Modeling Tesla Stock Returns using Environmental, Social and Governance (ESG) Reporting Metrics

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Agenda

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Thesis

Data Cleaning

Model Methodology

Correlation Analysis

Ridge Regression

Conclusion and Next Steps

Motivation

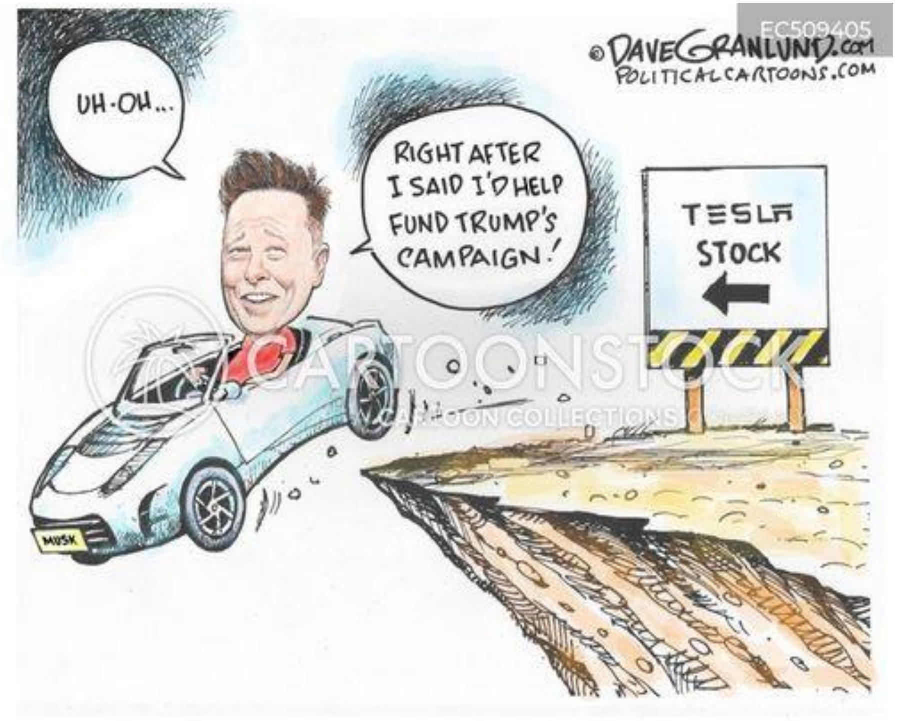
Why ESG?

- At the forefront of sustainable business!
- Growing performance metric for business and financial modeling
- Aligning with global sustainability goals

Why Tesla?

- Tesla's carbon footprint and energy efficiency are core to its value proposition
- ESG factors influence raw materials, labor standards, and overall supply chain costs

Tesla is going to expand with Tesla Energy and… is now a face of politics?? ☹



Thesis

This project aims to analyze the primary ESG predictors of Tesla (TSLA) using a global macro trading strategy to forecast stock returns.

Using Ridge regression and ESG data, we can quantify the impact of sustainability metrics on Tesla’s financial performance.

After identifying key predictors, we can develop a Long Short-Term Memory (LSTM) model to inform trading decisions, optimizing long and short positions based on ESG trends and supply chain cost fluctuations.

The Data

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Tesla Stock Return Close (Y)

ESG Indicators (X):

Merged 3 World Bank Datasets (ESG, Environment, and Carbon Credit Prices) Annual Data

- Tesla generates revenue from selling carbon credits
- Identify consumer countries with correlations between ESG metrics and Tesla stock

  US, China, UK, Germany, Canada, Australia, France, Japan, Netherlands, Norway, Sweden

Environment

Renewable Energy

GHG Emissions

Fossil Fuels

Social

Gini Coefficient

Population Density

Patent Applications

Governance

R&D Expenditure

Regulatory Quality: Estimate

Political Stability

Even. More. Data.

