HSO - 201
RESEARCH PROJECT

SOCIO-ECONOMIC IMPACTS OF COVID-19

SYNOPSIS PRESENTATION

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STUDY OBJECTIVES

1.

The main objective of this paper is to analyze the impact of COVID-19 on Economic Activity using mobility data as a proxy for it and also to check the impact of Covid on Air Quality.

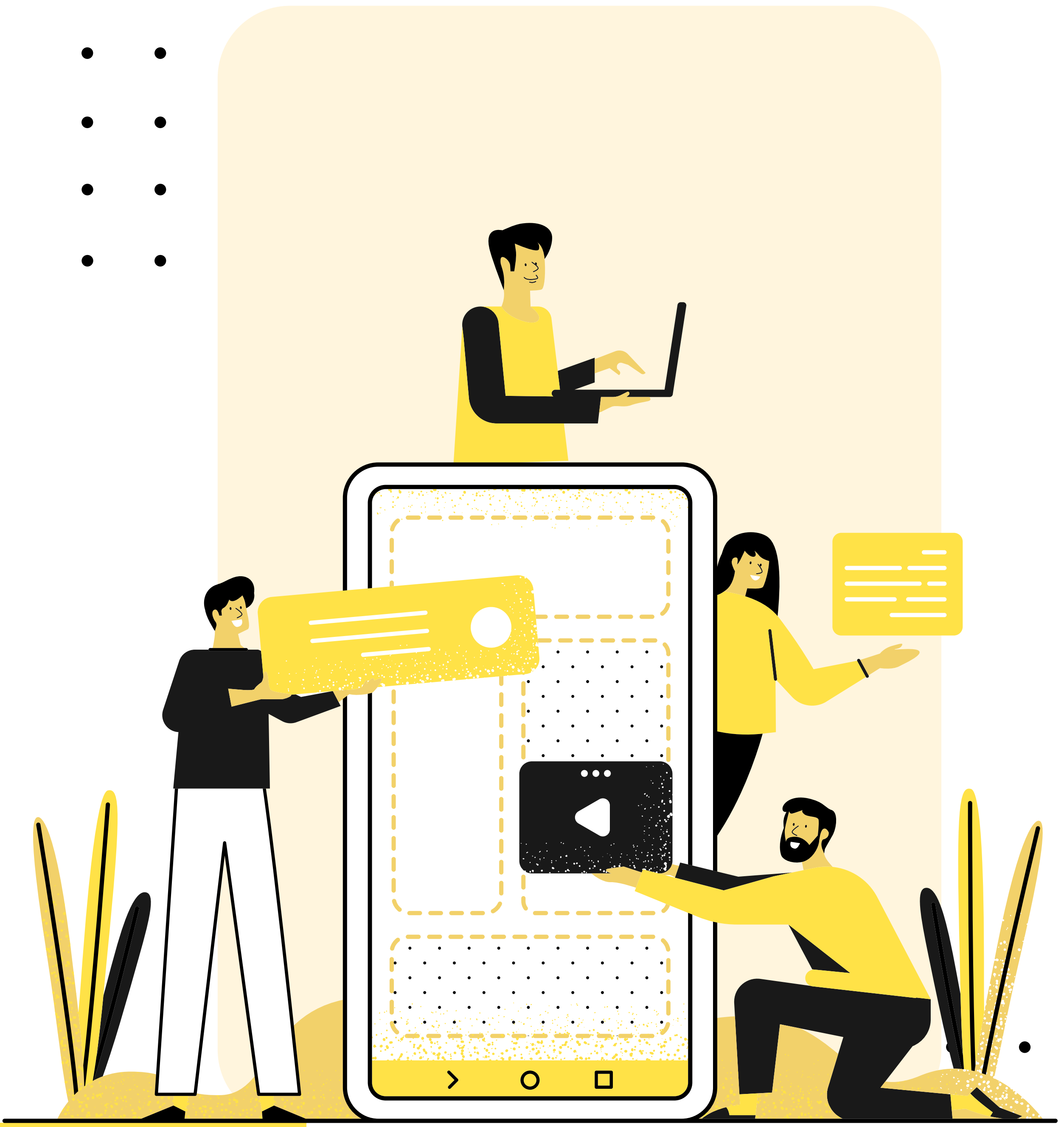
2.

Reviews the literature on the effectiveness of lockdown measures (stringency measures) and their relation with the pollution index.

3.

Summarizes their methodology, results and ending with a conclusion.

INTRODUCTION



01

The Coronavirus Disease pandemic has disrupted economic activity in India and throughout the world. This disease emerged in China and spread globally. The primary concern for COVID-19 includes its significant number of deaths, infections, mortality, and its effect on specific age groups.

02

Some of the significant decisions taken by various governments to control coronavirus's spread included Social restrictions or mobility restrictions policy that affected economic activity. These policies led to a declining GDP since it depends on the severity and duration of the policy.

03

In the pandemic era, GDP statistics become more critical to evaluate economic activity, and around the world, more attention is being paid to these statistics. GDP statistics give the signal to economists that the recession period is approaching.

