Energy Economics Assignment

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1 Descriptive analysis and summary statistics

(i)

There are 78 unique countries.

(ii)

62 countries out of 78 have 59 years of observations. This is almost 80% of the data. Further, the mean of observations is 55.29. I would make the assumption that the dataset it rather balanced than unbalanced. But still 1 of 5 are unbalanced so this dataset should be read carefully.

(iii)

Table 1: Summary Table

Statistic	N	Mean	St. Dev.	Min	Median	Max
gas_price	549	53.239	44.250	2.970	34.970	231.040
energy_cons	4,313	1,327.200	3,728.638	1.411	339.712	47,427.560
employment_share	3,700	0.413	0.094	0.137	0.422	0.763
hdd	3,375	1,906.641	1,591.553	0.000	1,935.135	6,126.162
cdd	3,375	1,174.834	1,179.358	0.000	724.264	4,052.866

The summary statistics show considerable variation across the variables. Natural gas prices range from CHF 2.97 to CHF 231.04, with an average of CHF 53.24, indicating high price volatility across countries and years. Energy consumption per capita also shows a wide distribution, with a mean of 1,327 kWh and a maximum exceeding 47,000 kWh, suggesting large differences in energy use across regions.

The employment share averages around 41%, with relatively low variability. Heating and cooling degree days, which reflect climate-related energy demand, vary substantially as well — with some countries experiencing no heating or cooling needs, while others show very high seasonal demand.

(iv)

See Figure 1.

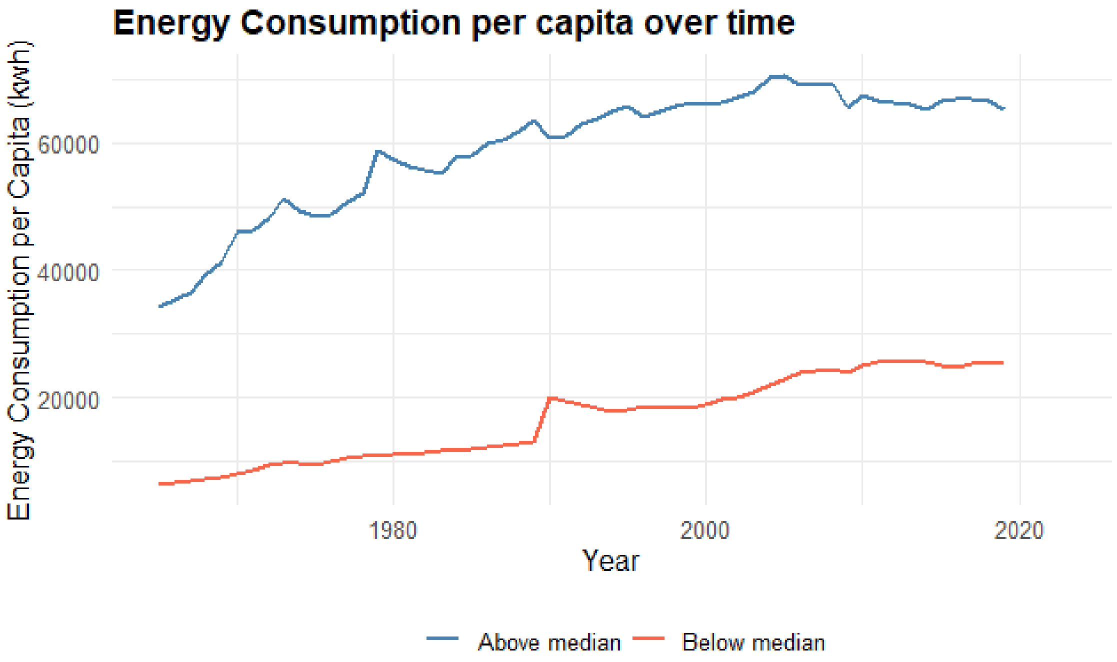

Figure 1: Energy consumption per capita over time

(v)

The number of countries with full electricity and gas prices is zero.

2 Demand analysis

(i)

See R-file.

(ii)

For the subtasks (ii), (iii) and (iv) Table 2 is used for the interpretation.