Metal Commodity Prices (X):

- Lithium, Nickel, and Aluminum Global Commodity Prices
  - International Monetary Fund
  - Key materials for Tesla Production and Supply Chain

Date	Commodity Name	Unit Name	Value
1990-01-01	Aluminum	Index	95.251042
1990-01-01	Nickel	Percent Change over Corresponding Period Previous Year	-60.192144
1990-01-01	Nickel	US Dollars	7056.000000
1990-01-01	Aluminum	Percent Change over Previous Period	-6.429884
1990-01-01	Aluminum	Percent Change over Corresponding Period Previous Year	-36.296876
1990-01-01	Aluminum	US Dollars	1528.000000
1990-01-01	Nickel	Index	73.536929
1990-01-01	Nickel	Percent Change over Previous Period	-19.900102
1990-02-01	Aluminum	Index	90.638099
1990-02-01	Nickel	Percent Change over Corresponding Period Previous Year	-62.453870
1990-02-01	Nickel	US Dollars	6977.000000
1990-02-01	Aluminum	Percent Change over Previous Period	-4.842932
1990-02-01	Aluminum	Percent Change over Corresponding Period Previous Year	-33.167767
1990-02-01	Aluminum	US Dollars	1454.000000
1990-02-01	Nickel	Index	72.713599
1990-02-01	Nickel	Percent Change over Previous Period	-1.119615
1990-03-01	Aluminum	Index	97.682188
1990-03-01	Nickel	Percent Change over Corresponding Period Previous Year	-45.985025

Dropped for now because

- Monthly time series data
  - Would need a model that can handle different time series → LSTM Neural Network!
- Only US data → would have to organize data differently
- Current Ridge is trained on completely non-financial data… which is kind of cool

Ridge Regression Model and Assumptions

Simple, linear regression model with L2 regularization term to prevent overfitting

$$\beta \;= \text{argmin} \sum (Y - X\,\beta)^2 + \lambda \sum \beta^2$$

Assumptions

- Features are independent of each other

Handling Missing Data & Time Misalignment

- Forward fill (ffill) to handle annual vs. daily data misalignment → monthly time series

Standardize input matrix using StandardScaler() and encoded countries using OneHotEncoder()

Model Evaluation Metrics: R^2 for Ridge Regression

Ridge Regression Model and Assumptions

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$$\beta \;=\; \text{argmin} \sum (Y - X\beta)^2 + \lambda \sum \beta^2$$

regularization term!

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Model Evaluation Metrics: R^2 for Ridge Regression

LSTM Model and Assumptions

Why LSTM?

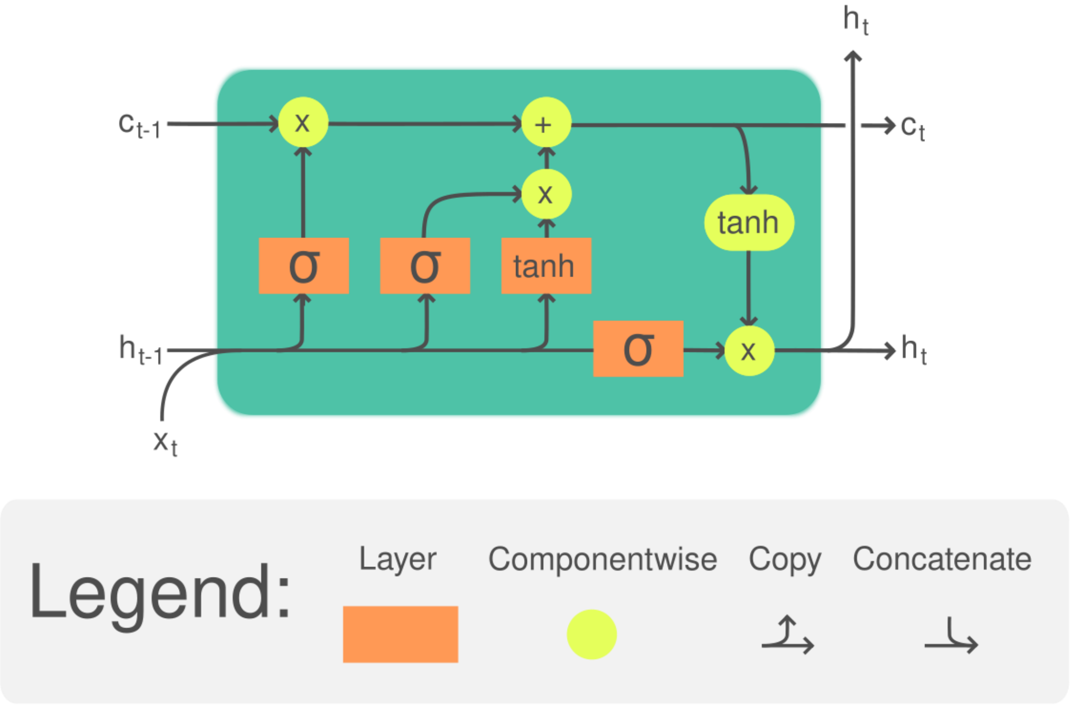
Neural Network that assumes big time series data