04

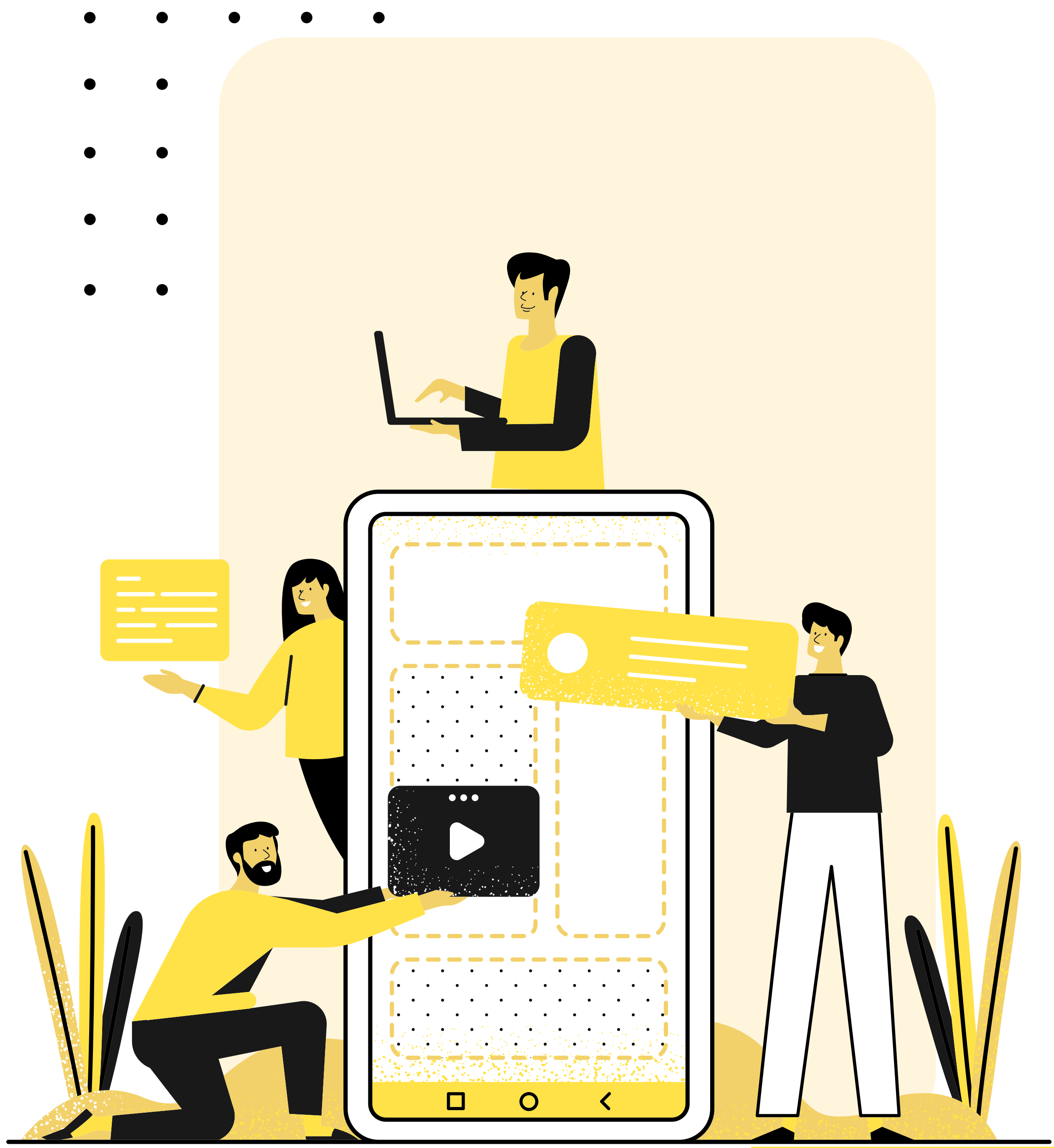
On 25 March 2020, India imposed a stringent lockdown on its 1.3 billion people, locking them in their homes initially for 21 days which eventually got extended for over two months. This caused a decline in manufacturing activities, reducing carbon emissions.

05

PM10 and PM2.5 concentrations reduced by about half in comparison to the pre-lockdown period. Carbon monoxide and nitrogen dioxide contents in the air have also shown a noteworthy decline during the lockdown. This reduction can be attributed to the fall in vehicular emissions as a result of the lockdown.

06

Pandemics are expected to have, at least in the short run, a drastic negative impact on economic activities. As many countries observe social distancing and self-quarantine, the reduced human interference in the natural environment has given nature a “healing time”.



LITERATURE REVIEW

01

Monitoring the Impact of Air Quality on the COVID-19 Fatalities in Delhi, India: Using Machine Learning Techniques

02

Association between weather data and COVID-19 pandemic predicting mortality rate: Machine learning approaches.

03

The COVID-19 lockdown in India: Impacts on the economy and the power sector, Tejal Kanitkar

04

The impact of odd-even transportation policy and other factors on pollution in Delhi: A spatial and RDD analysis

05

Measuring the Economics of a Pandemic: How People Mobility Depict Economics? Evidence of People's Mobility Data towards Economic Activities

01

MONITORING THE IMPACT OF AIR QUALITY ON THE COVID-19 FATALITIES IN DELHI, INDIA; USING MACHINE LEARNING TECHNIQUES :

- It discusses the effects of lockdown during COVID on the various air pollutants and hence the Air Quality Index.

- This has been done using multiple Machine learning techniques like Decision Trees, Linear Regression, and Random Forest, and therefore a comparison is done between the concentration of various air pollutants and air quality index during the lockdown period and previous two years i.e., 2018, 2019.

- The results show that there is a significant positive impact on the Air Quality Index due to lockdown.

02

ASSOCIATION BETWEEN WEATHER DATA AND COVID-19 PANDEMIC PREDICTING MORTALITY RATE: MACHINE LEARNING APPROACHES:

- This paper discussed the effect of weather variables like temperature, humidity on the spread of COVID-19 and the mortality rate because of it.
- In this experiment, Machine Learning algorithms and OLS models are being used to establish the relationship between the confirmed cases in many regions and the weather variables. Also, to predict the spread of Coronavirus, ML models are being used like SVM, KNN, Decision tree and many more.
- This experiment concludes that the mortality rate due to COVID can be predicted more precisely using the weather variable rather than population, age and urbanization.
- Also, it concluded that number of infection cases decreases as the temperature increases

03

THE COVID-19 LOCKDOWN IN INDIA: IMPACTS ON THE ECONOMY AND THE POWER SECTOR, TEJAL KANITKAR :

- This paper tries to establish dependence of India's economic loss on the COVID-19 by using a linear Input-Output(IO) Model.
- Also, discusses the impacts of COVID-19 on the demand and supply of electricity and CO2 emissions from the power sector.
- It concludes that Indian Economy is likely to face a loss of about 10-31% of its GDP, depending on the duration of lockdown.
- Also, the daily supply from coal-based power plants has reduced by 26% during the lockdown resulting in a possible emissions reduction of about 15–65 MtCO2.

04

THE IMPACT OF ODD-EVEN TRANSPORTATION POLICY AND OTHER FACTORS ON POLLUTION IN DELHI: A SPATIAL AND RDD ANALYSIS:

- This paper studies the impact of the odd-even transportation policy (environmental regulation), among other controlled factors like meteorological conditions, price of fossil fuel, ban on crackers, burning of agriculture residue, among others on Delhi's pollution levels using panel data.
- Firstly, spatial data analysis is used to understand the impact of climatic factors only on pollution levels existing in different locations in Delhi.
- Secondly, RDD exercise is performed with an extended model on panel data of concentration of pollutants to know whether the odd-even transportation policy has been able to reduce pollution in Delhi both in short & long run and its impact on pollution levels existing in Delhi. In the RDD model, Durbin-Wu Hausman test is used to determine whether to use Fixed Effects or Random Effects on the model with polynomial terms and the other without polynomial terms, respectively

05

MEASURING THE ECONOMICS OF A PANDEMIC: HOW PEOPLE MOBILITY DEPICT ECONOMICS? EVIDENCE OF PEOPLE'S MOBILITY DATA TOWARDS ECONOMIC ACTIVITES

- This paper discusses the impact of mobility on social interaction and economic activities.
- Human mobility has a significant association with social interaction and economic development. Mobility represents people's activity on a daily basis. Data on traffic lows and geo-positioning produced by mobile phones are used to reveal the status of regional economic development, which is derived from the information of human mobility.
- The Apple Mobility Trend Report and Google Community Mobility Report, Nighttime light data is used as a proxy to measure economic activities.
- Cluster analysis is used to classify regions based on their source of economic growth.
- K-Means clustering algorithm is used in the paper which aims to divide data into K clusters and then the within-cluster sum of squares is minimized. It is followed by a regression model which involves mobility change to predict GDP growth.
- The study found a consistently strong positive correlation between regional change on the average mobility report and the percentage changes of regional GDP in 34 provinces in Indonesia.

