Impact of Carbon Risk & Cost of Debt Financing in the Corporate World – Evidence from Indian Companies Operating in High Carbon Industries

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Thesis Presentation Outline

Introduction

01

Carbon Risk & COD

Emerging risk of the carbon emission on the cost of debt financing

02

Research Questions

- What is company's exposure to the environment risk?
- How would lenders respond to that?

03

Need for the Research

- To implement changes in corporate governance policies;
- Avoid Reputational Risk;
- Making financing more feasible

04

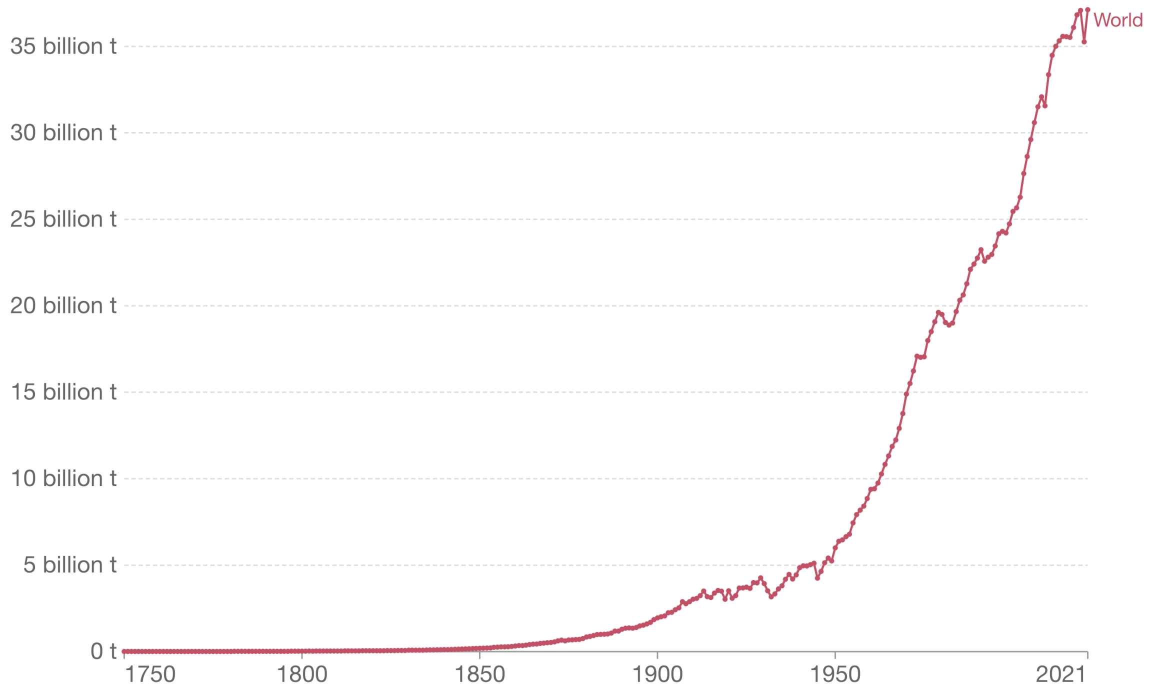
Goals & Objectives

Determine loan holders view in developing nation, with focus on Indian market

Annual Carbon Emission

Annual CO2 emissions

Carbon dioxide (CO_2) emissions from fossil fuels and industry[1] . Land use change is not included.

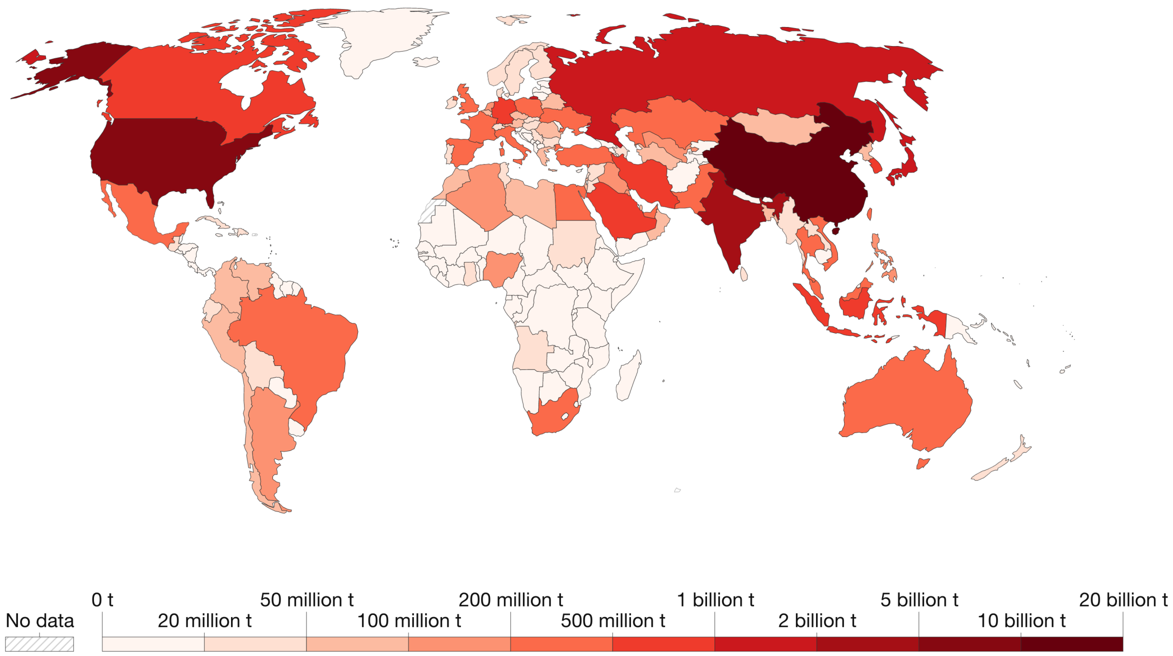


Source: Our World in Data based on the Global Carbon Project (2022) OurWorldInData.org/co2-and-other-greenhouse-gas-emissions/ • CC BY

1. Fossil emissions: Fossil emissions measure the quantity of carbon dioxide (CO_2) emitted from the burning of fossil fuels, and directly from industrial processes such as cement and steel production. Fossil CO_2 includes emissions from coal, oil, gas, flaring, cement, steel, and other industrial processes. Fossil emissions do not include land use change, deforestation, soils, or vegetation.

Annual CO2 emissions, 2021

Carbon dioxide (CO_2) emissions from fossil fuels and industry[1] . Land use change is not included.