Table 2:

	Dependent variable:		
	log_energy_pc		
	(1)	(2)	(3)
log_gas_price	-0.253^{***}	-0.220^{***}	-0.009^{**}
	(0.022)	(0.024)	(0.004)
log_gdp_pc	0.846^{***}	0.787^{***}	0.013
	(0.049)	(0.050)	(0.010)
employment_share	1.498^{***}	1.117^{***}	-0.066
	(0.338)	(0.337)	(0.054)
manufact	0.007^{**}	-0.001	0.0004
	(0.003)	(0.003)	(0.0005)
log_hdd		0.150^{***}	
		(0.035)	
log_cdd		-0.009	
		(0.015)	
lag_log_energy_pc			0.984^{***}
			(0.008)
Constant	13.783^{***}	12.616^{***}	0.276^{**}
	(0.338)	(0.458)	(0.120)
Observations	387	379	387
R^2	0.706	0.720	0.993
Adjusted R^2	0.703	0.716	0.993
Residual Std. Error	0.327 (df = 382)	0.316 (df = 372)	0.050 (df = 381)
F Statistic	229.492^{***} (df = 4; 382)	159.673^{***} (df = 6; 372)	$10{,}850.730^{***}$ (df = 5; 381)
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

This result is highly statistically significant at the 1% level. Energy consumption is price elastic with respect to gas prices — that is, people significantly reduce their energy use when gas becomes more expensive. On the other hand, the other three coefficients are positive and statistically significant, indicating that higher GDP per capita, a greater employment share, and a larger manufacturing sector are each associated with higher energy consumption per capita.

(iii)

The coefficient on natural gas price indicates that a 1% increase in natural gas prices leads to a 0.22% decrease in energy consumption per capita, holding all else constant. The results confirm that natural gas price has a strong, negative, and significant effect on energy consumption per capita. Income, employment, and heating needs are also strong positive drivers of demand. Cooling needs and manufacturing share, however, are not statistically significant in this model.

(iv)

In Model (3) of Table 2, the coefficients of all explanatory variables change considerably compared to Model (2).

- The absolute value of the coefficient on `log_gas_price` drops significantly from –0.220 to –0.009, indicating a much smaller estimated effect of gas prices on energy consumption.
- The coefficients on `log_gdp_pc` and `employment_share`, which were previously large and highly significant, also decrease sharply in magnitude and lose statistical significance.
- The coefficient on `manufact` remains very small and continues to be statistically insignificant.
- The newly included variable `lag_log_energy_pc` enters the model with a very high and strongly significant coefficient of 0.984, which dominates the regression.

(v)

These results in Table 3 are in line with expectations. In the short run, households and firms face technical and behavioral constraints that limit their ability to reduce energy consumption (e.g. heating systems, habits). The short-run elasticity of –0.009 indicates that energy consumption reacts only minimally to changes in gas

Table 3:

	Natural Gas Price
Short-run	-0.009
Long-run	-0.575

prices in the short term. Over the long run, however, they can adapt — by improving energy efficiency, investing in alternatives, or reducing demand — leading to a much stronger reaction to price changes. A long-run elasticity of –0.575 suggests that natural gas price increases have a moderate but meaningful effect on reducing energy demand over time.

(vi)

Due to the size of the regression table, it is not included in this document. Please refer to the R output for full results.

Table 4:

	Energy Price
Short-run	-0.035
Long-run	-0.064

(vii)

Since the electricity price regression includes a country fixed effect (`factor(iso3)`), we re-estimate the gas price model using the same specification. This ensures that both regressions are consistent and directly comparable.

Table 5:

	Natural Gas Price	Electro Price
Short-run	-0.054	-0.035
Long-run	-0.253	-0.064

As seen in Table 5, energy consumption is more responsive to natural gas prices than to electricity prices, especially in the long run. In the short run, a 1% increase in gas prices reduces energy consumption by 0.054%, compared to only 0.035% for electricity prices. In the long run, the difference becomes even more pronounced: gas price elasticity reaches –0.253, while electricity price elasticity remains low at –0.064. This suggests that consumers adjust much more to natural gas prices over time - possibly due to greater flexibility in heating systems or alternative fuel options - whereas electricity consumption is relatively inelastic even in the long term.