ECONOMIC ACTIVITY AND MOBILITY AS A PROXY

- We try to explore the impact of COVID on economy of India by using a different proxy for measuring economic activity using people mobility data, Google Mobility. Social and mobility restrictions affect economic activity. These restrictions affect differently towards a country's economic activities and declining GDP since it depends on the severity and duration of the lockdown. The strictest lockdown measures have been imposed to lead the countries to suffer the most significant decline in economic activity.
- Mobility regulations are different from total lockdown, which require all industries to close except the essential ones, such as health and groceries. Under social and mobility restrictions, the industries can still run their activity with new procedures**. A high-developed region provides a wide range of mobility, and the higher mobility individual diversification drives to higher economic opportunity, which leads to higher socio-economic development.**
- The effect of mobility on economic output depends on the economic structure and the industry contribution to GDP. For instance, countries that rely on labor-intensive industries requiring high people mobility may have a greater impact by social restriction .In addition, the country's formal and informal workers' composition will also determine the degree of the effect of mobility. On one hand, formal sectors can still produce output with lesser mobility, such as working from home while On the other hand, some jobs may require movement and hard to be done remotely and affected to a greater extent .
- All these show that Human mobility has a significant association with social interaction and economic development.

GOOGLE MOBILITY

The Google Community Mobility Reports show movement trends by region, across different categories of places. The Google reports chart movement trends over time by geography, across different types of places such as retail and recreation, groceries and pharmacies, parks, transit stations, workplaces, and residential (Google, 2020). These mobility reports are created with aggregated, anonymized data sets from users who have turned on the Google location history.

The datasets show how visits and length of stay at different places change compared to a baseline. The changes are calculated by using the same kind of aggregated and anonymized data used to show popular times for places in Google Maps. According to Google documentation, the baseline is the median value, for the corresponding day of the week, during the 5 weeks from January 3 to February 6, 2020, which is during the normal condition in almost all countries except in Hubei, China. This study uses a daily Google mobility report from February 15, 2020, to June 30, 2020.

No.	PLACE CATEGORIES	DESCRIPTION
1.	Retail & recreation	Mobility trends for places like restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theatres
2.	Grocery & Pharmacy	Mobility trends for places like grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies
3.	Parks	Mobility trends for places like local parks, national parks, public beaches, marinas, dog parks, plazas, and public gardens
4.	Transit stations	Mobility trends for places like public transport hubs, such as subway, bus, and train stations.
5.	Workplaces	Mobility trends for places of work
6.	Residential	Mobility trends for places of residence

ECONOMIC ACTIVITY (MOBILITY AS A PROXY)

In this we have tried to analyze the effect of deaths due to covid, recoveries, covid cases, and stringency index on Google Mobility Parameters which is a proxy we are using for tracking economic activity as people's mobility is closely related to economic activities. .

COUNTRY

- India

INDEPENDENT VARIABLES

- Total_deaths
- Total_Recoveries
- Total_Cases
- Stringency_Index

GOOGLE MOBILITY PARAMETERS

- *Retail & Recreation*
- *Grocery & Pharmacy*
- *Park*
- *Transit Stations*
- *Workspaces*
- *Residential*

TIME PERIOD(15 FEB 2020 - 4 MARCH 2021)

METHODOLOGY

EXPLANATION

INDEPENDENT VARIABLE

SNIP OF DATASET

location	date	cases_total	deaths_total	recovery_total	si
India	2020-02-15	3	0	0	10
India	2020-02-16	3	0	0	10

location	date	retail_and_recreation	grocery_and_pharmacy	parks	transit_stations	workplaces	residential
India	2020-02-15	1	2	3	3	5	0
India	2020-02-16	2	2	3	2	0	0

MOBILITY PARAMETER

DATE (T)

15 - 01 - 2020 to
09 - 04 - 2021

T = 418

COUNTRY

We have consider INDIA

No. of observations = 384

EACH MOBILITY PARAMETER'S VARIATION TO BE CHECKED USING OLS REGRESSION APPLIED OVER INDEPENDENT VARIABLE:

- SI(Stringency)
- Total Cases
- Total Deaths
- Total Recovery

OLS Regression

WHAT IS OLS REGRESSION ?

Ordinary least squares (OLS) regression is a statistical method of analysis that estimates the relationship between one or more independent variables and a dependent variable

HOW IT WORKS ?

The method estimates the relationship by minimizing the sum of the squares of the difference between the observed and predicted values with the help of dependent variables.

In the case of a model with q explanatory variables, the OLS regression model writes:

$$Z = \beta_0 + \Sigma_{j=1..q} \beta_j X_j + \varepsilon$$

where Z is the dependent variable, β0, is the intercept of the model, X j corresponds to the jth independent variable of the model (j= 1 to q), and e is the random error with expectation 0 and variance σ^2.

EQUATION

For each **Mobility Parmeter** = **{** Retail & Recreation , Grocery & Pharmacy , Park , Transit Stations , Workspaces , Residential **}** in India at time(date) t.

