

Problem Set 5 Sample Solutions

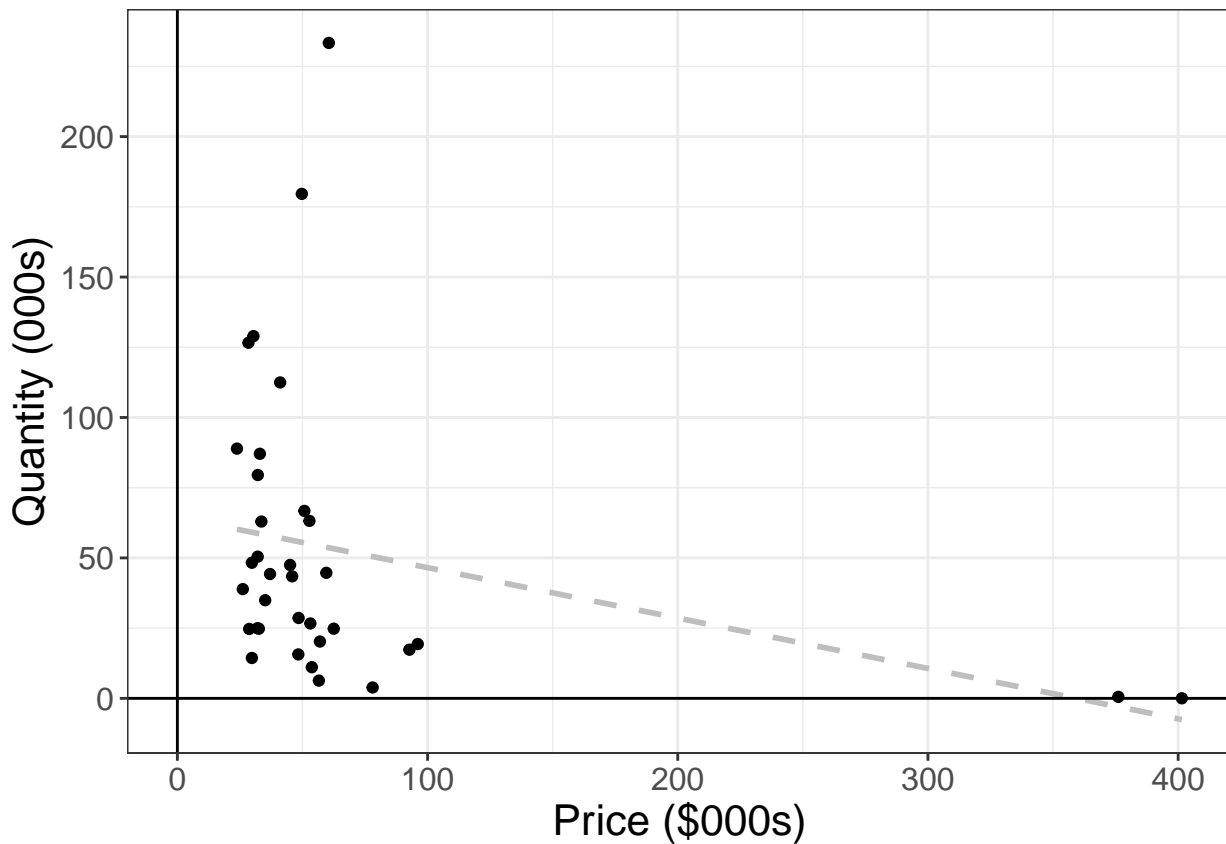
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Part 1

1.A

```
ggplot(data = df_EV, aes(x = price, y = quantity)) +  
  geom_point() +  
  geom_smooth(method = 'lm', color = 'grey', se = FALSE, linetype = 'dashed') +  
  geom_hline(aes(yintercept = 0)) + geom_vline(aes(xintercept = 0)) +  
  labs(x = 'Price ($000s)', y = 'Quantity (000s)')
```



1.B

This relationship is not plausibly causal. The plot shows that expensive vehicles are purchased less, which is consistent with the standard intuition of a (causal) downward sloping demand curve. However, confounders could also create a relationship between price and quantity. For example, if higher quality vehicles are also