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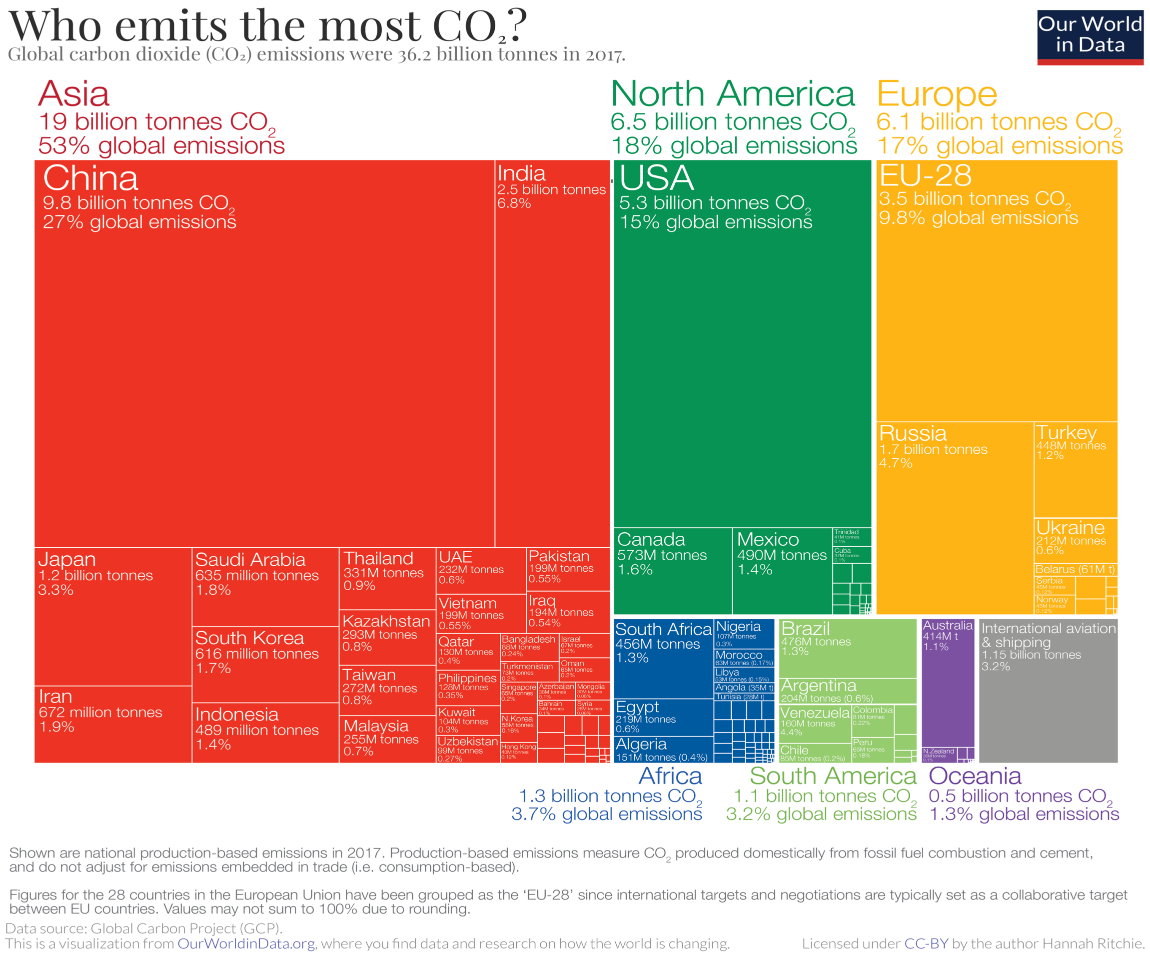
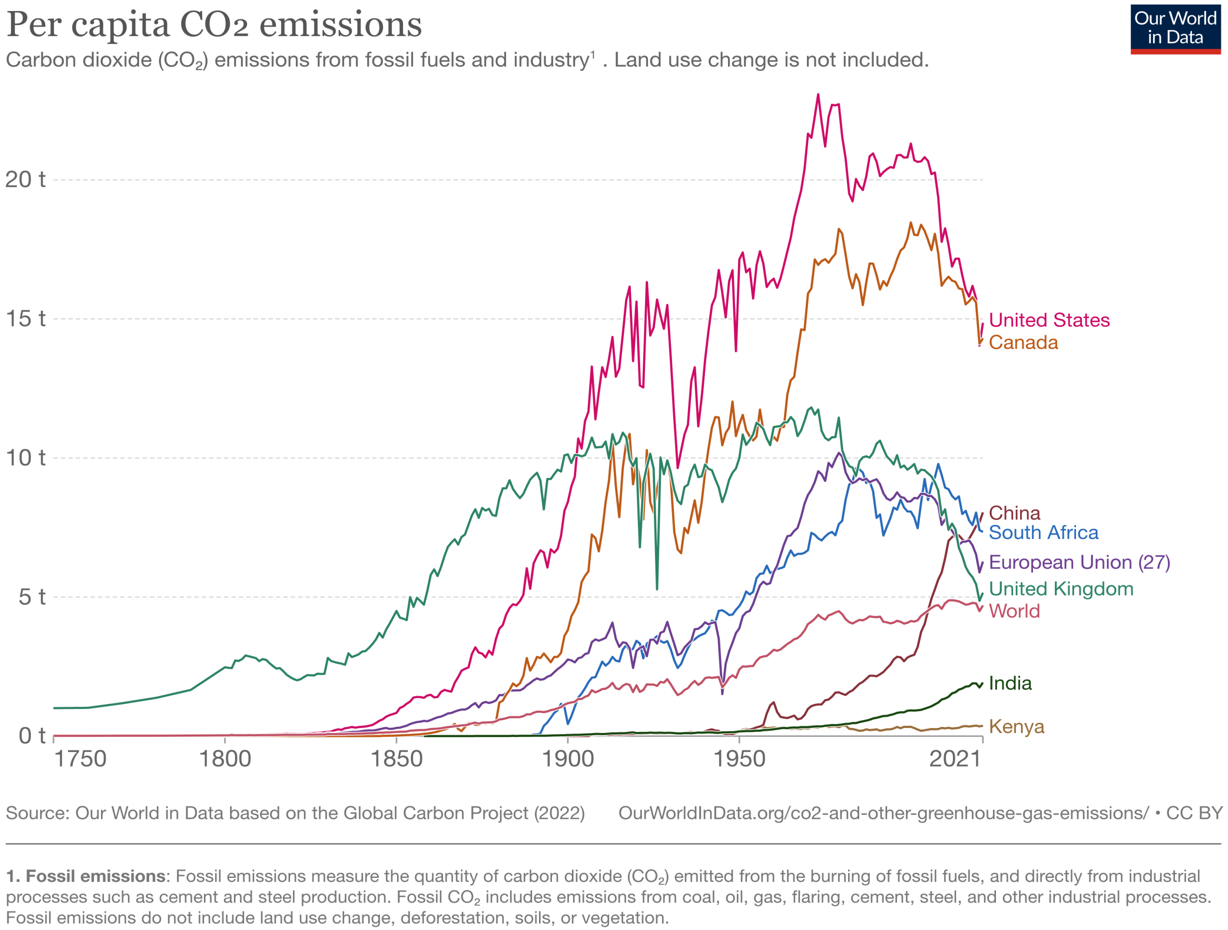
1. Fossil emissions: Fossil emissions measure the quantity of carbon dioxide (CO_2) emitted from the burning of fossil fuels, and directly from industrial processes such as cement and steel production. Fossil CO_2 includes emissions from coal, oil, gas, flaring, cement, steel, and other industrial processes. Fossil emissions do not include land use change, deforestation, soils, or vegetation.

According to **Busch & Hoffmann (2008)**, **carbon risk** is defined as "**any corporate risk related to climate change or the use of fossil fuels,**" is a **subset of environmental issues.**

Carbon Emission by Region & Per Capita





*Measuring the total carbon emission doesn't always paint the accurate picture of a country's contribution, if their population is not considered.

Literature Review

After reviewing 18 research papers, I have organized the thesis literature into four main divisions:

1 Carbon Taxation & Trading

- Carbon taxes internalise external effects by making payments equal to the social marginal cost.
- Carbon trading is the trading of extra carbon credits.

2 Carbon Pricing Initiatives

- Carbon pricing schemes are utilised globally to link the externality of carbon emissions to a price.
- Allows for the inclusion of carbon prices in economic or business decision-making.