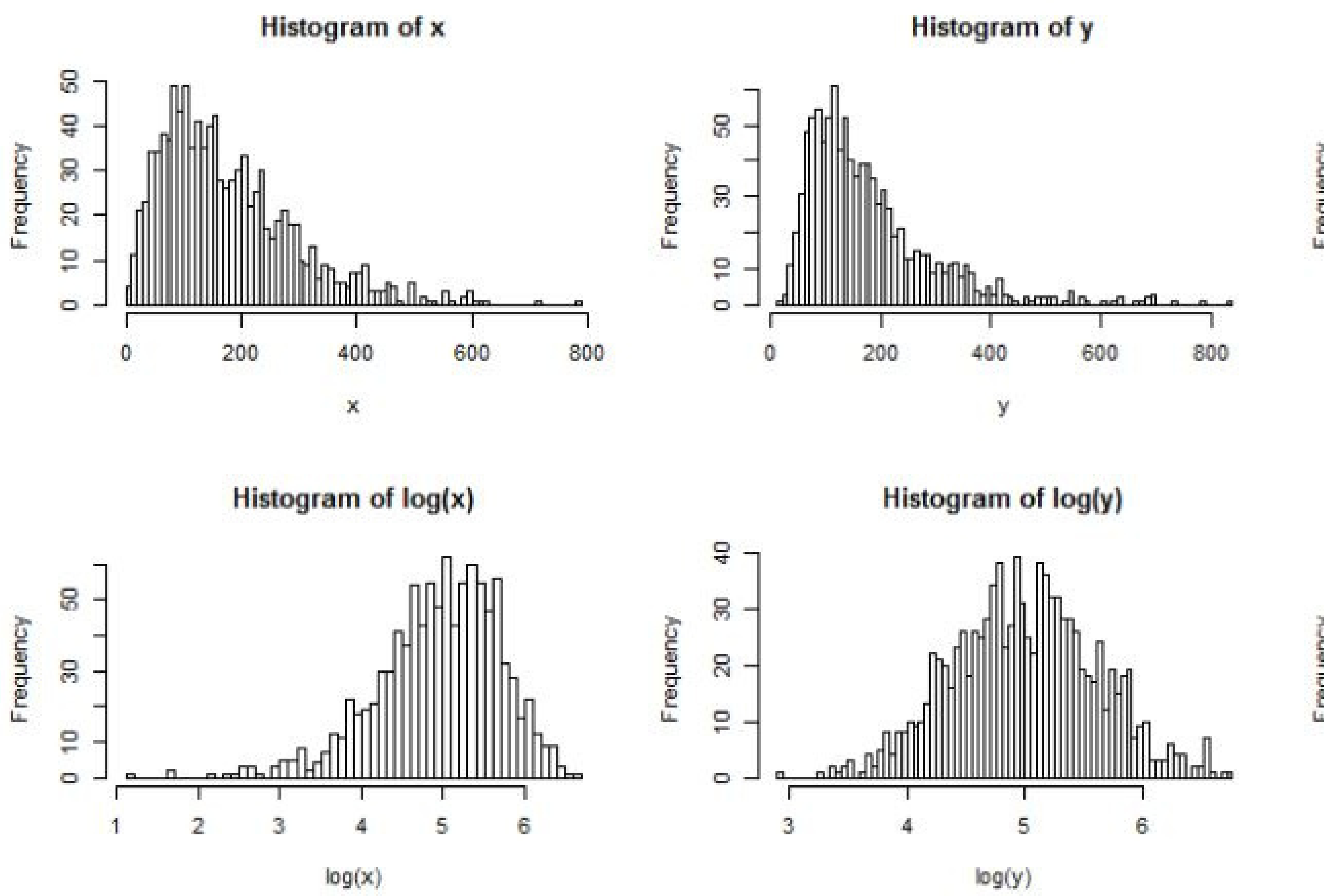
We will run OLS for independent variables using following equations :

$$(Mobility\_Parameter)_{it} = \beta_0 + \beta_1 Total\_deaths + \beta_2 Total\_Recoveries + \beta_3 Total\_Cases + \beta_4 Stringency\_Index + \varepsilon$$

We will be testing hypothesis for the variation of each independent variable on each Mobility parameter.

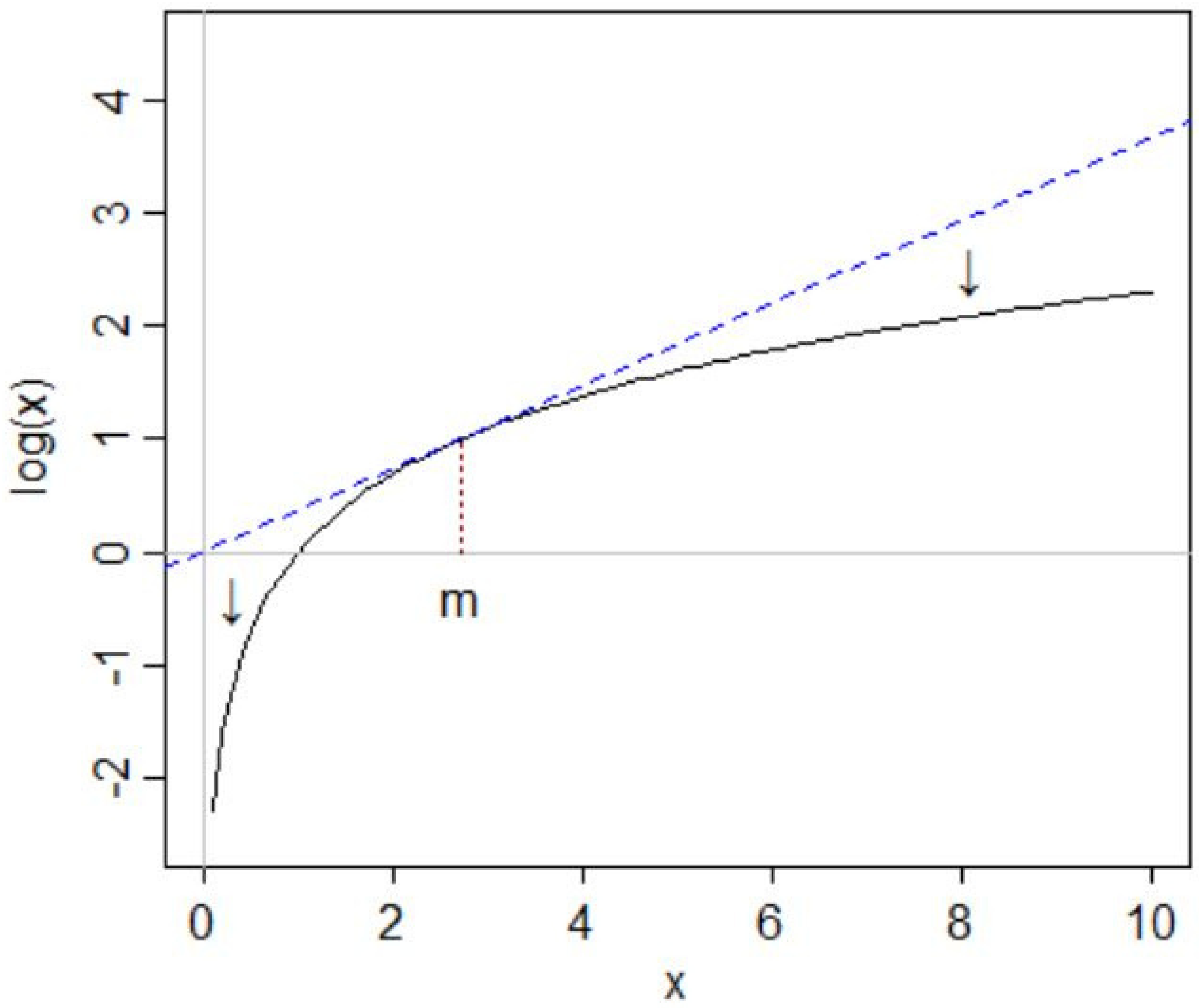
6 - Mobility Parameters ---- > 6 Regression Equations

Some of the independent variables have skewed distribution, having values ranging from(0- 1crore+). So we will use log to convert them into normalized for more accurate analysis.
We will use log if and only if the distribution of the target variable is right-skewed which can be observed by the box plot.



