

Machine Learning Project

Approach for Investigating the Impact of Circular Economy on
Taiwan's Economy and the Energy efficiency

Yuze Tsai

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Overview of Project Structure

- **Goal:** Investigate the impact of circular economy policies on Taiwan's economic development and energy efficiency (2014–2023).
- **Data:**
 - *Dependent Variables:* Income, Electricity consumption per capita, Housing vacancy rate
 - *Independent Variables:* Environmental taxes, recycling rate, green infrastructure, etc.
- **Methods(Previously):**
 - Panel data regression (Fixed vs. Random Effects)
 - Machine learning models: XGBoost, Random Forest, SVM

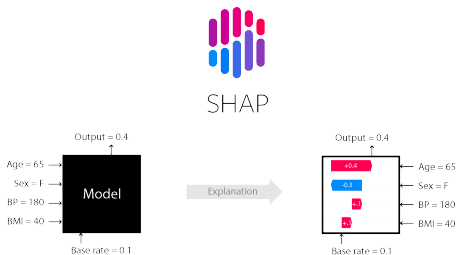
Version updated: Catboost, LightGBM ML models, and take R^2 and SHAP value for interpretation

Review the Assumptions

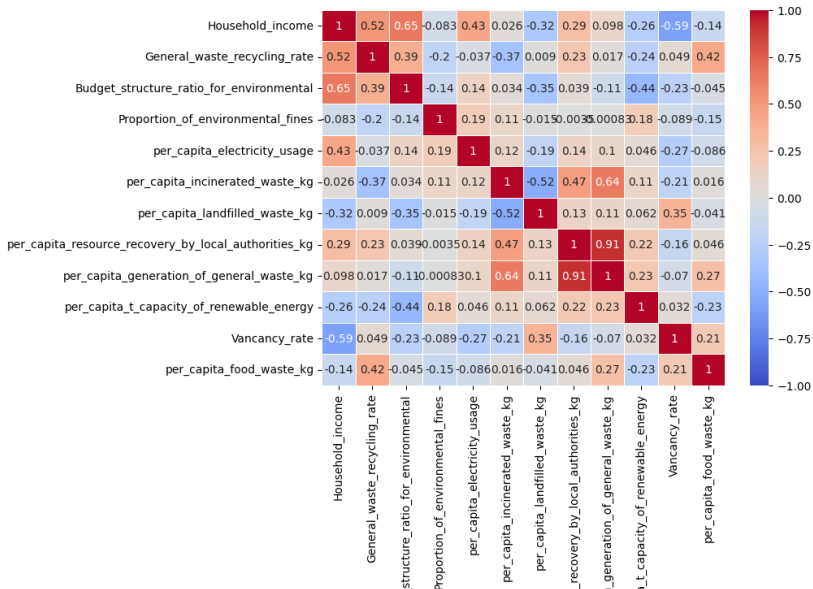
Hypothesis	Statement
1	Environmental budgets and recycling improve electricity efficiency
2	Landfill/incineration harm income, poor recycling lowers income
3	Waste positively linked to income and electricity usage, negatively to vacancy
4	Renewable energy capacity improves income and electricity efficiency

SHAP (SHapley Additive Explanations)

- SHAP assigns each feature an importance value for prediction.
- Based on cooperative game theory—accounts for all possible feature combinations.
- **Advantages:**
 - Global and local interpretability
 - Indicates both direction (+/-) and magnitude of effect
 - Helps identify nonlinear thresholds and interactions
- **Applied to:** XGBoost, CatBoost, LightGBM, RF, and SVM



Correlation Overview



Panel Regression: Household Income

- Fixed Effects (FE) vs Random Effects (RE) models.
- Preferred: FE due to focus on within-unit variation.
- **Within R^2 (FE): 0.5755**

Table: Model Comparison of Household Income

	Fixed Effects	Random Effects
Dep. Variable	Household_income	Household_income
R-squared	0.5755	0.5269
F-statistic	16.718	15.717
General_waste_recycling_rate	1.656e+04 (0.3543)	1.565e+04 (0.3247)
Budget_structure_ratio_for_environmental	-2.424e+04 (-1.5064)	-2.416e+04 (-1.4588)
Proportion_of_environmental_fines	-1656.4 (-0.3080)	-1520.4 (-0.2741)
per_capita_incinerated_waste_kg	-1.459e+04 (-1.0786)	-1.509e+04 (-1.0815)
per_capita_landfilled_waste_kg	-8152.9 (-0.7027)	-8504.2 (-0.7109)
per_capita_generation_of_general_waste_kg	9.208e+04 (0.9104)	9.113e+04 (0.8736)
per_capita_t_capacity_of_renewable_energy	2.426e+04 (2.6360)***	2.446e+04 (2.5775)***
per_capita_food_waste_kg	-6.258e+04 (-1.0021)	-6.412e+04 (-0.9958)
per_capita_resource_recovery_by_local_authorities_kg	-1.877e+04 (-0.1813)	-1.786e+04 (-0.1673)