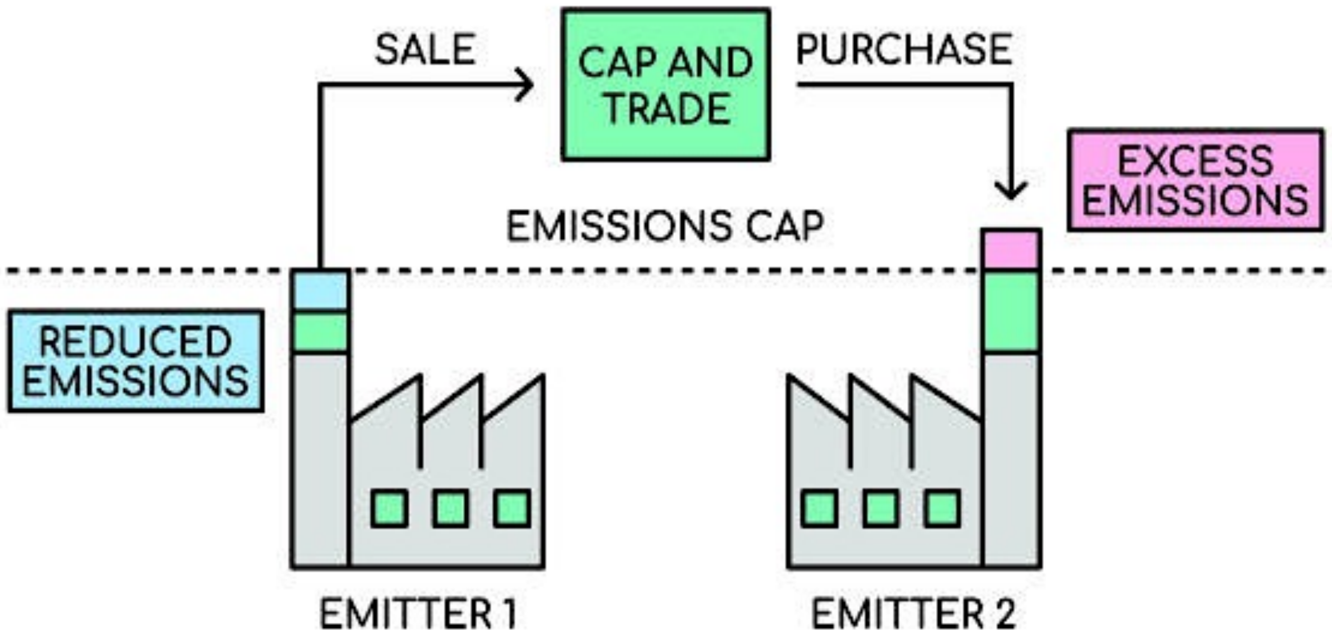
3 Carbon Market

- Compliance Carbon Market: Set up Govt Regulatory Authority.
- Voluntary Carbon Market: Set up by independent certification bodies.

4 Carbon Risk & COD

- Corporate environmental risk and cost of debt are positively associated.
- Banks & authorities imposes higher than normal rate on business have an adverse impact on environment.

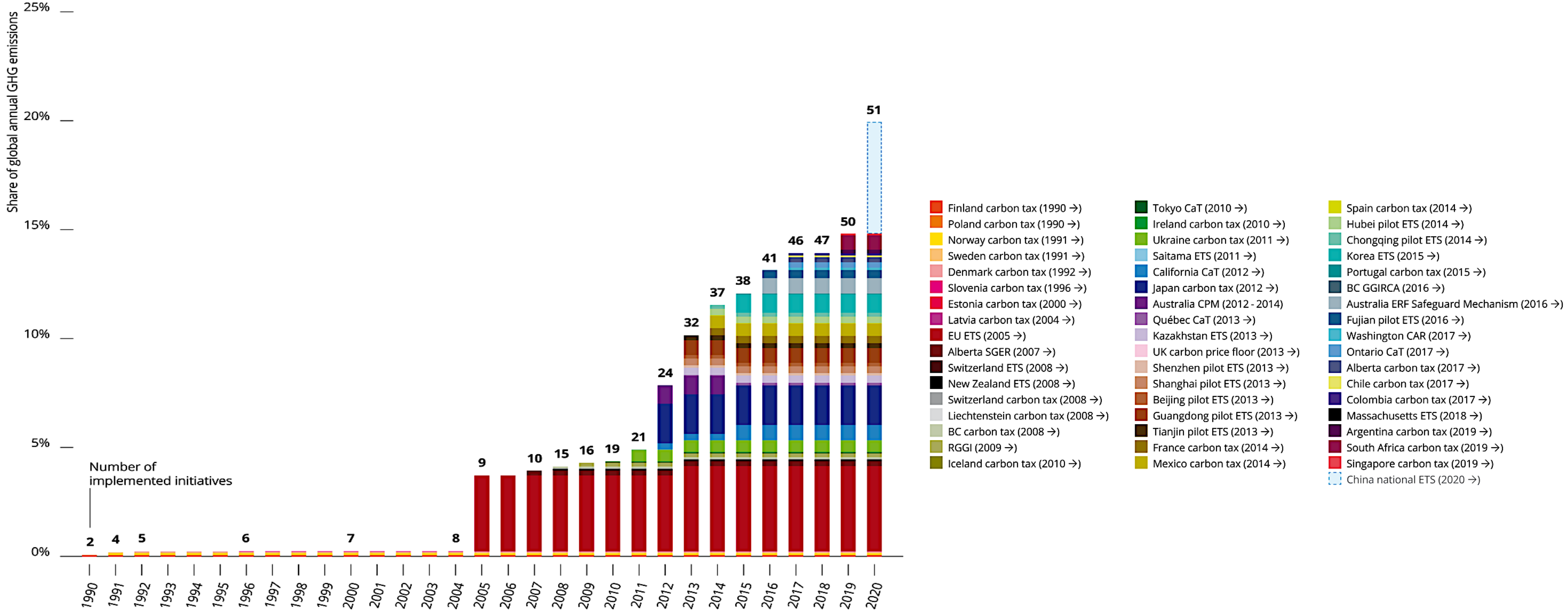
Cap & Trade



Veld-Merkoulova and Viteva (2016) tells both carbon taxes and trading systems have economic repercussions since they affect the cost structures of the compelled enterprises and, as a result, their ability to compete.

Chen and Gao (2012) cites lenders may perceive the business as being less creditworthy and require higher interest rates or more collateral due to added risk, eventually affecting the cost of debt.