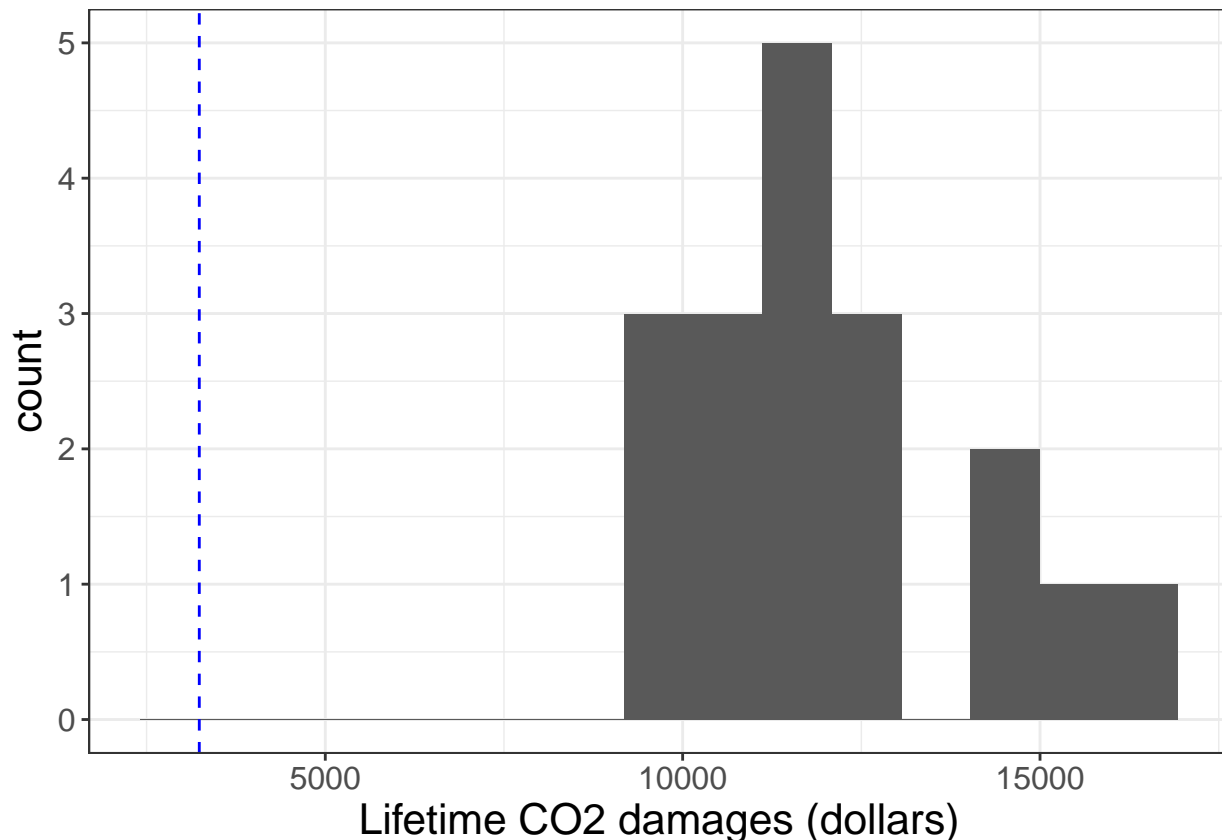
more expensive (seems plausible!) then there would be a spurious *positive* relationship between price and quantity. If quality is an omitted variable, then the true causal effect of price on quantity is steeper than the best fit line in this plot.