Panel Regression: Electricity Usage

- Dependent variable: Per Capita Electricity Usage.
- HOrriBE explanatory power: Within $R^2 = 0.0538$.**

Table: Model Comparison of Per Capita Electricity Usage

	Fixed Effects	Random Effects
Dep. Variable	p-c_electricity_usage	p-c_electricity_usage
R-squared	0.0538	0.0430
F-statistic	0.7588	0.6891
General_waste_recycling_rate	-1748.9 (-1.0245)	-1630.1 (-0.9591)
Budget_structure_ratio_for_environmental	1469.0 (1.5002)	1385.3 (1.4779)
Proportion_of_environmental_fines	-56.664 (-0.1633)	-9.4697 (-0.0272)
per_capita_incinerated_waste_kg	-446.12 (-0.5155)	-573.76 (-0.6610)
per_capita_landfilled_waste_kg	-246.51 (-0.3294)	-371.66 (-0.4985)
per_capita_generation_of_general_waste_kg	-3261.6 (-0.7386)	-2803.4 (-0.6335)
per_capita_t_capacity_of_renewable_energy	374.06 (0.6450)	415.61 (0.7202)
per_capita_food_waste_kg	5519.8 (1.7388)*	4844.5 (1.5677)
per_capita_resource_recovery_by_local_authorities_kg	4079.9 (0.9360)	3577.6 (0.8217)

Panel Regression: Vacancy Rate

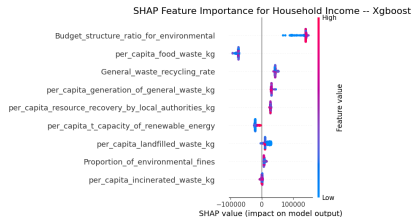
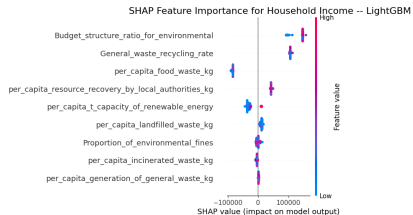
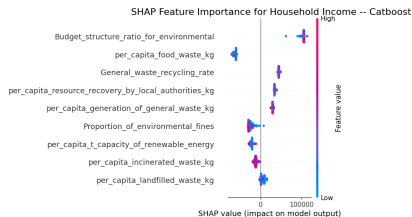
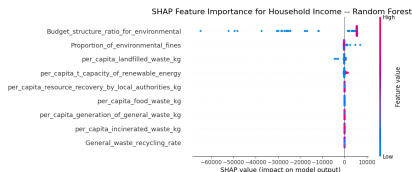
- Dependent variable: Vacancy Rate.
- Within $R^2 = 0.3796$.

Table: Model Comparison of Vacancy rate

	Fixed Effects	Random Effects
Dep. Variable	Vacancy_rate	Vacancy_rate
R-squared	0.3796	0.3371
F-statistic	8.1573	7.7976
General_waste_recycling_rate	1.1738 (4.8452)***	1.1819 (4.7618)***
Budget_structure_ratio_for_environmental	0.1066 (0.7670)	0.1001 (0.7037)
Proportion_of_environmental_fines	0.0098 (0.1999)	0.0108 (0.2138)
per_capita_incinerated_waste_kg	-0.1464 (-1.1922)	-0.1513 (-1.2023)
per_capita_landfilled_waste_kg	-0.3178 (-2.9923)***	-0.3194 (-2.9346)***
per_capita_generation_of_general_waste_kg	2.6392 (4.2111)***	2.6646 (4.1490)***
per_capita_t_capacity_of_renewable_energy	0.1055 (1.2815)	0.1081 (1.2824)
per_capita_food_waste_kg	-0.7543 (-1.6744)*	-0.7786 (-1.6881)*
per_capita_resource_recovery_by_local_authorities_kg	-2.7926 (-4.5143)***	-2.8214 (-4.4511)***

ML Model Comparison: Household Income

- Applied ensemble methods: RF, LightGBM, CatBoost, XGBoost.
- Compared feature importance via SHAP values.