RIGHTLY SKEWED AND AFFECT OF TAKING LOG

Taking logs "pulls in" more extreme values on the right (high values) relative to the median, while values at the far left (low values) tend to get stretched back, further away from the median.



HOW TAKING LOG WORKS IN RIGHT SKEWED

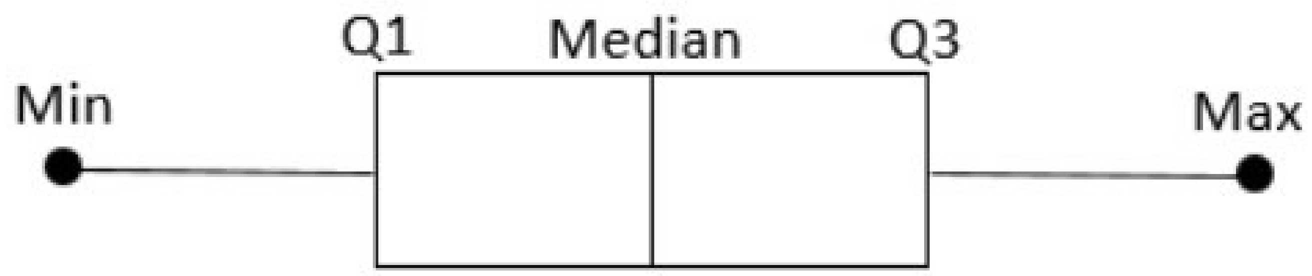
BOX PLOT

IN ORDER CHECK FOR RIGHTLY SKEWED INDEPENDENT VARIABLE, WE USE BOX PLOT

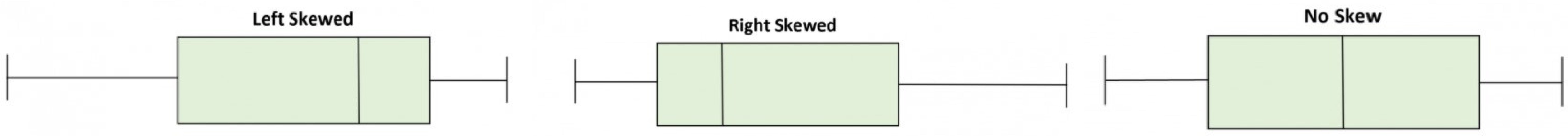
A **box plot** is a type of plot that displays the five number summary of a dataset, which includes:

- The minimum value
- The first quartile (the 25th percentile)
- The median value
- The third quartile (the 75th percentile)
- The maximum value

To make a box plot, we draw a box from the first to the third quartile. Then we draw a vertical line at the median. Lastly, we draw “whiskers” from the quartiles to the minimum and maximum value.



Depending on the location of the median value in the boxplot, we can tell whether or not a distribution is left skewed, right skewed, or symmetrical.



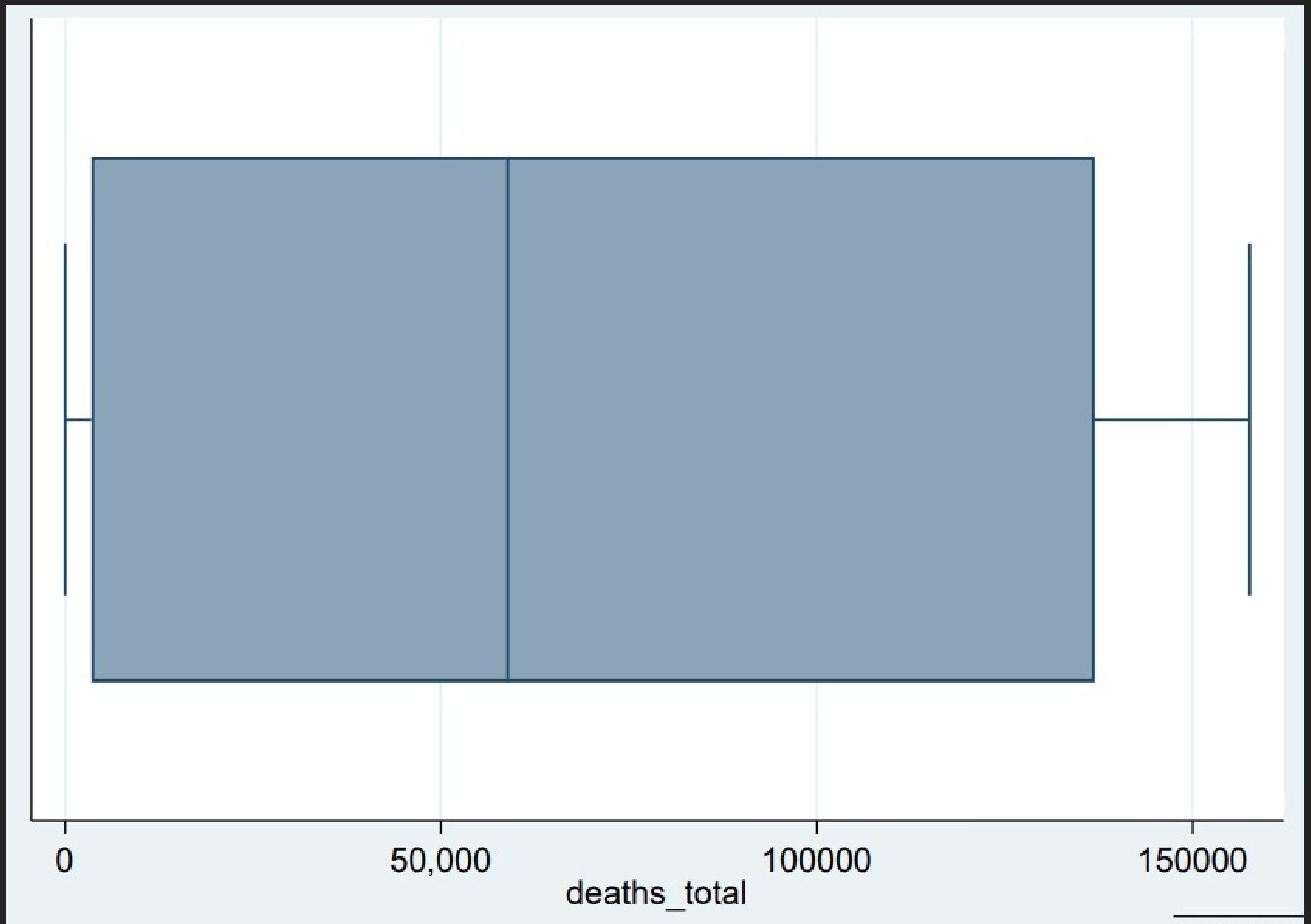
After analyzing using **box-method,** we get to know that the variables **Total_Deaths, Total_Recoveries, Total_Cases,** have right-skewed distribution so we will use the following equations for our analysis.