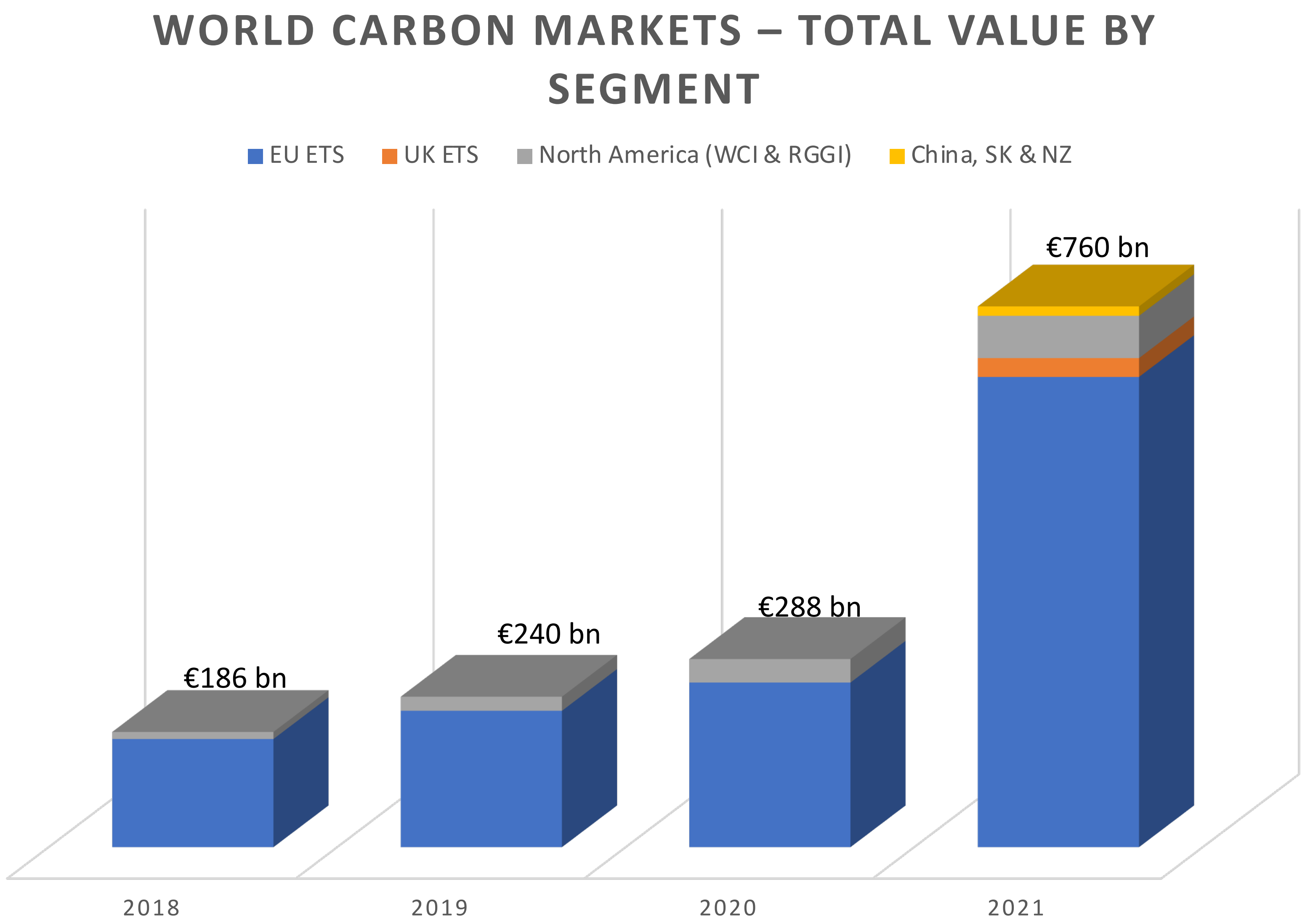
Carbon Pricing



According to **World Bank and Ecofys (2018),** Development of carbon pricing schemes globally over time and in terms of volume

Carbon Market

Global carbon markets today are valued at ~**750 Billion USD** and have grown every year for the last five years. 2021 was a banner year with **trading value increasing 2.5x** compared to previous year.

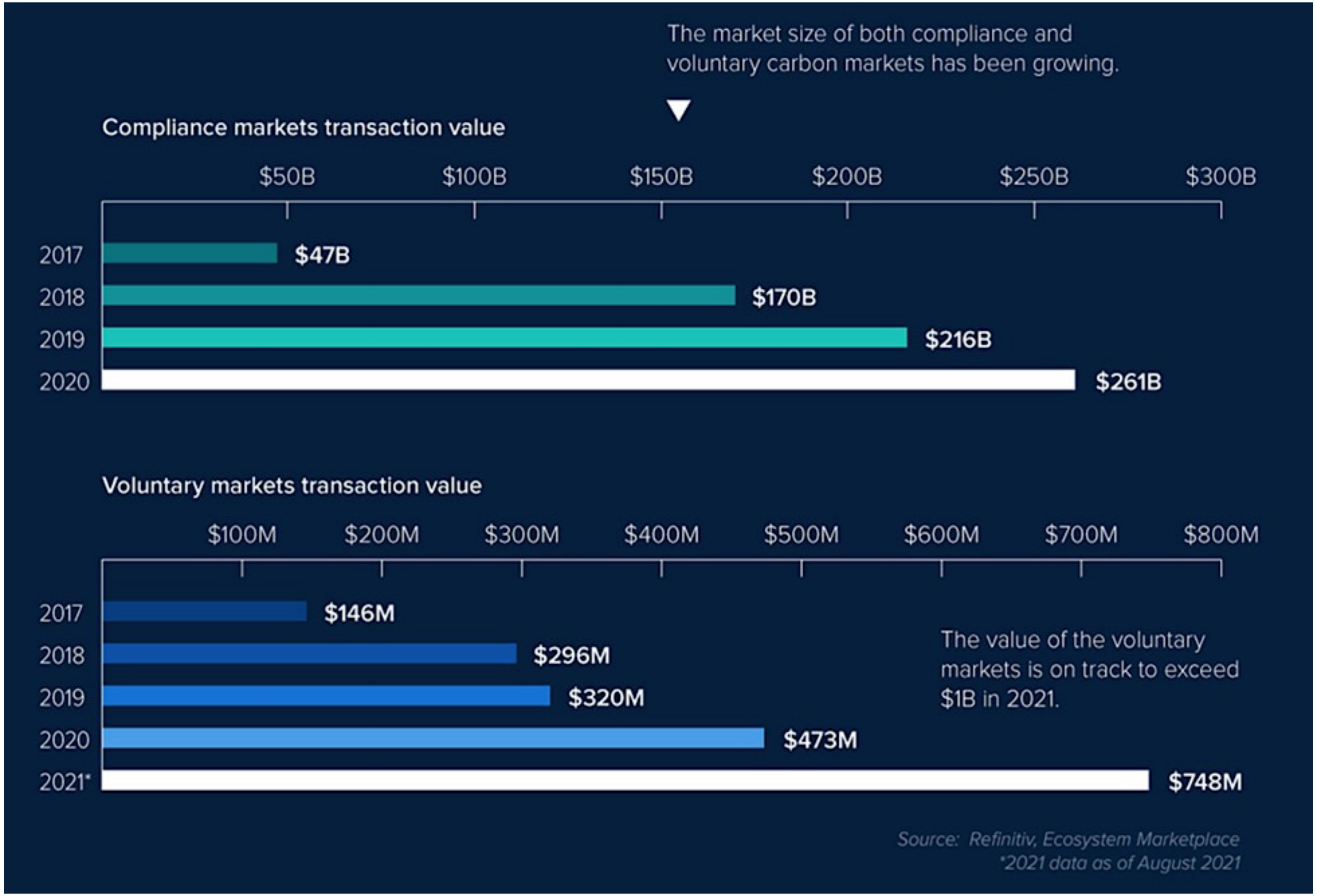


Carbon Market

Types of Carbon Market:

(Peters-Stanley and Yin, 2013) document that <u>Compliance carbon trading systems</u> require certain companies must follow the regulatory regime or face penalties.

In contrast, <u>voluntary carbon markets</u> allow businesses to buy and sell carbon offsets on a voluntary basis, often to improve their reputation or manage climate-related risks.