Where is SVM?

為什麼你的論文要鎖那麼久啊？
我：



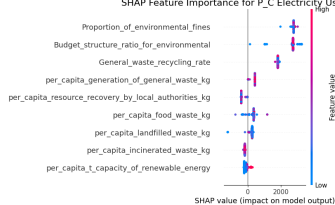
SHAP Summary: Top Features for Household Income

- SHAP values quantify each feature's impact on prediction.
- **Strongest positive influence: Budget structure ratio and Recycling rate**
- **Negative: Food waste per capita and renewable energy capacity.**

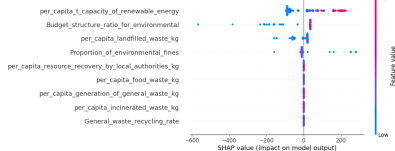
Feature	XGBoost	RF	CatBoost	LightGBM
Budget ratio (env.)	135392	184066	103778	140778
Recycling rate	43613	56781	44104	106733
Waste generation	30847	11152	29307	1692
Food waste per capita	-76820	-72989	-63354	-84387
Renewable capacity	-20539	-16840	-22892	-28026

Results for Per Capita Electricity Usage: Ensemble Models

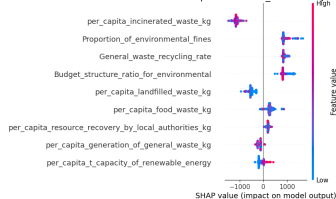
SHAP Feature Importance for P_C Electricity Usage -- LightGBM



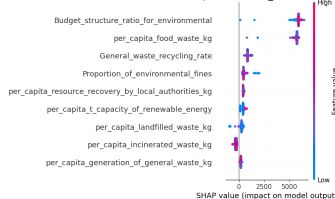
SHAP Feature Importance for P_C Electricity Usage -- Random Forest



SHAP Feature Importance for P_C Electricity Usage -- Catboost



SHAP Feature Importance for P_C Electricity Usage -- Xgboost



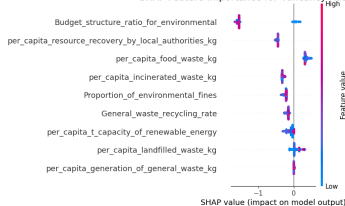
SHAP Summary: Feature Importance for Electricity Usage

- SHAP values indicate feature impact on model output.
- **Key features with highest influence: Budget structure ratio, Food waste per capita, Recycling rate.**
- **Lower influence or negative impact: Incinerated waste, landfilled waste.**

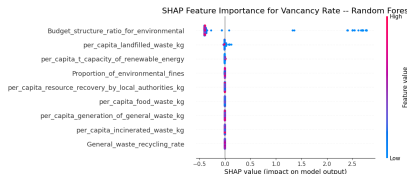
Feature	XGBoost	RF	CatBoost	LightGBM
Budget ratio (env.)	5818	3	872	2683
Food waste per capita	5680	0	292	307
General waste recycling rate	903	0	880	1825
Environmental fines prop	552	-1	902	2782
Incinerated waste per capita	-283	0	-1143	-195

Results for Vacancy Rate: Ensemble Models

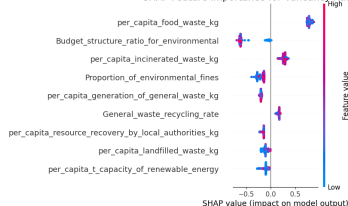
SHAP Feature Importance for Vacancy Rate -- LightGBM



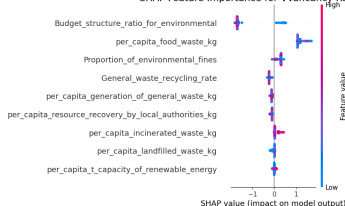
SHAP Feature Importance for Vacancy Rate -- Random Forest



SHAP Feature Importance for Vacancy Rate -- Catboost



SHAP Feature Importance for Vacancy Rate -- Xgboost



SHAP Summary: Feature Importance for Vacancy Rate

- SHAP values indicate feature impact on model output.
- **Key features with highest influence: Budget structure ratio, Food waste per capita, Recycling rate.**
- **Inconsistent results: Environmental fines prop.**

