

Anton Melnychuk ECON 3385 - Problem Set 2

January 26th, 2026

In [17]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import statsmodels.formula.api as smf

whale_data = pd.read_csv('whales_demand.csv')
whale_data.head()
```

Out[17]:

	year	price_sperm	price_oil	price_sperm_real	price_oil_real	sperm	oil	shipwrecks
0	1804	1.40	0.50	1.11	0.40	8.636	114.1065	0.064167
1	1805	0.96	0.50	0.68	0.35	6.390	42.1700	0.066090
2	1806	0.80	0.50	0.58	0.37	5.313	86.7370	0.067864
3	1807	1.00	0.50	0.77	0.38	0.270	65.1200	0.064410
4	1808	0.80	0.44	0.70	0.38	8.800	83.7500	0.064172

Question 1

a) For OLS to recover consistent estimates of β_1 when regressing equilibrium quantity on price, we need the error terms to be uncorrelated with price:

- $Cov(\epsilon_t^D, P_t^{oil}) = 0$ (demand shocks uncorrelated with price)
- $Cov(\epsilon_t^S, P_t^{oil}) = 0$ (supply shocks uncorrelated with price)

So that, if price moves independently of demand shocks, we can see how price affects quantity. Same regression will always recover consistent estimates of β_0 .

b) Solving for equilibrium:

$$Q_y^{oil,D} = Q_y^{oil,S}$$
$$\beta_0 + \beta_1 P_y^{oil} + \epsilon_y^D = \gamma_0 + \gamma_1 P_y^{oil} + \epsilon_y^S$$

Rearranging:

$$(\beta_1 - \gamma_1) P_y^{oil} = \gamma_0 - \beta_0 + \epsilon_y^S - \epsilon_y^D$$
$$P_y^{oil} = \frac{\gamma_0 - \beta_0 + \epsilon_y^S - \epsilon_y^D}{\beta_1 - \gamma_1}$$

Since P_y^{oil} depends on both ϵ_y^S and ϵ_y^D , the conditions fail. Price is endogenous.

Question 2

Now we include shipwrecks (Z_y) in the supply equation:

Demand: $Q_y^{oil,D} = \beta_0 + \beta_1 P_y^{oil} + \epsilon_y^D$

Supply: $Q_y^{oil,S} = \gamma_0 + \gamma_1 P_y^{oil} + \gamma_2 Z_y + \epsilon_y^S$

where Z_y represents shipwrecks and ϵ_y^S captures other supply shifters.

Solving for equilibrium price:

$$P_y^{oil} = \frac{\gamma_0 + \gamma_2 Z_y - \beta_0 + \epsilon_y^S - \epsilon_y^D}{\beta_1 - \gamma_1}$$

Now price depends on shipwrecks Z_y in addition to the error terms.

Question 3

For 2SLS to recover consistent estimates, two conditions must hold:

1. Exclusion condition: $Cov(\epsilon_y^D, Z_y) = 0$

- Shipwrecks must not affect demand directly
- Shipwrecks only shifts supply

2. Relevance condition: $Cov(P_y^{oil}, Z_y) \neq 0$

- Shipwrecks must affect price
- From the equilibrium price equation, Z_y enters through γ_2

Why shipwrecks satisfies these:

From the equilibrium price equation, Z_y does not appear in the demand equation, so $Cov(\epsilon_y^D, Z_y) = 0$ holds. And, since P_y^{oil} depends on Z_y (through the $\gamma_2 Z_y$ term), shipwrecks affects price.

Question 4

Now regress price on shipwrecks to get predicted price \hat{P}_y^{oil} .

In [23]:

```
stage_1 = smf.ols('price_oil_real ~ shipwrecks', data=whale_data).fit()
print(stage_1.summary())
```

OLS Regression Results

Dep. Variable:	price_oil_real	R-squared:	0.266			
Model:	OLS	Adj. R-squared:	0.259			
Method:	Least Squares	F-statistic:	39.08			
Date:	Mon, 26 Jan 2026	Prob (F-statistic):	8.30e-09			
Time:	12:35:59	Log-Likelihood:	92.431			
No. Observations:	110	AIC:	-180.9			
Df Residuals:	108	BIC:	-175.5			
Df Model:	1					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

Intercept	0.2619	0.031	8.402	0.000	0.200	0.324
shipwrecks	2.5235	0.404	6.251	0.000	1.723	3.324
=====						
Omnibus:	5.480	Durbin-Watson:	0.669			
Prob(Omnibus):	0.065	Jarque-Bera (JB):	4.881			
Skew:	0.450	Prob(JB):	0.0871			
Kurtosis:	3.505	Cond. No.	40.4			
=====						

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Interpretation:

- **Intercept:** 0.2619 units expected real price when shipwrecks = 0
- **Shipwrecks coefficient:** 2.524 change in real price per 1 unit increase in shipwrecks. This makes sense, since 100% of ships lost would mean a significant increase in prices per barrel.

- **Positive coefficient** makes sense: more shipwrecks -> fewer ships -> less supply -> higher prices
- **F-statistic**: should be > 10 for a strong instrument -> good

Question 5

We regress quantity on predicted price from first stage

In [19]:

```
whale_data['p_hat_oil'] = stage_1.predict(whale_data)
stage_2 = smf.ols('oil ~ p_hat_oil', data=whale_data).fit()
print(stage_2.summary())
```

OLS Regression Results

```
=====
Dep. Variable:          oil      R-squared:                0.055
Model:                  OLS      Adj. R-squared:           0.046
Method:                 Least Squares      F-statistic:           6.302
Date:                  Mon, 26 Jan 2026      Prob (F-statistic):       0.0135
Time:                  12:13:36      Log-Likelihood:         -718.68
No. Observations:      110      AIC:                   1441.
Df Residuals:          108      BIC:                   1447.
Df Model:               1
Covariance Type:       nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	504.6173	114.904	4.392	0.000	276.857	732.378
p_hat_oil	-639.9404	254.911	-2.510	0.014	-1145.219	-134.662

```
=====
Omnibus:                15.658      Durbin-Watson:           0.125
Prob(Omnibus):           0.000      Jarque-Bera (JB):        9.893
Skew:                    0.589      Prob(JB):                0.00711
Kurtosis:                 2.121      Cond. No.                19.1
=====
```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [24]:

```
whale_data.describe()
```

Out[24]:

	year	price_sperm	price_oil	price_sperm_real	price_oil_real	sperm	oil
count	110.000000	110.000000	110.000000	110.000000	110.000000	110.000000	110.000000
mean	1858.500000	0.965320	0.480067	0.905273	0.446364	60.928918	218.971159
std	31.898276	0.426035	0.225719	0.295013	0.122427	50.578117	171.985297
min	1804.000000	0.400000	0.235000	0.420000	0.250000	0.270000	12.280000
25%	1831.250000	0.651250	0.338125	0.680000	0.350000	17.794000	80.013250
50%	1858.500000	0.850000	0.399500	0.840000	0.430000	45.036500	144.246500
75%	1885.750000	1.245000	0.538750	1.100000	0.510000	94.882500	349.836500

	year	price_sperm	price_oil	price_sperm_real	price_oil_real	sperm	oil
max	1913.000000	2.550000	1.450000	1.610000	0.780000	186.219000	594.675000

Question 6

Short summary:

Parameter	Coefficient	Standard Error
β_0 (Intercept)	504.62	114.90
β_1 (Price)	-639.94	254.91

- $\beta_1 = -639.94$ is negative, which is the correct sign for a demand curve. Higher prices lead to lower quantities demanded, consistent with the law of demand.
- In other words, a 1-unit increase in real price (in the units of the price variable) reduces quantity demanded by approximately 640 units. This means, the coefficient is economically meaningful. Small price increase -> a substantial decrease in quantity demanded.
- β_1 is statistically significant at the 5% level ($p < 0.05$), meaning we can reject the null hypothesis that price has no effect on quantity with 95% confidence. This provides strong evidence that the negative relationship between price and quantity is not due to random chance.
- The low $R^2 = 0.055$ (5.5% can be explained by instrument) is expected—the focus is on causal identification rather than model fit. The 2SLS estimate successfully identifies the demand curve.