(viii)

Again, due to the size of the regression table, it is not included in this document. Please refer to the R output for full results.

Table 6:

	Above median	Below median
Short-run	-0.057	-0.019
Long-run	-0.095	-0.034

(ix)

Table 6 shows that countries with a GDP per capita *above the median* in 2019 react more strongly to changes in electricity prices than countries *below the median.* In the short run, the elasticity for the high-income group is -0.057, while it is only -0.019 for the lower-income group. This difference becomes even more noticeable in the long run: -0.095 versus -0.034.

One possible explanation is that in wealthier countries, households have more flexibility to adjust their electricity use for example, by investing in energy-efficient appliances or making lifestyle changes. In lower-income countries, electricity is often used for essential needs, so there's less room to cut back even if prices go up.

However, we should be cautious: The analysis has some limitations:

- *Data gaps:* Many countries are missing electricity price data, which limits the number of observations and might bias the results.

- *Simplified assumptions:* The model doesn't account for potential feedback between electricity demand and prices or include all relevant country-specific factors.
- *National averages:* We're looking at country-level data, which hides variation within countries - like differences between rural and urban areas.
- *Static median split:* Grouping countries based on their 2019 GDP per capita ignores how income levels have changed over time.

All in all, while the results suggest that electricity demand is more price-sensitive in richer countries, the analysis simplifies a complex reality. It's a useful starting point, but definitely not the full picture.

3 Mode of transport choice

(i)

Alternative-variant: *traveltime, cost, frequency, alt, choice.*
Alternative-invariant: *case, noalt, male, income, cost-coverage.*

(ii)

The share of women who participated in the survey is: 21.73%.

(iii)

Share of individuals with 3 alternatives: 91.11%. Average number of alternatives per individual: 2.91. I would say that the dataset is relatively balanced. The average number of alternatives per individual is around 2.91 and more than 90% of the dataset takes all 3 alternatives.

(iv)

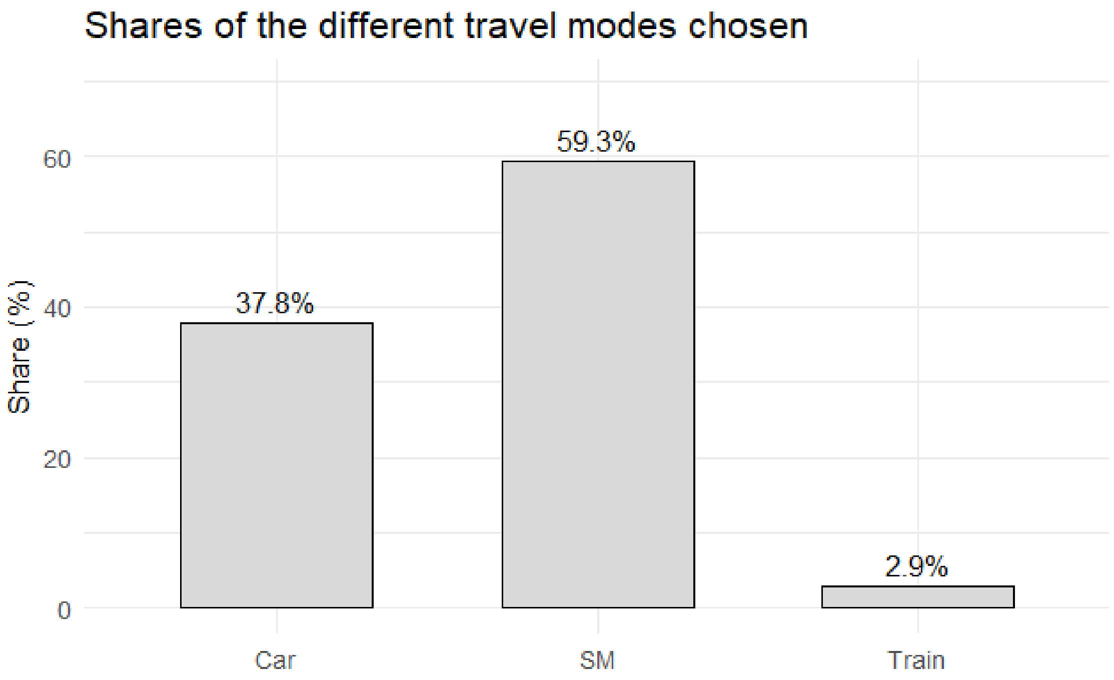

Figure 2: Shares of the different travel modes chosen

(v)

Take a look at Table 7.