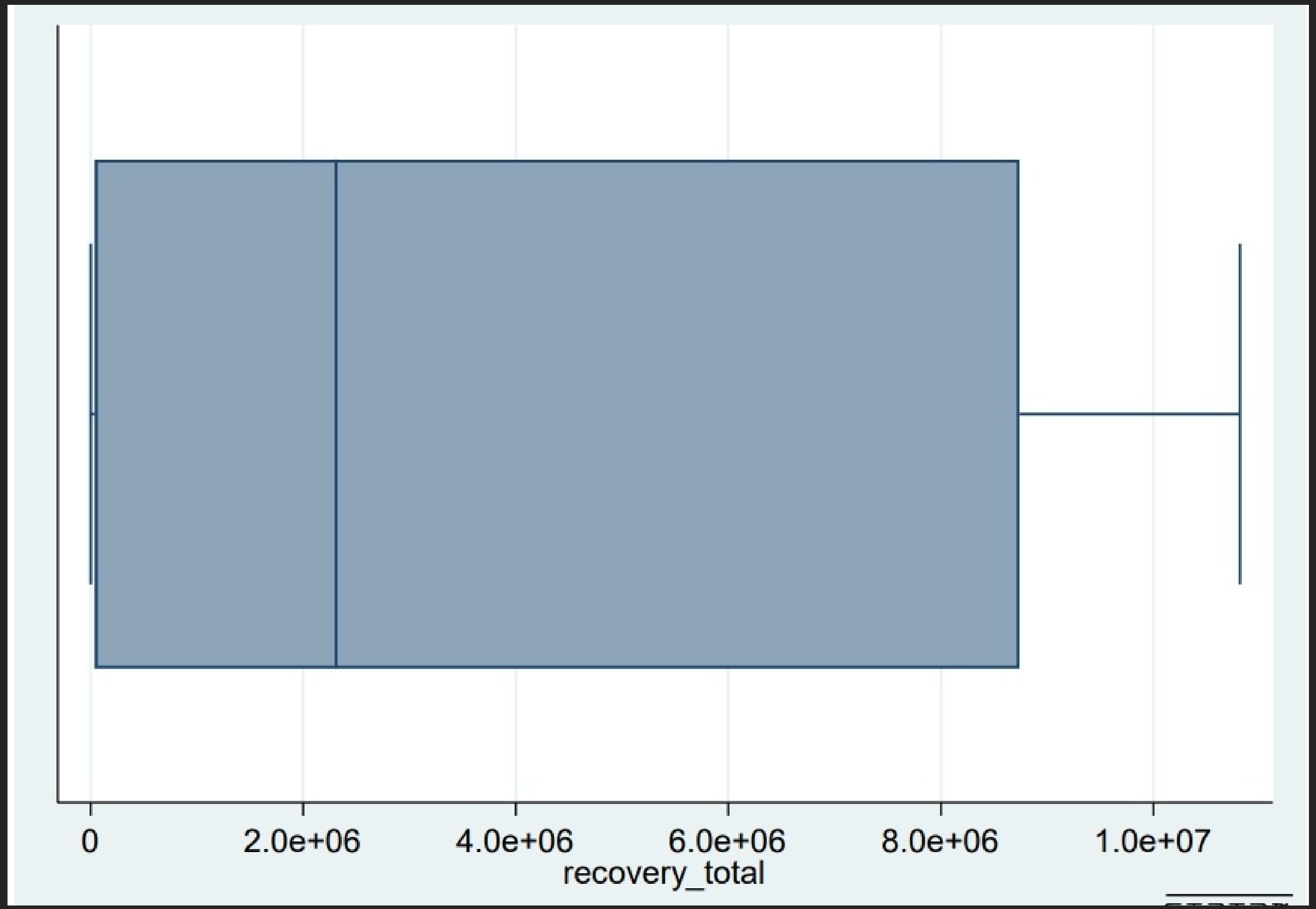
FINAL EQUATION

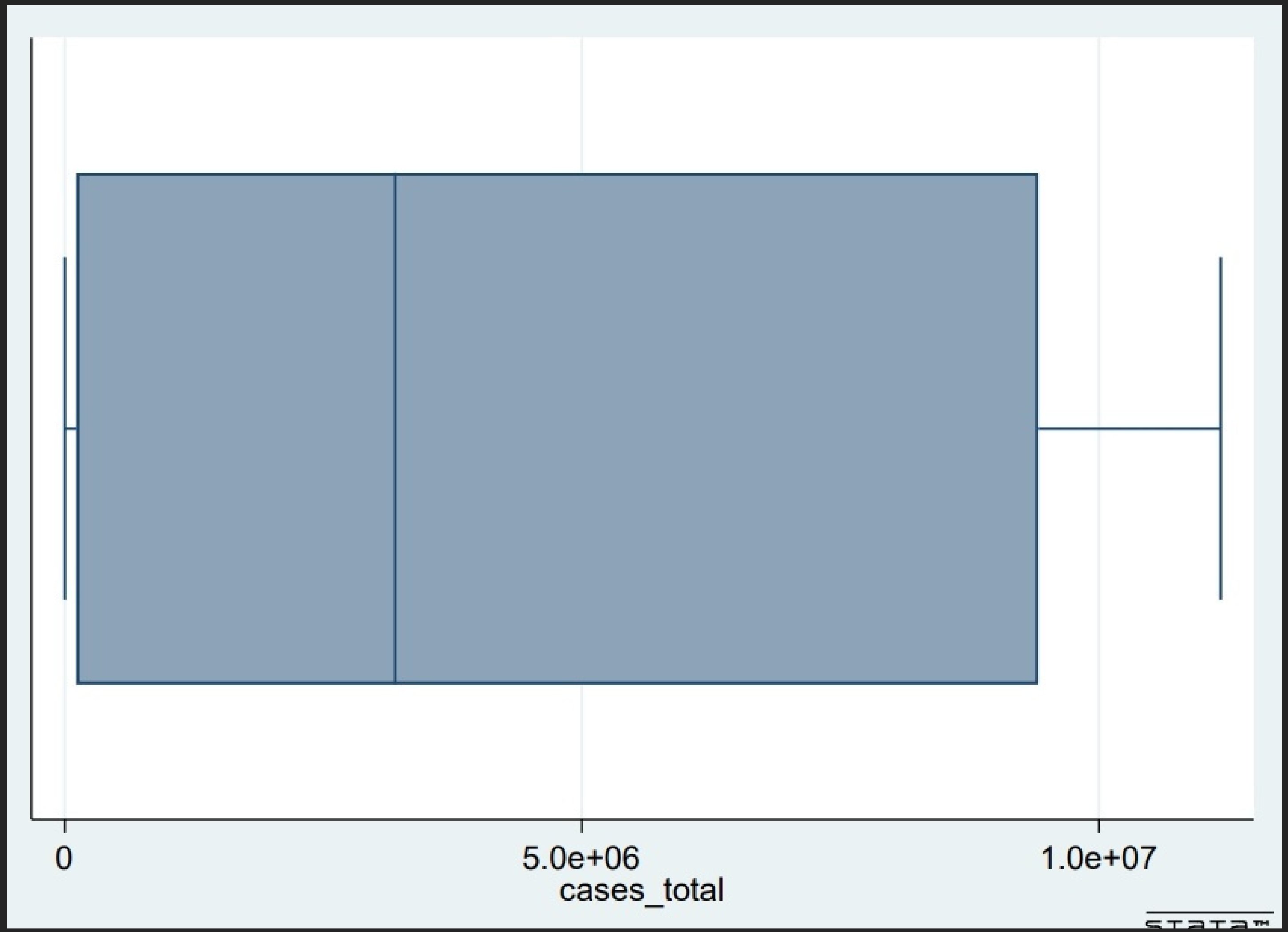
$$(Mobility\_Parameter)_{it} = \beta_0 + \beta_1 \log(Total\_deaths) + \beta_2 \log(Total\_Recoveries) + \beta_3 \log(Total\_Cases) + \beta_4 \, Stringency\_Index + \varepsilon$$

