mean Lerner Index for the top five brands. Fiat has the highest mean Lerner Index at 8.43, meaning that Fiat has a strong market power and may be able to raise its prices more than others. Renault being a close second similarly has a solid ability to set prices above marginal costs. Fiat and Renault might have more leeway to implement price increases, while VW, Ford, and Opel may need to be more cautious with pricing.

Part 1d Code

```
top5brand <- data %>%
  group_by(brand) %>%
  summarize(total_qu = sum(qu, na.rm = TRUE)) %>%
  top_n(5, total_qu) %>%
  arrange(desc(total_qu))

view(top5brand)
```

	brand	total_qu
1	fiat	28596359
2	renault	27491175
3	ford	26650589
4	opel	25065926
5	VW	24096639

```
top5summary <- data %>%
  filter(brand %in% top5brand$brand) %>%
  group_by(brand) %>%
  summarize(mean_lerner_index = mean(lerner_index, na.rm = TRUE))
  arrange(desc(mean_lerner_index))

view(top5summary)
```

	brand	mean_lerner_index
1	fiat	8.429928
2	renault	7.125511
3	VW	6.561084
4	ford	6.081216
5	opel	6.041592

Part 2a Summary

I created a variable for marginal cost based on the equilibrium condition. For more, read explanation for 2b.

Part 2a Code

```
data <- data %>%
  mutate(mc = scaledeurpr + (1 / alpha * (1-sj)))
```

Part 2b Summary

Using the equilibrium condition and the estimated demand, obtain an estimate of

the marginal cost for every car-market-year observation in the data

The Lerner Index is equal to $\frac{p_j - MC_j}{p_j}$, so $MC_j = p_j * (1 - L_j)$. Since the Lerner Index is also equal to $-\frac{1}{\alpha*(1-s_j)*p_j}$, we can combine the two formulas to write the marginal cost as $p_j + \frac{1}{\alpha*(1-s_j)}$ or as $p_j * (1 - L_j)$. Then, using the market and year as fixed effects, I ran an OLS-Fixed effects regression where the dependent variable was the estimated value of the marginal cost. Looking at the results, we can see that hp, he, and we had positive coefficients, li and wi had negative coefficients, and home had a coefficient that was not statistically significant from 0. Each coefficient indicates the change in marginal cost for a one-unit increase in the respective explanatory variable, holding other variables constant. For example, a positive coefficient for horsepower suggests that more powerful cars lead to higher marginal costs. Since I used fixed effects, the model accounts for unobserved factors that do not change over time within each market or year, which provides a clearer and more direct view of how the included product characteristics affect marginal costs.

Part 2b Code

```
library(fixest)
model <- feols(mc ~ hp + li + wi + he + we + home | ma + ye, data = data)
summary(model)
 OLS estimation, Dep. Var.: mc
 Observations: 11,549
 Fixed-effects: ma: 5,  ye: 30
 Standard-errors: Clustered (ma)
       Estimate Std. Error    t value   Pr(>|t|)
 hp    0.125088   0.002668  46.875810 1.2389e-06 ***
 li   -0.461758   0.019521 -23.654135 1.8939e-05 ***
 wi   -0.034521   0.004856  -7.108232 2.0695e-03 **
 he    0.021496   0.003321   6.472589 2.9357e-03 **
 we    0.006979   0.000285  24.467568 1.6556e-05 ***
 home -0.053325   0.254021  -0.209924 8.4399e-01
 ---
 Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
 RMSE: 2.19399     Adj. R2: 0.843346
                 Within R2: 0.715147
```

Part 2c Summary

1. Create competing product characteristics and a column to identify if its own product is there.
2. Calculate average characteristics for competing products.
3. Run the IV regression for marginal cost and look at the summary to find the estimate for the coefficient of quantity.

Part 2c Code

```
library(dplyr)
library(fixest)

data <- data %>%
  group_by(ma, ye) %>%
  mutate(
```

```
    is_own_product = ifelse(brand == first(brand), TRUE, FALSE),

    hp_comp = mean(hp[!is_own_product], na.rm = TRUE),  # Average horsepower of
competitors
    we_comp = mean(we[!is_own_product], na.rm = TRUE),  # Average weight of competitors
    li_comp = mean(li[!is_own_product], na.rm = TRUE),  # Average fuel type of competitors
    wi_comp = mean(wi[!is_own_product], na.rm = TRUE),  # Average width of competitors
    he_comp = mean(he[!is_own_product], na.rm = TRUE)  # Average height of competitors
  ) %>%
  ungroup()

model_iv <- feols(mc ~ qu | hp_comp + li_comp + wi_comp + he_comp + we_comp, data =
data)

summary(model_iv)
OLS estimation, Dep. Var.: mc
Observations: 11,549
Fixed-effects: hp_comp: 150,  li_comp: 150,  wi_comp: 149,  he_comp: 148,  we_comp: 150
Standard-errors: Clustered (hp_comp)
   Estimate Std. Error  t value  Pr(>|t|)
qu -1.5e-05   1.53e-06 -9.90217 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
RMSE: 3.99823     Adj. R2: 0.441342
                Within R2: 0.018767
```

Part 2d Summary

1. Extract the coefficient for quantity (qu) from the IV model
2. Calculate the change in marginal cost for an increase of 10,000 units
3. The value in change_in_mc is the estimated change in marginal cost when the output increases by 10,000 units.

A change in marginal cost of −0.1519518 Euros when increasing output by 10,000 units implies that the marginal cost decreases by about 15.20 Euros for every additional 10,000 units produced. Given that we have a very low p-value for your quantity estimate, this indicates that the relationship between quantity and marginal cost is statistically significant. Thus, the result is most likely not due to random variation. This change is plausible because it is consistent with the industry norms and supported by statistical significance.

Part 2d Code

```
qu_coefficient <- coef(model_iv)["qu"]
change_in_mc <- qu_coefficient * 10000
print(change_in_mc)
        qu
 -0.1519518
```