Table 7:

	Dependent variable:	
	choice	
	(1)	(2)
(Intercept):Car	0.050	−0.155
	(0.296)	(0.312)
(Intercept):Train	-1.676^{**}	-1.531^{**}
	(0.786)	(0.778)
traveltime	-0.007^{***}	-0.007^{***}
	(0.001)	(0.001)
cost	-0.006^{***}	-0.007^{***}
	(0.001)	(0.001)
freq	0.004	0.004
	(0.005)	(0.005)
income:Car	−0.007	−0.084
	(0.119)	(0.123)
income:Train	−0.331	−0.188
	(0.313)	(0.327)
cost_coverage:Car	-0.413^{**}	-0.479^{***}
	(0.173)	(0.175)
cost_coverage:Train	−0.773	−0.657
	(0.522)	(0.529)
male:Car		0.505^{**}
		(0.214)
male:Train		−0.714
		(0.468)
Observations	830	830
R^2	0.060	0.067
Log Likelihood	−608.987	−604.281
LR Test	77.125^{***} (df = 9)	86.536^{***} (df = 11)
Note:		*p<0.1; **p<0.05; ***p<0.01

(vi)

Table 8:

Statistic	N	Mean	St. Dev.	Min	Max
#Df	2	10.000	1.414	9	11
LogLik	2	−606.634	3.327	−608.987	−604.281
Df	1	2.000		2	2
Chisq	1	9.411		9.411	9.411
Pr(>Chisq)	1	0.009		0.009	0.009

Based on the results of the likelihood ratio test in Table 8, we observe a Chi-squared statistic of 9.411 with 2 degrees of freedom and a p-value of 0.009. Since the p-value is below the 5% significance threshold, the result is statistically significant. The model that includes the `male` variable provides a significantly better fit compared to the model without it. Therefore, the choice model should include the `male` variable.

(vii)

In Model (2) of Table 7, both travel time and cost have negative and statistically significant coefficients at the 1% level, indicating that longer trips and higher prices significantly reduce the likelihood of a transport mode being chosen. This is consistent with standard economic expectations.

The coefficient for `male:Car` is positive and statistically significant at the 5% level, suggesting that male respondents are more likely to choose the car over Swissmetro. In contrast, the coefficient for `male:Train` is negative but not significant, implying no clear gender preference for the train option.

Cost coverage by employers appears to discourage the use of car transport, with a statistically significant negative effect on car choice at the 1% level. While cost coverage also shows a negative effect for the train option, it is not statistically significant. Lastly, the variables for frequency of service and income do not exhibit significant effects in this model.

(viii)

Table 9:

	SM	Car	Train
SM	-0.002	0.002	0.0001
Car	0.002	-0.002	0.0001
Train	0.0001	0.0001	-0.0002

Observed in Table 9, if the traveltime increases by 1 unit (here 1 minute), then the probability of choosing this mode of transport decreases, while the probability of the other 2 modes increase. The effects are small but significant. This is consistent with the expectations that people prefer shorter time for traveling.

4 Investment calculation

(i)

I would advise my parents **not to invest**, as the expected net present value (NPV) is **CHF –2,238.59**, which represents a loss from a purely economic perspective.

(ii)

I would advise my parents **to invest**, as the expected net present value (NPV) is **CHF 235.82**, which represents a profit from a purely economic perspective.

This result indicates that the PV system is even more attractive economically. Since electricity from the grid has become more expensive due to the carbon pricing, generating clean electricity at home becomes relatively more cost-effective.

(iii)

The feed-in tariff must be at least **CHF 0.126** for the investment in the PV system to be economically worthwhile for the parents.