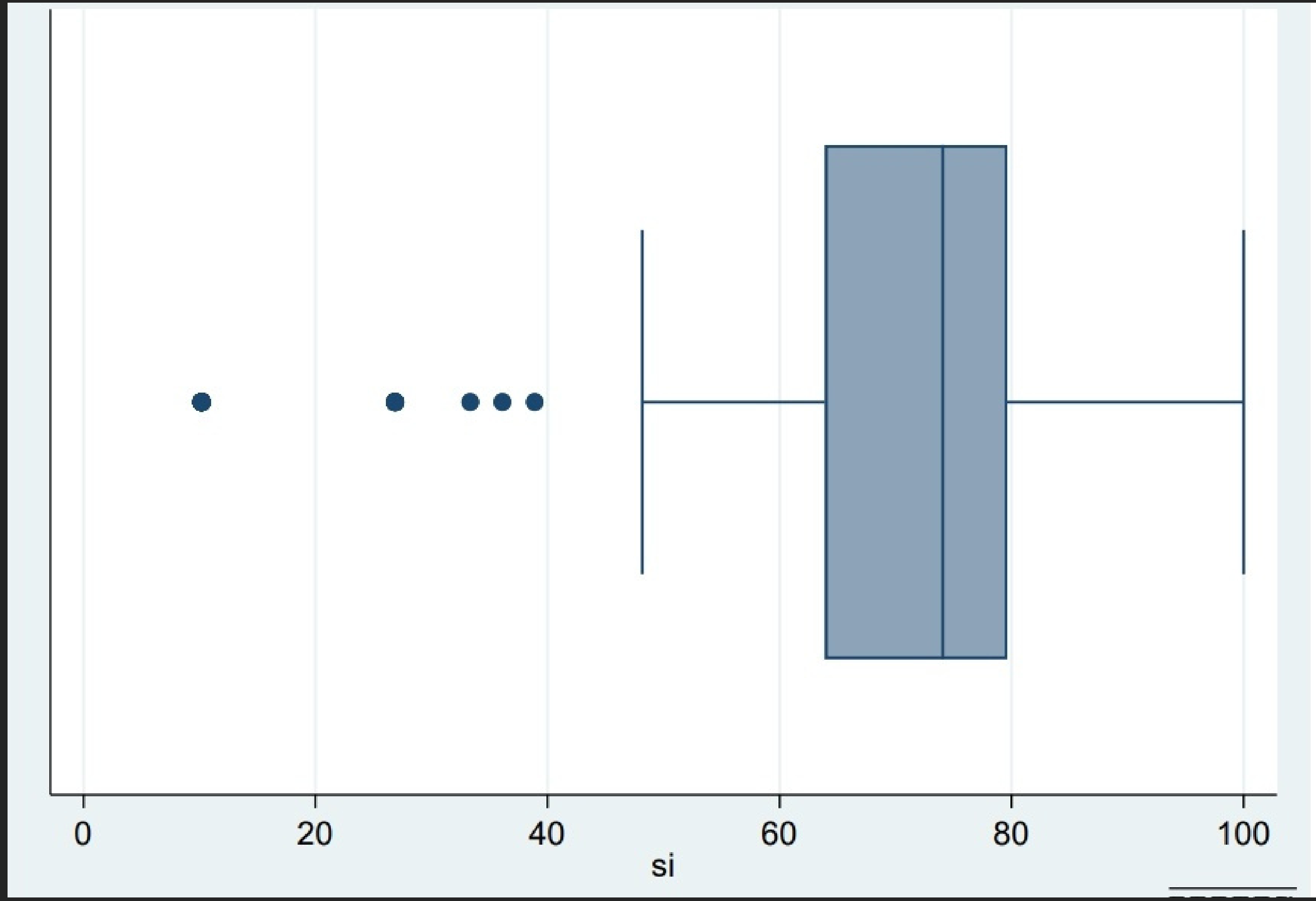
6 - Mobility Parameters ---- > 6 Regression Equations

REAL ESTATE LISTING — JANUARY 2020









DATA BASE & HYPOTHESIS

Variables	Data Source	Grocery & Pharmacy	Parks	Transit stations	Retail & Recreation	Work places	Residential
SI STRINGENCY INDEX	OxCGRT data oxford stringency index	NEGATIVE	NEGATIVE	NEGATIVE	NEGATIVE	NEGATIVE	POSITIVE
TOTAL DEATHS	COVID-19 Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University & Data from World Bank	NEGATIVE	NEGATIVE	NEGATIVE	NEGATIVE	NEGATIVE	POSITIVE
TOTAL RECOVERIES		POSITIVE	POSITIVE	POSITIVE	POSITIVE	POSITIVE	NEGATIVE
TOTAL CASES		POSITIVE	POSITIVE	POSITIVE	POSITIVE	POSITIVE	NEGATIVE

Hypothesis (Explanation)

- As the **stringency** increases, we expect the Residential mobility to show an increasing trend as people would tend to remain in residential area. A decreasing trend is expected by the other 5 mobility parameters, as more stringency indicates less movement of people outside their houses .
- For **total number deaths** , we expect to have a negative trend with mobility paramters and positive with residential .High number of deaths are usually alarming and becomes an eye opener for everyone . Hence people in order to protect themselves and their closed ones , prevent going out of their houses and take precautions .
- For **total recoveries** , we expect a positive relationship with mobility factors and negative with residential parameters . People generally take recoveries positively and start coming out of their homes. Recoveries are taken as a sign of the "return of normalcy" , and hence normal day to day activities are resumed. They become a little careless and overconfident and start coming out of their houses for essentials and recreational activities as well which explains the positive impact.
- For **total cases** , we expect a positive relation with mobility parameters and negative with residential,which is self-explanatory, as more people come out of their houses, the greater is the risk and more people get infected which leads to rise in the number of total cases.