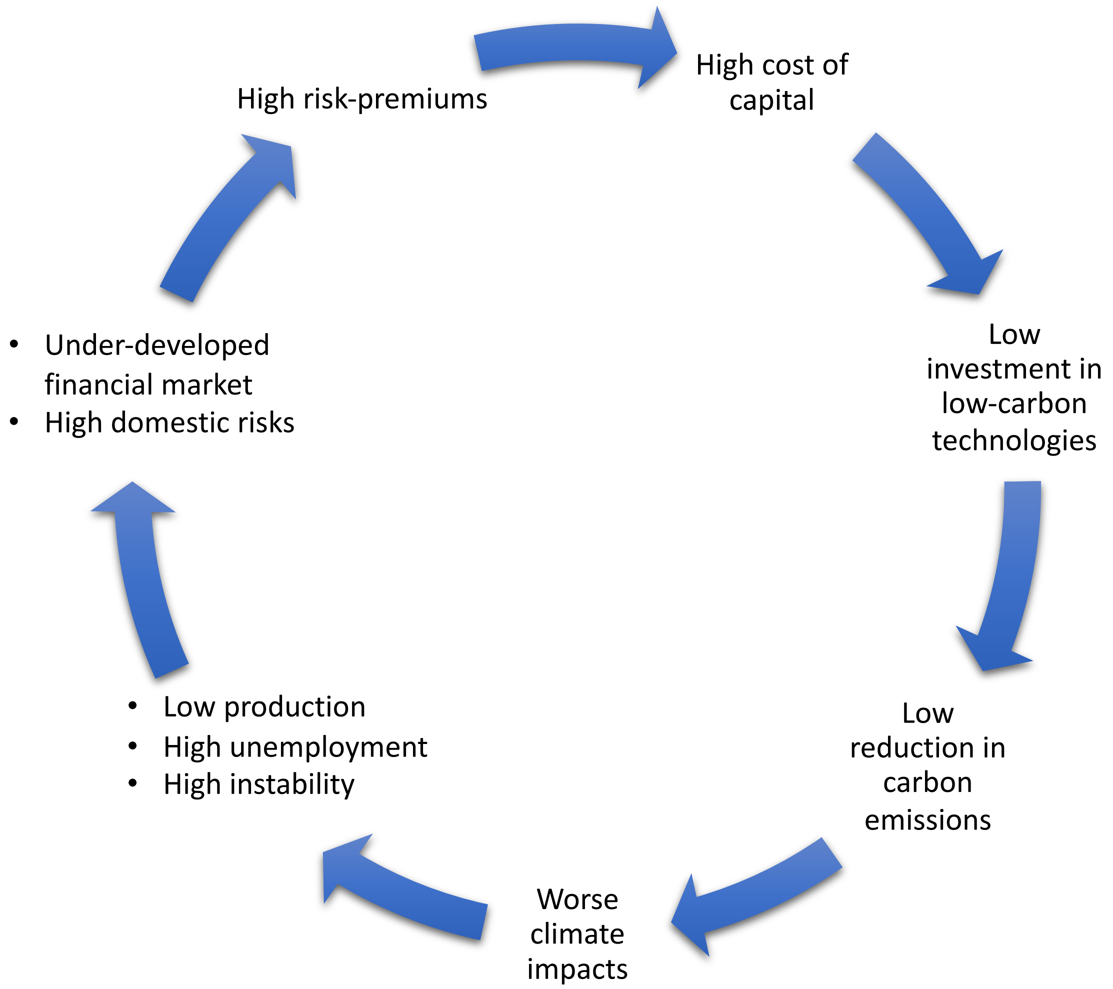


Climate Investment Traps for Developing Nations

- **Saunders & Allen (2002)** explains theoretically, a company's ability to repay its debts depends on its capital stock, profitability, and liquidity, which are known as counterparty credit risks and are a major factor in default risk.

- **Lin, Li, He, and Zhou (2014)** discovered that organisations with greater social responsibility have lower debt financing costs than companies with lesser or no social responsibility.

- **Jung et al., (2018)** cites the fact that developing countries could be caught in "climate investment traps," whereby the higher cost of capital in those countries combines with increasingly extreme climate impacts to make credit even less accessible.



Research Gap

1

The study will focus on understanding the relationship between carbon emission & COD, as well as lenders response to high carbon emitting industries in India.

2

This study aims to examine how debtholders in developing countries, specifically India, assess the specific carbon risk of businesses in various sectors.

Methodology

H_1: The firm's carbon emission is positively related to the COD

Industrial Sectors
Consumer
Energy
Aviation
Informational Technology
Materials
Telecommunications
Healthcare
Utilities
Chemical

Variables	Code	Measurement
Cost of Debt	COD	(Total Interest)/(Total Long–Term Debt)
Emission	Em	Direct emissions in metric tons
Beta	Be	Systematic risk associated with the industry
Interest Coverage Ratio	ICR	(total operating income)/(total interest expense of the firm)
Risk-Free Rate	Rf	Long-term risk-free rate of return
Leverage Ratio	Lev	(Today Debt)/(Total Debt + Total Equity)
Size	Sz	Size of the firm
Book to Market Value	BMV	company's book value over its market value
Net Profit	NP	Profit after tax