Feature	XGBoost	RF	CatBoost	LightGBM
Food waste per capita	1.146	0.000	0.786	0.334
Environmental fines prop	0.273	0.000	-0.201	-0.229
Incinerated waste per capita	0.093	0.000	0.268	-0.320
Resource recovery by local gov	-0.113	0.000	-0.149	-0.457
Budget ratio (env.)	-1.418	0.017	-0.547	-1.327

R-squared Comparison Across Models

Feature	XGBoost	RF	LightGBM	CatBoost	FE Panel
Household Income	0.720	0.688	0.699	0.752	0.578
Per Capita Electricity	0.427	0.479	0.474	0.420	0.054
Vacancy Rate	0.736	0.659	0.600	0.743	0.380

- **Household Income:** CatBoost leads (0.752), showing strong prediction capability (overall $R^2 > 0.5$).
- **Electricity Usage:** All models weak ($R^2 < 0.5$), Random Forest best (0.479); FE is **terrible**.
- **Vacancy Rate:** CatBoost and XGBoost both Strongest

Variable Importance: Overview

- Significance based on SHAP for ML and statistical significance for FE.
- Summary scores computed: +1 (positive effect), -1 (negative), 0 (non-significant).

Variable	Household Income	Pc Electricity Usage	Vacancy Rate
Budget structure ratio for environmental	+4	+4	-2
General waste recycling rate	+3	+2	+1
Per capita generation of general waste (kg)	0	0	+1
Per capita resource recovery by local authorities	0	0	-2
Per capita landfilled waste (kg)	0	-1	0
Proportion of environmental fines	-1	+2	0
Per capita incinerated waste (kg)	0	-1	0
Per capita capacity of renewable energy	+1	+1	-1
Per capita food waste (kg)	-4	+2	+1

Table: Summary of Variable Scores across Models

Selected Variable Interpretations

- **Environmental Budget:** Positively linked to income and electricity use, lowers vacancy.
- **Recycling Rate:** Generally positive across all \Rightarrow boosts income, slight energy trade-off.
- **Food Waste:** Negatively affects income, increases usage and vacancy \Rightarrow inefficiency signal.
- **Renewable Capacity:** Some income gains, inconsistent electricity effects.

Evaluation of Assumptions

Hypothesis	Statement	Conclusion
1	Environmental budgets and recycling improve electricity efficiency	Inversely supported
2	Landfill/incineration harm income, poor recycling lowers income	Partially supported
3	Waste positively linked to income and electricity usage, negatively to vacancy	Partially supported
4	Renewable energy capacity improves income and electricity efficiency	Partially supported

Reconsideration



Future Directions I: Data and Comparative Scope

Richer Circular Economy Indicators:

- Extend circular economy metrics:
 - Material Use Rate, Secondary Raw Materials Share
 - Proportion of Resource-Circulation Enterprises
- Improve measurement of policy implementation intensity

Comparative Scope:

- Cross-country or cross-regional comparisons
- Robustness checks in different policy contexts

Additional Outcomes:

- Forecast CO₂ emissions, AQI, or house prices using ML
- Explore long-run dynamics of sustainability indicators

Future Directions II: Methods Insight

Causal Inference:

- Explore Regression Discontinuity on environmental budget shares
- Investigate feasibility of quasi-experimental designs

Structural Analysis:

- Integrate circular economy into the Environmental Kuznets Curve (EKC) framework
- Combine theory-driven models with data-driven tools

Conclusion: Summary of Findings

Study Goal: Assess how circular economy policies affect income, electricity use, and vacancy rates across Taiwan's 22 cities (2014–2023).

Methods: Panel regression vs. Machine Learning (CatBoost, XGBoost, etc.)

Key Findings:

- Environmental budgets, renewables \Rightarrow \uparrow income
- Food waste \Rightarrow \uparrow electricity use and \uparrow vacancy
- **ML models outperform regression**, especially CatBoost (SHAP used for interpretation)
- SVM underperformed due to computational inefficiency

Conclusion: Policy and Methodological Takeaways

Model Implications:

- **ML excels at prediction** — best for income and vacancy
- **Electricity usage hard to model** — needs richer features
- **Method should match goal:** prediction vs. explanation

Policy Relevance:

- Recycling and environmental investment show economic benefits
- Mixed/uncertain effects call for **re-examining assumptions**
- Circular economy indicators can inform **evidence-based, local-level policy**

Thanks !