(iv)

If my parents own an electric vehicle or already have a heat pump installed, the investment in the PV system becomes more financially attractive. Both technologies significantly increase household electricity consumption, allowing a larger share of the electricity generated by the PV system to be self-consumed rather than fed into the grid. This shift in consumption pattern increases the value of the electricity produced, as using it directly avoids paying the higher retail electricity price of CHF 0.32 per kWh. In contrast, feeding excess electricity into the grid yields only a lower feed-in tariff. Consequently, higher self-consumption leads to greater annual cost savings and a more favorable net present value (NPV), thereby strengthening the economic case for the investment.

(v)

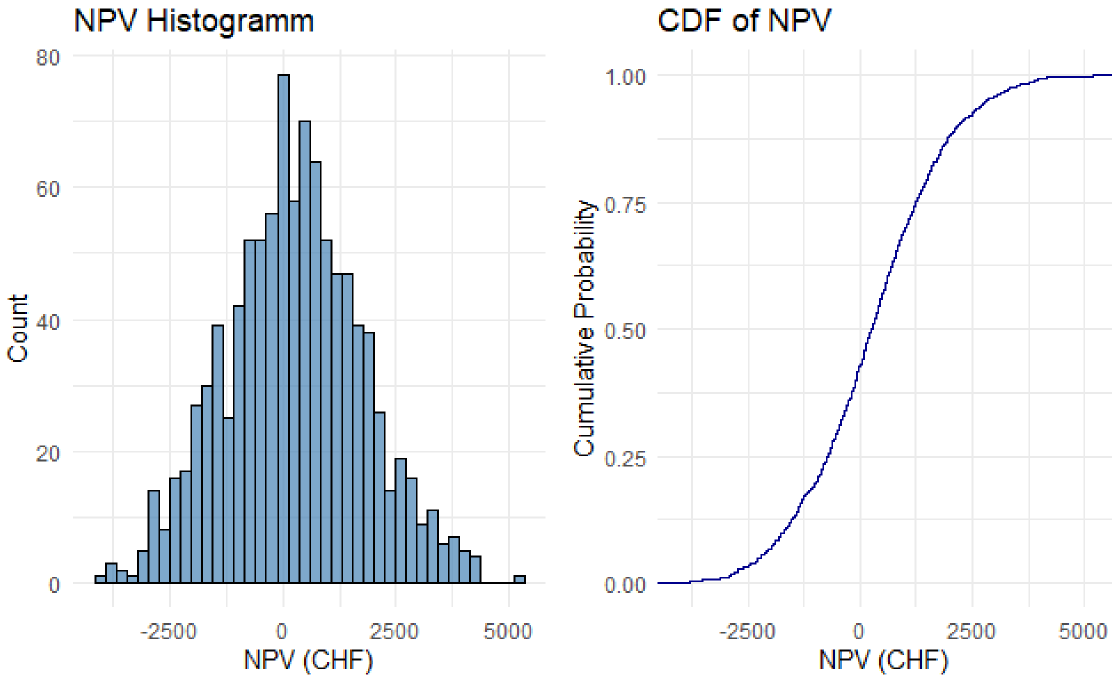

Figure 3: Monte Carlo simulation - Histogramm and Cumulative Distribution Function of the NPV

The share of positive NPV outcomes is **57%**, with a mean NPV of **CHF 1,293.82** when the investment is profitable. However, the overall average NPV - including both positive and negative outcomes - is only around **CHF 260.40**.

From a purely probabilistic perspective, the investment appears worthwhile, as the chance of achieving a positive return exceeds 50%. However, it remains a relatively risky investment. Moreover, considering the modest average return of CHF 260.40 on an initial investment of CHF 20,000 over 25 years, it may not be attractive for those focused solely on financial gain.

Nonetheless, when taking environmental benefits into account—such as reducing carbon emissions and supporting the energy transition—the investment in a PV system can still be considered worthwhile. In light of this, I would recommend that my parents proceed with the investment.

5 Paper - Interpretation

(i)

According to Greenstone (2024), higher energy prices affect a person's utility in two key ways:

1. **Reduced consumption of other goods:** Since energy does not provide direct utility but is a derived demand input for goods and services (e.g., steel production, heating), an increase in energy prices forces individuals to allocate more of their income toward energy-related costs. This reduces their ability to consume other goods such as food, shelter, or healthcare, which directly contribute to utility.