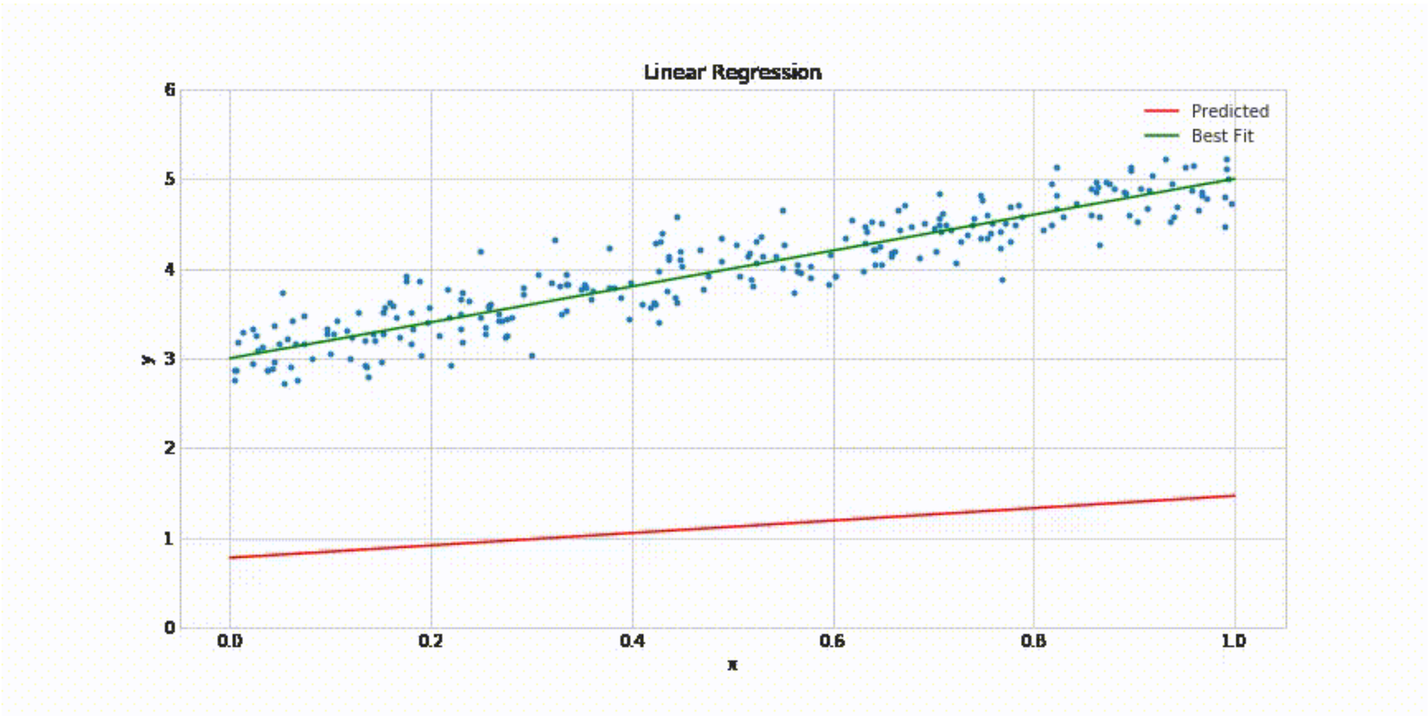
Dataset

Year	com	ind	cod	em	beta	icr	rf	lr	sz	bmv	np
2016	Hindustan Unilever Limited	Consumer	0.050	54135	1.39	53.65	0.072	0.36	189810	183611	4083
2016	Reliance Industries Limited	Energy	0.063	13484204	1.25	7.02	0.072	0.46	634954	420824	27630
2016	InterGlobe Aviation Limited	Aviation	0.063	155155	0.93	22.68	0.072	0.93	23181	7100	1782
2016	Tata Consultancy Services Limited	Informational Technology	0.030	85460	1.10	210.75	0.072	0.05	480571	229444	23149
2016	Tata Steel Limited	Materials	0.077	22130000	1.23	1.71	0.072	0.59	68892	47684	-3043
2016	Bharti Airtel Limited	Telecommunications	0.047	1734605	0.68	4.15	0.072	0.53	135585	102704	3800
2016	Sun Pharmaceutical Industries Limited	Healthcare	0.038	87279	0.62	64.91	0.072	0.29	191542	97996	3489
2016	NTPC Limited	Utilities	0.072	84367000	0.82	3.67	0.072	0.94	126726	89118	9385
2016	Gujarat State Fertilizers & Chemicals Limited	Chemical	0.074	94486	0.86	2.87	0.072	0.60	9625	3324	-519
2017	Hindustan Unilever Limited	Consumer	0.048	318132	0.85	53.34	0.067	0.18	177478	32432	19060
2017	Reliance Industries Limited	Energy	0.062	22858304	0.92	12.53	0.067	1.04	709396	3535	34212
2017	InterGlobe Aviation Limited	Aviation	0.059	1625654	1.09	3.59	0.067	8.44	28069	76767	1605
2017	Tata Consultancy Services Limited	Informational Technology	0.042	55350	1.17	98.61	0.067	0.15	585407	23247	25826
2017	Tata Steel Limited	Materials	0.055	23751302	1.02	5.10	0.067	0.69	48083	56765	6924
2017	Bharti Airtel Limited	Telecommunications	0.054	1636702	0.77	3.26	0.067	3.36	175952	237755	6899
2017	Sun Pharmaceutical Industries Limited	Healthcare	0.057	94212	0.87	8.15	0.067	0.79	152581	674322	4680
2017	NTPC Limited	Utilities	0.054	56550382	0.44	5.43	0.067	0.61	149492	4645	9385
2017	Gujarat State Fertilizers & Chemicals Limited	Chemical	0.058	28535	1.10	3.05	0.067	0.88	10026	4646	618
2018	Hindustan Unilever Limited	Consumer	0.028	84782	0.92	164.50	0.075	0.09	528190	392081	5237
2018	Reliance Industries Limited	Energy	0.073	20901122	1.15	20.40	0.075	0.56	702680	853105	36080
2018	InterGlobe Aviation Limited	Aviation	0.075	227366	1.18	23.80	0.075	1.17	60778	26662	2242
2018	Tata Consultancy Services Limited	Informational Technology	0.034	106300	0.90	105.40	0.075	0.01	655154	538578	25927
2018	Tata Steel Limited	Materials	0.054	24034	1.31	6.70	0.075	0.65	72906	40824	2399
2018	Bharti Airtel Limited	Telecommunications	0.058	316879	0.87	8.80	0.075	2.52	242358	117558	4141
2018	Sun Pharmaceutical Industries Limited	Healthcare	0.046	6812	0.94	31.20	0.075	0.34	157779	131693	1730
2018	NTPC Limited	Utilities	0.071	28728889	0.85	2.90	0.075	0.55	119014	112616	9385
2018	Gujarat State Fertilizers & Chemicals Limited	Chemical	0.068	9160	1.01	12.80	0.075	0.54	16563	5603	1127
2019	Hindustan Unilever Limited	Consumer	0.036	267247	0.66	207.43	0.066	0.49	350839	492932	6496
2019	Reliance Industries Limited	Energy	0.076	25128201	1.08	8.12	0.066	1.28	865955	1342951	39588
2019	InterGlobe Aviation Limited	Aviation	0.056	161487	1.28	7.91	0.066	4.14	65368	68104	2242
2019	Tata Consultancy Services Limited	Informational Technology	0.046	53897	0.78	76.21	0.066	0.22	717334	1157188	31472
2019	Tata Steel Limited	Materials	0.082	2310000	1.36	4.84	0.066	1.03	77839	43179	3075
2019	Bharti Airtel Limited	Telecommunications	0.079	209282	0.59	8.28	0.066	1.88	135225	203363	6724
2019	Sun Pharmaceutical Industries Limited	Healthcare	0.063	13712	0.53	50.60	0.066	0.17	132819	157008	2470
2019	NTPC Limited	Utilities	0.087	2523000	0.56	3.38	0.066	1.15	118482	100223	11180
2019	Gujarat State Fertilizers & Chemicals Limited	Chemical	0.099	84148	1.42	1.60	0.066	1.66	6571	3985	2336
2020	Hindustan Unilever Limited	Consumer	0.033	139534	0.80	32.48	0.058	0.62	525057	436908	6625
2020	Reliance Industries Limited	Energy	0.056	25083660	0.78	15.59	0.058	1.56	1496142	84609	39266
2020	InterGlobe Aviation Limited	Aviation	0.072	147510	0.96	4.77	0.058	5.75	55662	35464	-2331
2020	Tata Consultancy Services Limited	Informational Technology	0.025	10193	0.85	239.54	0.058	0.03	913660	235367	32763
2020	Tata Steel Limited	Materials	0.055	2832213	0.82	3.62	0.058	1.73	50688	56755	-2226
2020	Bharti Airtel Limited	Telecommunications	0.033	1472829	1.07	4.57	0.058	4.14	341662	6754	14852
2020	Sun Pharmaceutical Industries Limited	Healthcare	0.044	82484	1.32	16.95	0.058	0.47	143610	5640	3885
2020	NTPC Limited	Utilities	0.052	6798836	0.44	6.78	0.058	3.03	124660	56432	10945
2020	Gujarat State Fertilizers & Chemicals Limited	Chemical	0.034	325433	1.01	3.49	0.058	2.23	9071	209334	254

Sheet1 Sheet2 +

ML Model-1: Predictive Linear Regression for COD

Technique: Optimizing the model with help of Stochastic Gradient Descent, while also minimizing the Cost Function.



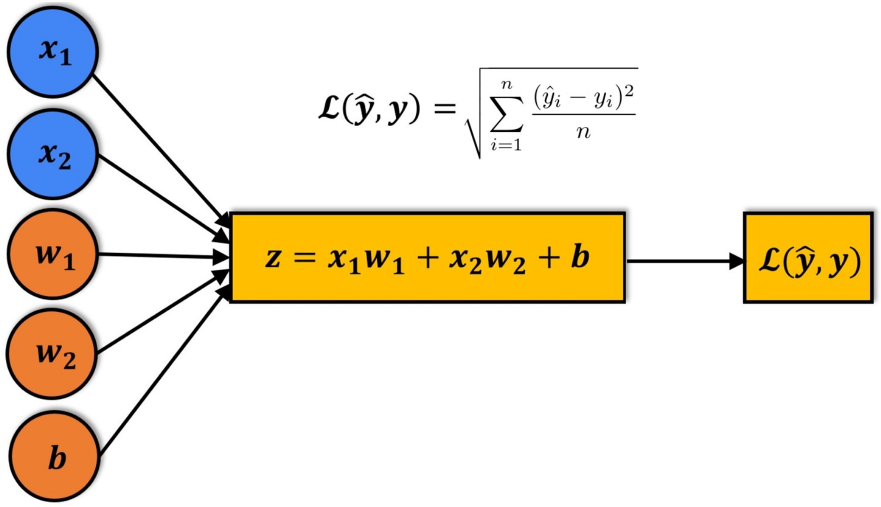
$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (Predicted_i - Actual_i)^2}{N}}$$