- Identifies complex, nonlinear relationships that Ridge Regression cannot
- Maintains long-term memory that RNNs do not
- LSTMs handle missing or irregularly spaced time intervals effectively

Model Evaluation Metrics

- MSE for LSTM to capture directional accuracy

  for stock movement prediction



Cleaned Dataset for EDA and Ridge Regression Training

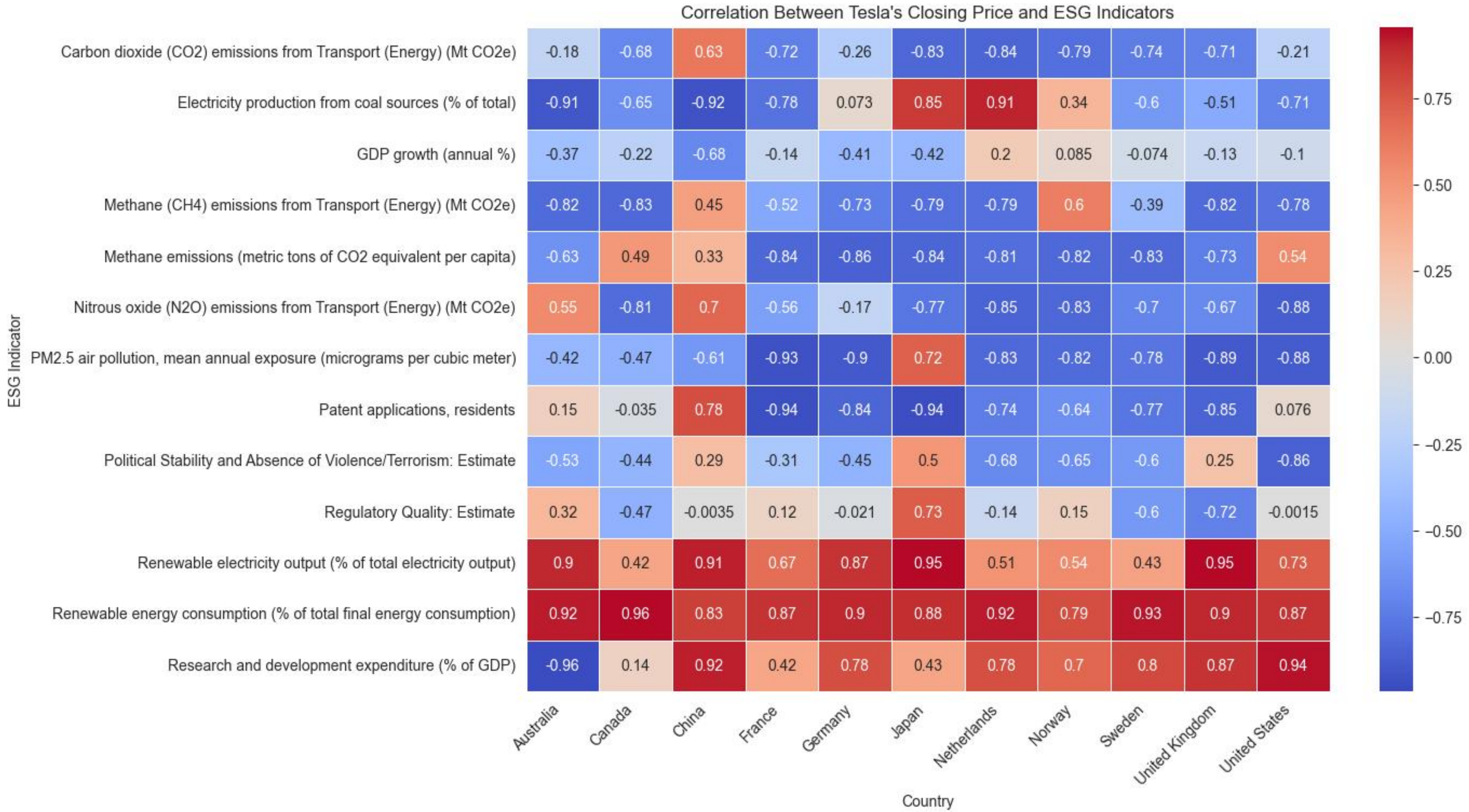
Indicators / Features

Countries / Trials

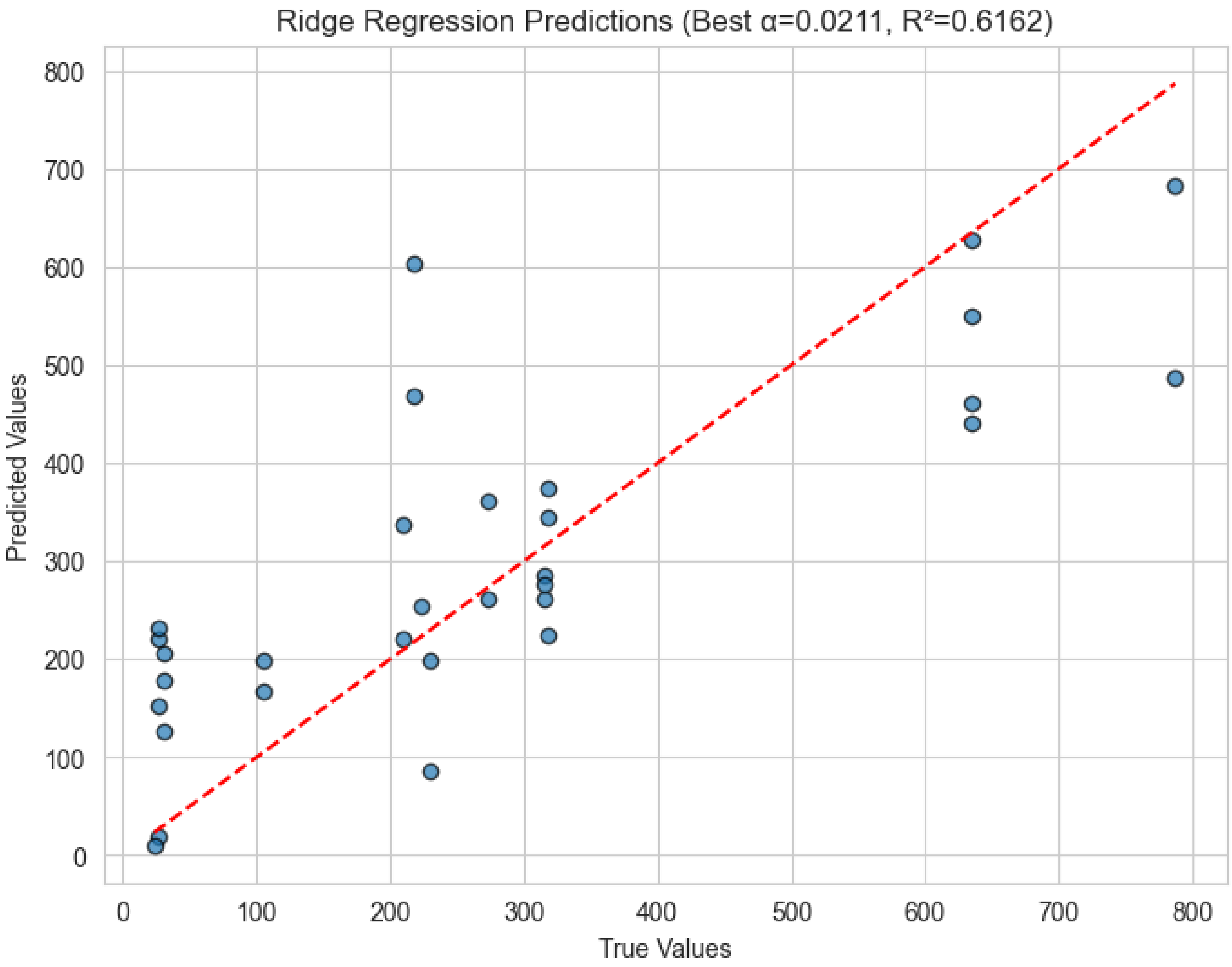
1-100 154 rows × 14 columns

	Country ...	Year	Carbon ...	Electricity ...	Gini ...	Methane...	Net migration	Patent...	Population...
40	Australia	2010	87.6345	71.327642	34.7	0.2926	166833.0	2409.0	2.867859
364	Netherlands	2010	34.0545	21.631592	27.8	0.0994	35628.0	2527.0	492.599881
256	Germany	2010	148.1233	43.642422	30.3	0.3344	267047.0	47047.0	234.606908
418	Norway	2010	15.0107	0.085201	25.7	0.0314	42906.0	1117.0	13.386262
202	France	2010	123.2710	4.663424	33.7	0.1998	86355.0	14748.0	118.764941
472	Sweden	2010	20.6653	1.297993	27.7	0.0594	60639.0	2196.0	23.022863
148	China	2010	568.7798	77.187194	43.7	4.5609	-216417.0	293066.0	142.487743
526	United Kingdom	2010	116.8489	28.745924	33.7	0.2022	281588.0	15490.0	259.440189
94	Canada	2010	169.4329	13.172180	33.6	0.8452	227724.0	4550.0	3.792822