1.C and 1.D

```
scc = 190 # social cost of carbon
df_EV = df_EV %>% mutate(co2cost = co2*scc)

avg_EV_co2cost = mean(df_EV[df_EV$ev==1,]$co2cost)
avg_nonEV_co2cost = mean(df_EV[df_EV$ev==0,]$co2cost)

ggplot(data = df_EV %>% filter(!ev, price<50), aes(x = co2cost)) +
  geom_histogram(bins = 15) +
  geom_vline(aes(xintercept = avg_EV_co2cost), color = 'blue', linetype = 'dashed') +
  labs(x = 'Lifetime CO2 damages (dollars)')
```



The average CO2 damages for EVs is \$3237 (blue dotted line on graph). The average cost for non-EVs is 1.3809×10^4 . To be fair, the non-EV average is misleading since two outliers with very low market share (Rolls Royce Phantom and Lamborghini Aventador) also have very high CO2 damages. Nevertheless, it's clear from the histogram that 1) all non-EVs have higher CO2 costs than EVs and 2) even among mass-market EVs there is significant heterogeneity in CO2 costs.

Part 2

Table 1: Logit Results

	(1)
Price (000s)	-0.0251 (0.0053)
Electric Vehicle	1.3 (1.1)
Weight (tons)	-1.83 (0.71)
Horsepower (00s)	0.49 (0.21)
Constant	-7.11 (0.84)
Num.Obs.	35
R2	0.797
R2 Adj.	0.762
AIC	94.4
BIC	105.3
RMSE	0.76

The leave-out group is sedan

```
#define market shares
market_size = 250000000
df_EV = df_EV %>% mutate(share = quantity * 1000 / market_size)
# define share of outside option
share_buy = sum(df_EV$share)
s0 = 1-share_buy
# define DV
df_EV = df_EV %>% mutate(lns1s0 = log(share/s0))

# cosmetic changes for the table
df_EV$class = factor(df_EV$class)
df_EV$class = ref(df_EV$class, 'sedan')
df_EV$fuel_cost_thousands = df_EV$fuel_cost/1000

logit_out = lm_robust(data = df_EV,
                      formula = lns1s0 ~ price + weight + fuel_cost + hp + ev)

Tab1 = modelsummary(logit_out,
                     coef_map = coef_map,
                     notes = 'The leave-out group is sedan',
                     title = 'Logit Results',
                     fmt = fmt_significant(2))

Tab1

price_coef = logit_out$coefficients['price']
ev_coef = logit_out$coefficients['ev']
```

2.B

The results indicate a thousand dollar price increase is associated with a -2.5% change in market share, and that EVs have 125.1% higher market share than non-EVs, all else equal. The EV coefficient is not statistically significant, but the price effect is.

2.C

I think the estimate of η is biased towards zero. Unobservable quality is likely positively correlated with both price and demand, which will cause an upwards bias in our coefficient estimate (in this case, pushing towards zero). Since the set of observables is not *that* rich here, omitted variable bias could be large in magnitude.

Part 3

3.A

Policy incidence falls on the less elastic group. We're assuming perfectly elastic supply. Therefore, all of the incidence will fall on consumers.

3.B

```
avg_CO2_tax = mean(df_EV$co2cost)
```

The cross-vehicle average CO2 tax is $\$1.0789 \times 10^4$.

3.C

In this model, the car's value is $V_j = \eta p_j + \beta X_j + \xi_j$. We want to hold everything constant except the a price change, and see how V changes. Note that $V^{New} - V^{Baseline} = \beta(p^{New} - p^{Baseline})$. I use this identity to compute the new Vs. Then, I can back out the market shares according to the following formula:

$$s_j = \frac{e^{V_j}}{1 + \sum_k e^{V_k}}$$

```
# Step 1: create new price variables (taking care for units!)
cvc_subsidy = 7.5
df_EV = df_EV %>%
  mutate(p1 = price + co2cost/1000,
         p2 = price - eligible * cvc_subsidy)

# Step 2: create change in price variables
df_EV = df_EV %>%
  mutate(del_p1 = p1 - price,
         del_p2 = p2 - price)

# step 3: define V0 from baseline shares
# (note that this line is redundant but the new variable name makes code easier to read)
df_EV$V0 = df_EV$lns1s0

# step 4: compute new "V"s
df_EV$V1 = df_EV$V0 + logit_out$coefficients['price'] * df_EV$del_p1
df_EV$V2 = df_EV$V0 + logit_out$coefficients['price'] * df_EV$del_p2

cat('Avg V at baseline: ', mean(df_EV$V0), '\n')
```

```
## Avg V at baseline: -9.114336
cat('Avg V with tax: ', mean(df_EV$V1), '\n')

## Avg V with tax: -9.385245
cat('Avg V with subsidy: ', mean(df_EV$V2), '\n')

## Avg V with subsidy: -9.071289

# step 5: compute key term for denominator of share definition
sum_exp_V1 = sum(exp(df_EV$V1))
sum_exp_V2 = sum(exp(df_EV$V2))

# step 6: counterfactual market shares
df_EV = df_EV %>%
  mutate(
    s1 = exp(V1)/(1+sum_exp_V1),
    s2 = exp(V2)/(1+sum_exp_V2)
  )

# Step 7: illustrate with a few vehicles
df_illustrate = df_EV %>%
  filter(model == 'model y' | model == 'civic' | model == 'tacoma') %>%
  select(make, model, co2cost, share, s1, s2) %>%
  arrange(co2cost)

# total vehicle purchases
sum_share_baseline = sum(df_EV$share)
sum_share_1 = sum(df_EV$s1)
sum_share_2 = sum(df_EV$s2)
```

In the baseline scenario 0.74% of potential consumers buy a car. In the carbon tax scenario, this number decreases to 0.58%, while in the subsidy scenario it increases to 0.78% (these numbers are the inverse of the share for the outside option). Since taxes raise the price of vehicles on average, while subsidies decrease the price of vehicles on average, the direction of these effects make sense.

3.D

The code for 3.D is given in the 3.C block.

In Table 2 I present market results for three specific vehicles that illustrate the main effects. The carbon tax decrease consumption of all car types, but the percent reduction in market share is larger for more carbon-intensive vehicles (Toyota Tacoma) and smaller for less carbon intensive vehicles (Tesla). The EV subsidy increases consumption of the Tesla, while having only a minor effect on consumption of the two gas vehicles. Importantly, the EV subsidy treats the low-emissions gas car (Honda Civic) the same way it treats the Tacoma, which demonstrates that the policy does not perfectly target emissions reduction.

```
kableExtra::kable(df_illustrate, booktabs = T, caption = 'Illustration of Policy Effects for Three Vehicles',
  col.names = c('Make', 'Model', 'Lifetime CO2 costs',
    'Baseline share', 'Carbon tax share', 'EV Subsidy share'))
```

3.E

$\Delta PS = 0$ by assumption. I use the following formulas for the other components of surplus change (from the slides, where 1 denotes the post-policy value and 0 denotes the pre-policy value).

Table 2: Illustration of Policy Effects for Three Vehicles

Make	Model	Lifetime CO2 costs	Baseline share	Carbon tax share	EV Subsidy share
tesla	model y	3237.018	0.0009334	0.0008619	0.0011263
honda	civic	9192.808	0.0005064	0.0004027	0.0005062
toyota	tacoma	16776.875	0.0004499	0.0002957	0.0004497

$$\Delta CS = \frac{1}{-\eta} \cdot \left(\log \left(1 + \sum_j e^{V_j^1} \right) - \log \left(1 + \sum_j e^{V_j^0} \right) \right)$$