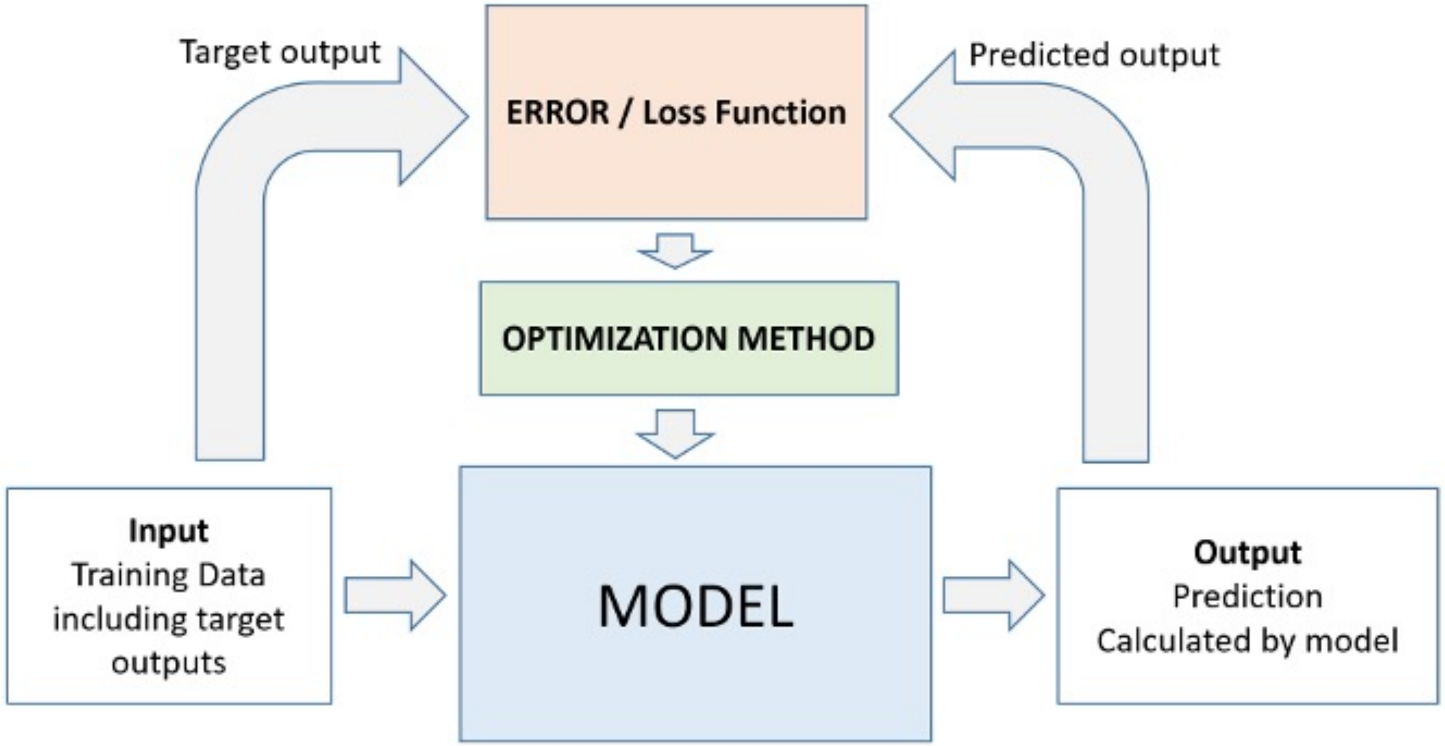
Stochastic Gradient Descent uses a iterative approach, starting with a random values of w and b and slowly improving them using derivatives.

Cost Function represents information loss in the model; the lower the loss, the better the model.

Inside the ML Model: How it Works

Supervised Learning: Develop predictive model based on both input variables (features) & target variable (label)
Common examples, Regression & Classification (logistic)





Computational Tools: Python & MS Excel

MS Excel for:

- Data Cleaning
- Data Wrangling

Python for:

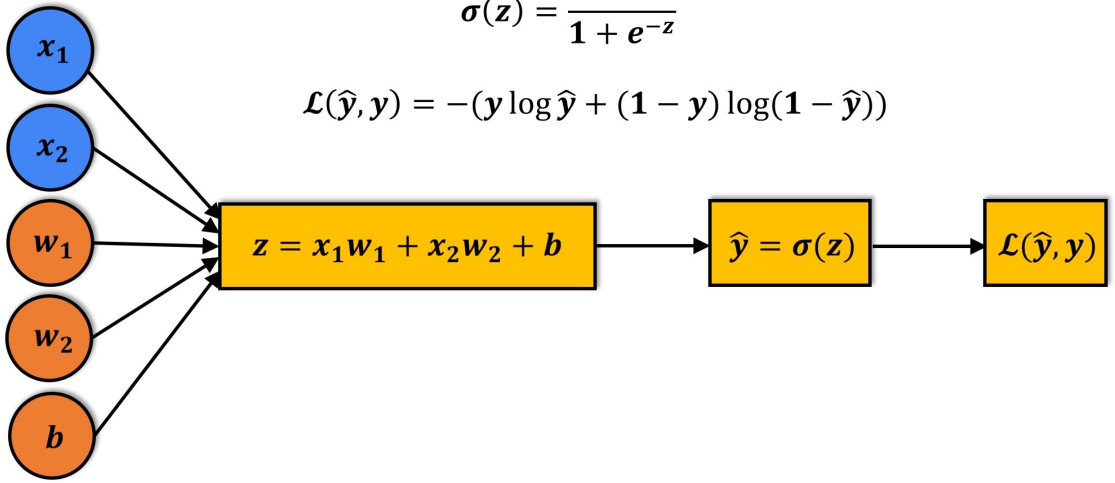
- Data Manipulation
- Exploratory Data Analysis
- Modelling

ML Model-2: Logistic Classification for Loan Defaults

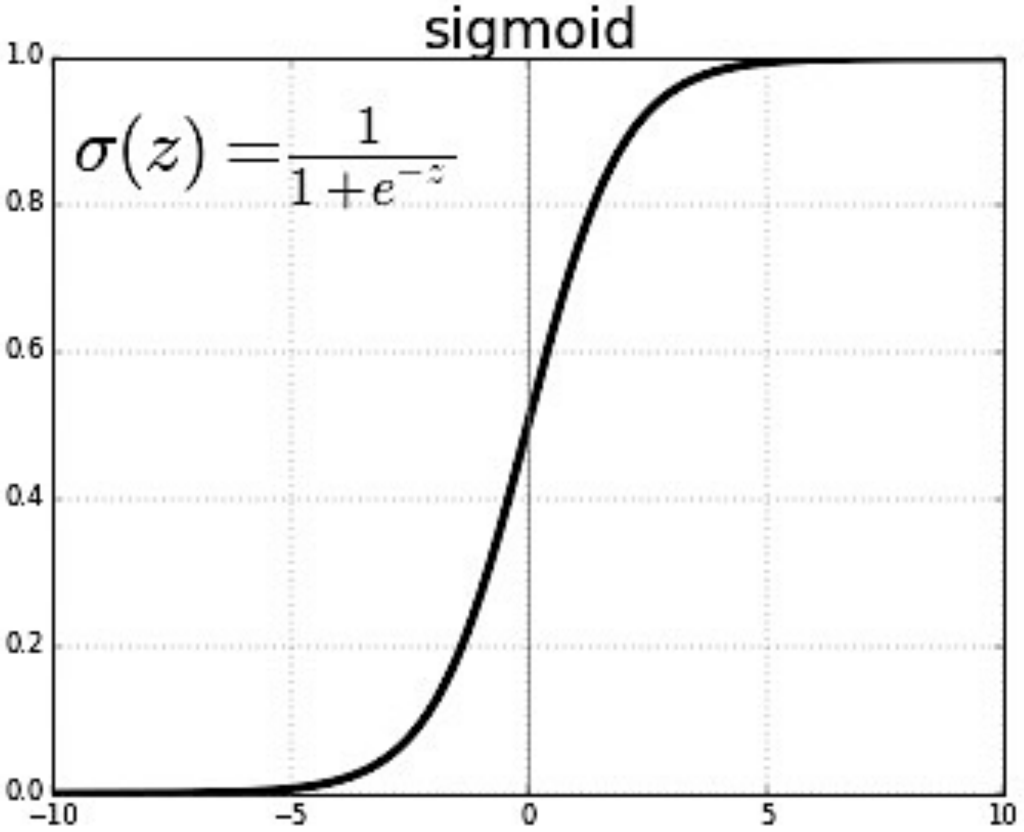
Logistic regression is a commonly used technique for solving binary classification problems.