580	United States	2010	1679.7732	45.797606	40.0	5.8840	1030731.0	241977.0	33.815780
310	Japan	2010	228.6503	27.155142	32.1	0.7871	148460.0	290081.0	351.358025
581	United States	2011	1633.5907	43.345764	40.9	5.2604	1322433.0	247750.0	34.062444
311	Japan	2011	223.0273	27.099953	32.1	0.7648	139793.0	287580.0	350.707819
203	France	2011	128.1588	3.111211	33.3	0.1942	65188.0	14655.0	119.339599
149	China	2011	621.8900	78.877123	42.4	4.9070	-147585.0	415829.0	143.268510
419	Norway	2011	14.9825	0.104455	25.3	0.0295	47281.0	1122.0	13.561039
473	Sweden	2011	20.3745	0.971688	27.6	0.0764	65397.0	2004.0	23.197378

Heatmap Visualization from Correlation Analysis



Ridge Regression True vs. Predicted Closing Price



25 total predictors after encoding the countries

(no commodities)

Identify Top Global ESG Predictors of Tesla Stock

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Country	Environment	Social	Governance
1st United States	2nd Renewable energy consumption (% of total energy)	13th Patent applications, residents	8th Regulatory Quality: Estimate
3rd China	4th Nitrous oxide emissions from Transport (Energy) (Mt CO2e)	14th GDP growth (annual %)	9th Research and development expenditure (% of GDP)
5th Japan	6th Electricity production from coal sources (% of total energy)	15th Net migration	16th Political Stability and Absence of Violence/Terrorism
7th Netherlands	10th Air pollution mean annual exposure	17th Gini Index/Coefficient	19th Population density

Conclusion

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Tesla Stock Return can be modeled accurately with non-financial ESG metrics

Identify top ESG KPIs to use in complex model

Improve model interpretability and explainability to better inform investment decisions

Provide insight into data multicollinearity and hidden patterns that black box neural networks hinder

Next Steps

Explore non-linear effects and latent factors that affect Tesla with deep learning

Add commodity price data to visualize hidden variance with unsupervised learning

Incorporate ESG Sentiment Analysis to improve model

After identifying ESG impact on Tesla, expand to using ESG as a performance metric generally

Transition to back-tested, trading strategies

1. Calculate ESG risk and predict volatility spikes
2. Model global ESG trends to identify renewable energy firms that will fill US market gaps over next 4 years
3. Pairs Trading on ESG-linked assets (commodities)

Thank You

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Appendix

Access Link to Research Paper