$$\Delta G = \sum_j t_j s_j^1$$

$$\Delta E = \sum_j -\phi_j (s_j^1 - s_j^0)$$

$$\Delta TS = \Delta CS + \Delta G + \Delta E$$

And cost/ton of carbon abated is $(\Delta CS + \Delta G)/\Delta Carbon$. In cases where $\Delta Carbon$ is negative, I simply report “undefined”. I present results in Table 3.

```
# Tax
Del_CS_1 = - 1000/logit_out$coefficients['price'] * (
  log(1 + sum(exp(df_EV$V1))) - log(1 + sum(exp(df_EV$V0)))
) # note the unit conversion (multiply by 1000)

Del_G_1 = sum(df_EV$s1 * df_EV$co2cost)
Del_E_1 = sum(-df_EV$co2cost * (df_EV$s1 - df_EV$share))
Del_TS_1 = Del_CS_1 + Del_G_1 + Del_E_1

Del_carbon_1 = sum(df_EV$co2 * (df_EV$s1 - df_EV$share))
CE_1 = (Del_CS_1 + Del_G_1)/Del_carbon_1

# Subsidy
Del_CS_2 = - 1000/logit_out$coefficients['price'] * (
  log(1 + sum(exp(df_EV$V2))) - log(1 + sum(exp(df_EV$V0)))
)

Del_G_2 = sum(df_EV$s2 * df_EV$eligible * -7500)
Del_E_2 = sum(-df_EV$co2cost * (df_EV$s2 - df_EV$share))
Del_TS_2 = Del_CS_2 + Del_G_2 + Del_E_2

Del_carbon_2 = sum(df_EV$co2 * (df_EV$s2 - df_EV$share))
CE_2 = (Del_CS_2 + Del_G_2)/Del_carbon_2
CE_2 = 'Undefined' # ad-hoc change since this is < 0...

Surplus_Tab = data.frame(
  'Label' = c('Change in CS ($/consumer-year)', 'Change in PS ($/consumer-year)', 'Change in G ($/consumer-year)',
  'CO2 Tax' = round(c(Del_CS_1, 0, Del_G_1, Del_E_1, Del_TS_1, CE_1),0),
  'EV Subsidy' = c(round(c(Del_CS_2, 0, Del_G_2, Del_E_2, Del_TS_2),0),CE_2)
)

kableExtra::kable(Surplus_Tab, booktabs = T, caption = 'Effect of Policies on Surplus')
```

Table 3: Effect of Policies on Surplus

Label	CO2.Tax	EV.Subsidy
Change in CS (\$/consumer-year)	-64	17
Change in PS (\$/consumer-year)	0	0
Change in G (\$/consumer-year)	55	-19
Change in E (\$/consumer-year)	20	-1
Change in TS (\$/consumer-year)	10	-3
Cost-effectiveness (\$/ton of CO2 abated)	90	Undefined

Part 4: Summary

Conceptually, a carbon tax will have a more positive impact on total surplus than an EV subsidy for at least two reasons.

First, a carbon tax induces socially beneficial substitution away from more carbon-intensive gas-using vehicles and towards less carbon-intensive gas-using vehicles (e.g, from the Tacoma to the Civic). The histogram in figure 4 demonstrates that there is significant heterogeneity in externality costs even across gas-using vehicles, so these gains may be important.

Second, the carbon tax discourages EV consumption relative to the outside option of not buying a car, while the EV subsidy encourages EV consumption. Since EVs do use carbon, this effect is undesirable. The subsidy is good to the extent that it encourages substitution from carbon-intensive cars to EVs but bad to the extent that it encourages substitution from not driving to EVs. The overall change in externality (and therefore the overall change in total surplus) is negative in this example because the bad type of substitution outweighs the good type of substitution.

The above is a sound policy argument in favor of the carbon tax. However, the distributional consequences of the two policies are drastically different. The carbon tax hurts consumers and increases government revenue, but the EV subsidy benefits consumers and decreases government revenue. To the extent that government revenue is redistributed to people with high marginal values of money (e.g, through welfare payments or social insurance), this may constitute a distributional argument in favor of the carbon tax. If you believe government funds are less valuable, this argument has less bite.

In practice, this difference may explain why EV subsidies are more politically feasible than carbon taxes. The government costs and benefits are diffuse and consumers may not notice the marginal impact of the extra tax revenue, while consumers do notice extra costs every time they go to the gas pump or a large discount on their electric vehicle purchase.

We made many modelling assumptions here. I think the most important one was that our demand estimation was unconfounded. It seems plausible that unobservable quality would be correlated with price. If this was true, then consumers are more elastic than our estimates indicate. Higher elasticities amplify responses to taxes and subsidies, so this story would mean our estimates of the surplus changes were all biased towards zero.