$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

$$\mathcal{L}(\hat{y}, y) = -(y \log \hat{y} + (1 - y) \log(1 - \hat{y}))$$



- Apply the **Sigmoid Function** to the result to obtain a number between 0 and 1
- Instead of RMSE, the **Cross Entropy** loss function is used to evaluate the results



Findings & Analysis: Hypothesis Testing

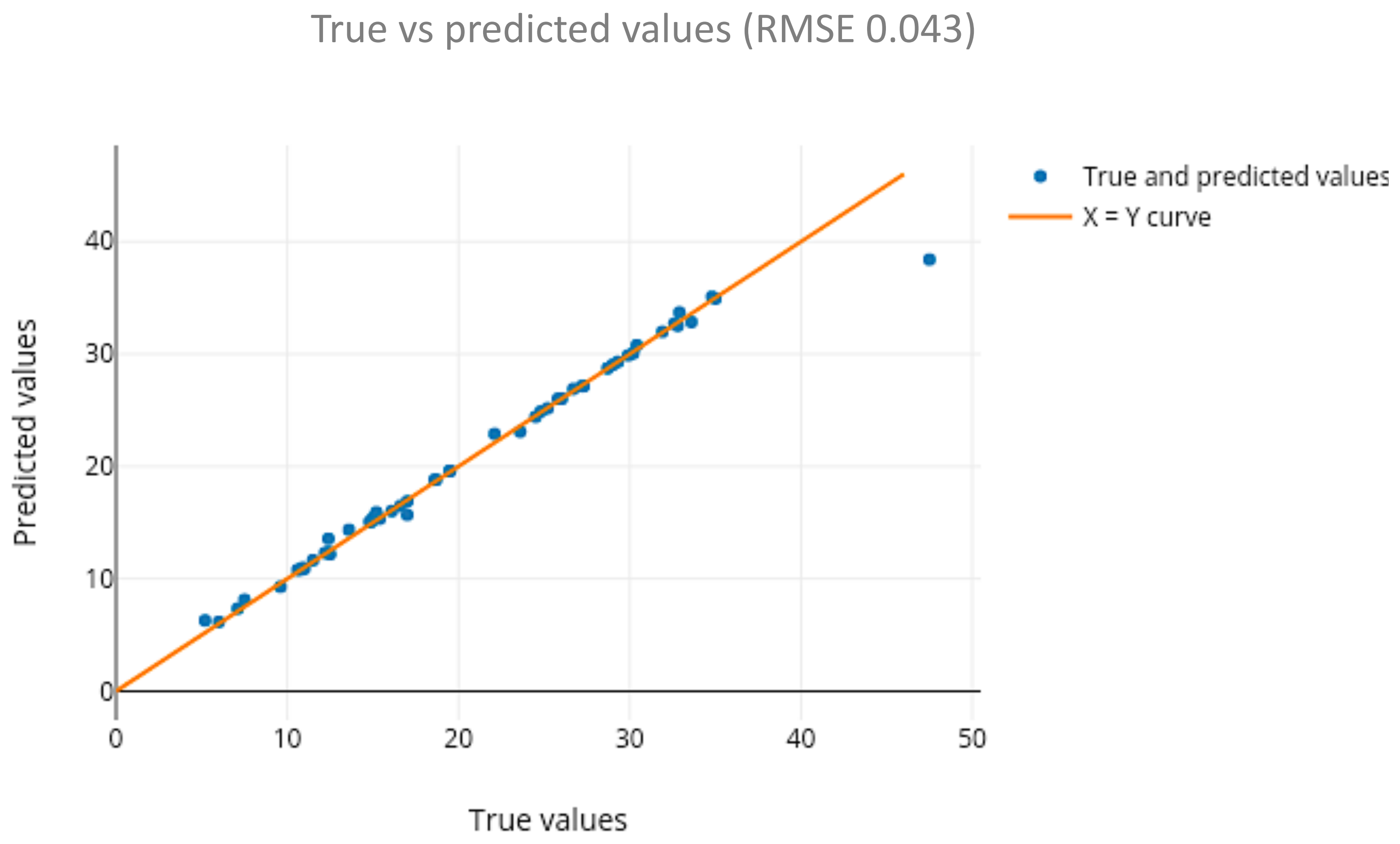
Consistent with the hypothesis, coefficients of:

- **EMISSIONS** is positively and significantly associated with **COD** at the 5 percent levels.
- Company's **ICR** is negatively and significantly associated with the **COD.**
- Long-term **RFs** is positively and significantly related to **COD.**

Variables	Expected Sign	Coefficient (p-values)
Emission	+	7.2900 (0.0044)
Beta	+	0.0043 (0.5195)
ICR	-	-0.0004 (0.0741)
Risk-Free Rate	+	0.0134 (0.0000)
Leverage Ratio	+	-0.0211 (0.2395)
Size	-	1.1700 (0.4081)
Intercept		-0.0414 (0.1336)
Adjusted R^2		0.7204

**Dropped independent variables–Net Profit & Book to Market–with the highest probability value to counter the multicollinearity!

Findings & Analysis: Predictive Linear Regression



The model gives the RMSE of 0.043 i.e., the model predicted values deviate from the true values only by 0.043 in extreme case.

Conclusion

First Attempt	To examine the impact of direct carbon emissions on the COD for Indian businesses. (~positively correlated & significant at 5 percent level)
Risk of Debt Financing	Firms with higher pollution levels face significant risks in obtaining debt financing. Lenders expect higher returns from environmentally polluting companies.
Importance of Environmental Considerations	Companies should consider emissions levels when designing their capital structure. Incorporating carbon accounting & adjusting COD can align financial planning with environmental factors.
Regulatory Implications	Regulatory measures can control interest rates for environmentally polluting companies, enabling better financial planning.

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Script

```python
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import statsmodels.api as sm
import statsmodels.formula.api as smf
from linearmodels import PanelOLS
from linearmodels.panel import PooledOLS, RandomEffects
from sklearn.linear_model import LinearRegression
from sklearn.decomposition import PCA
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import SGDRegressor
from sklearn.metrics import mean_squared_error

df = pd.read_csv('/Users/aakashagarwal/Downloads/Book7.csv')

# Drop the columns that are not needed for regression analysis
X = df.drop(['com', 'ind', 'Year', 'cod'], axis=1)

# Standardize the independent variables
scaler = StandardScaler()
X_std = scaler.fit_transform(X)

# Apply PCA to reduce multicollinearity
pca = PCA(n_components=3)
X_pca = pca.fit_transform(X_std)

# Add the dependent variable back to the dataframe
y = df['cod']

# Fit the linear regression model
model = LinearRegression()
model.fit(X_pca, y)

# Print the coefficients
print(model.coef_)

# Create the dependent and independent variables
y = df['cod']
X = df[['em', 'beta', 'icr', 'rf', 'lr', 'sz', 'bmv', 'np']]

# Add a constant term to the independent variables
X = sm.add_constant(X)

# Fit a linear regression model
model = sm.OLS(y, X).fit()

# Print the summary of the model
print(model.summary())
```

```python
# Print the coefficients in normal format
print(f"Coefficients: {model.params.round(4)}")

# select the relevant columns for correlation matrix
corr_data = df[['cod', 'em', 'beta', 'icr', 'rf', 'lr', 'sz', 'bmv', 'np']]

# generate correlation matrix
corr_matrix = corr_data.corr()

# display the correlation matrix
print(corr_matrix)

fig, ax = plt.subplots(figsize=(10, 10))
sns.heatmap(corr_matrix, annot=True, cmap='seismic', center=0, ax=ax)
plt.title('Correlation Matrix')
plt.show()

g = sns.pairplot(corr_matrix, diag_kind="hist")
g.map(sns.regplot)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Scale the data
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Set a random seed
seed = 42

# Train the model using stochastic gradient descent
sgd = SGDRegressor(random_state=seed)
sgd.fit(X_train, y_train)

# Make predictions on the testing set
y_pred = sgd.predict(X_test)

weights_df = pd.DataFrame({
    'feature': np.append(X.columns.values, 'Intercept'),
    'weight': np.append(model.params.values, model.params[-1])
})
weights_df

# Calculate the RMSE
rmse = mean_squared_error(y_test, y_pred, squared=False)
print("RMSE:", rmse)
```