Question 7

Now we run 2SLS on sperm whale oil.

In [25]:

```
# Repeat Q4-Q6 for sperm whale oil
first_stage_sperm = smf.ols('price_sperm_real ~ shipwrecks', data=whale_data).fit()

whale_data['p_hat_sperm'] = first_stage_sperm.predict(whale_data)

second_stage_sperm = smf.ols('sperm ~ p_hat_sperm', data=whale_data).fit()

print("First Stage (Sperm):")
print(first_stage_sperm.summary())
print("\nSecond Stage (Sperm):")
print(second_stage_sperm.summary())
```

First Stage (Sperm):

OLS Regression Results

```
=====
Dep. Variable:    price_sperm_real    R-squared:                0.169
Model:                OLS            Adj. R-squared:           0.162
Method:             Least Squares     F-statistic:              22.00
Date:                Mon, 26 Jan 2026  Prob (F-statistic):       8.01e-06
```

Time: 12:56:52 Log-Likelihood: -11.101
 No. Observations: 110 AIC: 26.20
 Df Residuals: 108 BIC: 31.60
 Df Model: 1
 Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
Intercept	0.5505	0.080	6.890	0.000	0.392	0.709
shipwrecks	4.8534	1.035	4.691	0.000	2.802	6.904
Omnibus:	2.947		Durbin-Watson:		0.291	
Prob(Omnibus):	0.229		Jarque-Bera (JB):		2.915	
Skew:	0.352		Prob(JB):		0.233	
Kurtosis:	2.624		Cond. No.		40.4	

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Second Stage (Sperm):

OLS Regression Results

Dep. Variable: sperm R-squared: 0.103
 Model: OLS Adj. R-squared: 0.095
 Method: Least Squares F-statistic: 12.41
 Date: Mon, 26 Jan 2026 Prob (F-statistic): 0.000627
 Time: 12:56:52 Log-Likelihood: -581.19
 No. Observations: 110 AIC: 1166.
 Df Residuals: 108 BIC: 1172.
 Df Model: 1
 Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
Intercept	182.0424	34.684	5.249	0.000	113.292	250.793
p_hat_sperm	-133.7867	37.977	-3.523	0.001	-209.064	-58.509
Omnibus:	11.971		Durbin-Watson:		0.153	
Prob(Omnibus):	0.003		Jarque-Bera (JB):		5.696	
Skew:	0.337		Prob(JB):		0.0580	
Kurtosis:	2.113		Cond. No.		15.1	

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Short summary:

Parameter	Coefficient	Standard Error
β_0 (Intercept)	182.04	34.68
β_1 (Price)	-133.79	37.98

- $\beta_1 = -133.79$ is negative and significant at the 1% level ($p < 0.01$), consistent with the law of demand: higher prices lead to lower quantities demanded.
- A 1-unit increase in the real price of sperm whale oil reduces quantity demanded by approximately 134 units.
- The elasticity exceeds that of regular oil (-1.3), showing that sperm oil consumers are more responsive to price changes.
- The $R^2 = 0.103$ indicates that roughly 10% of the variation in sperm whale oil quantity is accounted for by the instrumented price – nearly double the R^2 for regular oil (5.5%).

The coefficient magnitude differs from regular oil, but the scales are different (mean quantity for oil ≈ 219 vs sperm ≈ 61). The price elasticity of sperm oil is higher than regular oil, indicating more price-sensitive demand. This makes sense as sperm is a premium good with more substitutes available.

If non-sperm and sperm oil are substitutes, an increase in sperm price should increase demand for regular oil (positive cross-price effect). To model this, we could extend the demand equation:

$$Q_t^{oil} = \beta_0 + \beta_1 P_t^{oil} + \beta_2 P_t^{sperm} + \epsilon_t^D$$

This would require instrumenting both prices with supply shifters.