2. **Lower wages and purchasing power:** Higher energy prices increase production costs for firms. This can lead to lower wages or reduced employment, particularly in energy-intensive sectors, which further diminishes individuals' purchasing power and ability to consume utility-generating goods and services.

These mechanisms illustrate how rising energy costs can indirectly reduce overall well-being, despite energy itself not entering the utility function directly.

(ii)

The finding from the exercise session appears to conflict with Figure 4, Plot B in GGreenstone (2024), where wind power is depicted as being more expensive than gas power. This difference arises from a broader and more realistic assessment of cost in Greenstone's framework.

As Greenstone (2024) notes, the LCOEs reported in the early sets of bars reflect only the direct generation cost. However, wind and solar are intermittent sources that cannot consistently provide baseload electricity. To compare them fairly with dispatchable sources like natural gas, Greenstone adjusts the LCOEs to include the cost of **backups and grid integration** required to ensure reliability.

Specifically, he states that *"these LCOEs are more than double the cost of a baseload natural gas plant"* once these system-level costs are included. The final set of bars in Figure 4 accounts for storage and backup capacity, transforming the LCOE into a more comprehensive cost metric. Thus, Greenstone (2024) shows that while the generation cost of renewables is low, their **reliability-adjusted cost** is much higher—explaining the apparent contradiction with Exercise 4.

In short, Greenstone (2024)'s analysis highlights that traditional LCOE underestimates the true cost of renewables by ignoring intermittency and the need for continuous power supply, which are essential for a fair comparison with fossil baseload technologies.

(iii)

Two important sectors not included in the damage estimates of Greenstone (2024):

1. **Political instability and migration:** Climate change can increase migration by reducing the habitability and productivity of certain regions through rising temperatures, sea level rise, and more frequent extreme weather events. These migration pressures may result in overcrowded urban areas, strained public services, and heightened risks of civil unrest or political instability. Greenstone (2024) explicitly acknowledges this gap, noting that *"These papers provide detailed projections of climate change impacts in these sectors but undoubtedly*

are missing several other sectors where climate change is likely to influence human well-being (e.g., migration) and any cross-sector interactions." This migration-related channel is not included in his damage estimates.

Reference: Burke et al. (2015)

2. **Biodiversity loss and ecosystem services:** Climate change leads to habitat destruction, species extinction, and degradation of ecosystems, which in turn impacts services such as pollination, water purification, and carbon sequestration. These losses can have profound economic and societal effects but are typically omitted from narrow economic damage models.

   Reference: Pecl et al. (2017)

(iv)

Particulate Matter Costs: These are computed as the ratio of total annual mortality damages from $\text{PM}_{2.5}$ to total energy generation. The damages within a census tract are calculated using the following logic:

$$\text{PM Cost} = \frac{\sum_{\text{tracts}} (\Delta PM_{2.5} \times \text{Population} \times \text{Mortality Response} \times \text{VSLY})}{\text{Total Energy Generation}}$$

The variables include the change in ambient $\text{PM}_{2.5}$ concentrations from electricity generation, population size, a concentration-response function for mortality risk, and the value of a statistical life year (VSLY). The cost reflects the health damages caused by exposure to $\text{PM}_{2.5}$ emitted during power generation.

GHG Costs:

$$\text{GHG Cost} = \frac{\sum_{t=1}^{T} (\text{Emissions}_{\text{per kWh}} \times \text{Generation}_t \times \text{SCC}) / (1+r)^t}{\sum_{t=1}^{T} (\text{Generation}_t / (1+r)^t)}$$

The greenhouse gas (GHG) cost per kWh is computed by dividing the present-discounted sum of annual GHG damages by the present-discounted sum of annual electricity generation. Annual GHG damages are calculated as the lifecycle CO_2e emissions per kWh multiplied by the annual generation and scaled by the Social Cost of Carbon (SCC). This approach ensures that both the damages and the generation are consistently discounted over the system's lifetime, allowing for a levelized cost comparison across technologies.

References

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