AQI INDEX DEPENDENCY

In this we have tried to figure out dependency of Air Quality Index(AQI) on various factors such as Lockdown, temperature, wind speed, humidity and petrol prices. For our study, we have considered 8 Indian Cities and air pollutant p $\in$ { PM2.5, PM10} .

CITIES

- Bengaluru
- Chandigarh
- Hyderabad
- Delhi
- Kolkata
- Mumbai
- Nagpur
- Patna

INDEPENDENT VARIABLES

- Lockdown Stringency(SI)
- Temperature
- Humidity
- Windspeed

DEPENDENT VARIABLE

- Air Quality Index

TIME PERIOD(JAN 2020 - FEB 2021)

We have collected data for each independent and dependent variables for each city over 4 particular days of month ranging from Jan 2020 - Feb 2021.

LOCKDOWN DURATION - 21/ 03 /2020 - 31/05/2020

DATE : MONTH :YEAR

DATE { 07, 14, 21,28 }

MONTH { 01 - 12 }

YEAR { 2020 , 2021 }
*FOR YEAR = 2021 --> MONTH = 01 , 02

METHODOLOGY

EXPLANATION

SNIP OF DATASET

date	country	city	specie	aqi	temp	humidity	wind_speed	lockdown
07-01-2020	IN	Bengaluru	pm10	46	24	68	1	0
07-01-2021	IN	Bengaluru	pm10	18	24	83	1	0

DATE (T)

07 - 01 - 2020
14 - 01 - 2020
21 - 01 - 2020
28 - 01 - 2020
this extends for 14 months
(Jan 2020 - 21)
4 * 14 = 56 = T

CITY (N)

We have consider 8 cities
N = 8

WE HAVE PANEL DATA WITH TOTAL OBSERVATIONS =448

WE INTEND TO USE FIXED EFFECTS , RANDOM EFFECT AND LATER USE HAUSMAN TEST TO DECIDE BETWEEN THEM

Panel Members = N = 8
Time Periods = T = 56
No. of observations = N*T = 448

```
xtset city_grp date_num,weekly
       panel variable:  city_grp (strongly balanced)
        time variable:  date_num, 1960w2 to 1961w5
                delta:  1 week
```

BALANCED PANEL DATASET

PANEL DATA

A panel has the form:

$X_{it}, \quad i = 1, \ldots, N, \quad t = 1, \ldots, T,$ where *i* is the individual dimension and *t* is time dimension.

PANEL ANALYSIS

A common panel data regression model is of form $y_{it} = a + bx_{it} + \varepsilon_{it}$, where *y* is dependent variable, x is independent variable, *a* and *b* are coefficients, *i* and *t* are indices for individuals and time. The error term ε_{it} is very important in the analysis, it can be written in this format :

$$\varepsilon_{it} = \mu_i + \nu_{it}$$

μ_i are individual-specific, time-invariant effects which are fixed over time, ν_{it} is a time-varying random component.

FIXED EFFECT

WHAT IS FIXED EFFECT ?

A fixed effects regression is an estimation technique employed in a panel data setting that allows one to control for time-invariant unobserved individual characteristics that can be correlated with the observed independent variables.

HOW IT WORKS?

Lets assume we have a vector of random variables and a dependent random variable y, with μ being an unobserved random variable characterizing each unit of observation i and ε the stochastic error uncorrelated with x.

In OLS we assumed that there is no correlation between error terms and regressors. Here we assume we have N units for T periods of time, and that the unobservable variable μ is time invariant, we can write our model as:

y it = β' x it + μ + ε; with i = 1, ..., N and t = 1, ..., T

In fixed Effect we assume that corr(μ,X) ≠ 0.

FIXED EFFECT

In fixed effect we subtract the time mean from each variable in the model and then estimating the resulting transformed model by Ordinary Least Squares.

$\tilde{y}_{it} = \beta' \tilde{x}_{it} + \tilde{\varepsilon}_{it}$

where $\tilde{y}_{it} = y_{it} - \bar{y}_i$ with $\bar{y}_i$ be time averaged y_{it}. Because a μ_i is fixed over time we have its difference to be 0.

In other words, the slopes of the regression are common across units (the coefficients of $x_1, x_2, \ldots, x_K$) whereas the intercept is allowed to vary. Which is taken care by Fixed effect.

WHAT ARE THE DRAWBACK?

Does not allow one to include time-invariant independent variables in the regression, because they get eliminated similarly to the fixed unobserved component.

RANDOM EFFECT

WHAT IS RANDOM EFFECT ?

Random effects regression model is also an estimation technique which is applied on the panel data setting. It helps to control unobserved characteristics that is constant over time and which cannot be correlated with the observed independent variables.

HOW IT WORKS?

In the random effects model the individual-specific component α is not treated as a parameter and it is not being estimated.

$y_{it} = \mu + \beta_1 x_{1,it} + \beta_2 x_{2,it} + \cdots + \beta_k x_{k,it} + \alpha_i - \mu + \varepsilon_{it}$,

where μ is the average individual effect. Let $u_{it} = \alpha_i - \mu + \varepsilon_{it}$

equation can be rewritten as

$y_{it} = \mu + \beta_1 x_{1,it} + \beta_2 x_{2,it} + \cdots + \beta_k x_{k,it} + u_{it}$,

In Random Effect we assume that corr(μ,X) = 0.

WHAT ARE THE DRAWBACK?

If it turns out that there is correlation between the error term u_{it} and the factors used in the model, then either pooled or fixed effects models must be used

HAUSMAN TEST

The Hausman Test (also called the Hausman specification test) detects endogenous regressors (predictor variables) in a regression model.

In order to know which model random effects or fixed effects is suitable for our data, we will run Hausmen's specification test.

HOW IT WORKS?

The tests tells us if there is a correlation between the unique errors and the regressors in the model. The null hypothesis is that there is no correlation between the two.

H(0): Null Hypothesis, Random effects model is consistent
H(A): Alternate Hypothesis, Fixed effects model is consistent

If p-value of the test is >0.05, then we accept the null hypothesis H(0)

- RE model is consistent and efficient

If p-value of the test is <0.05, then we accept the alternate hypothesis H(A)

- FE model is consistent and efficient

P - VALUE

WHAT IS P-VALUE ?

In statistics, the p-value is the probability of obtaining results at least as extreme as the observed results of a statistical hypothesis test, assuming that the null hypothesis is correct. A smaller p-value means that there is stronger evidence in favor of the alternative hypothesis.

HOW ITS CALCULATED ?

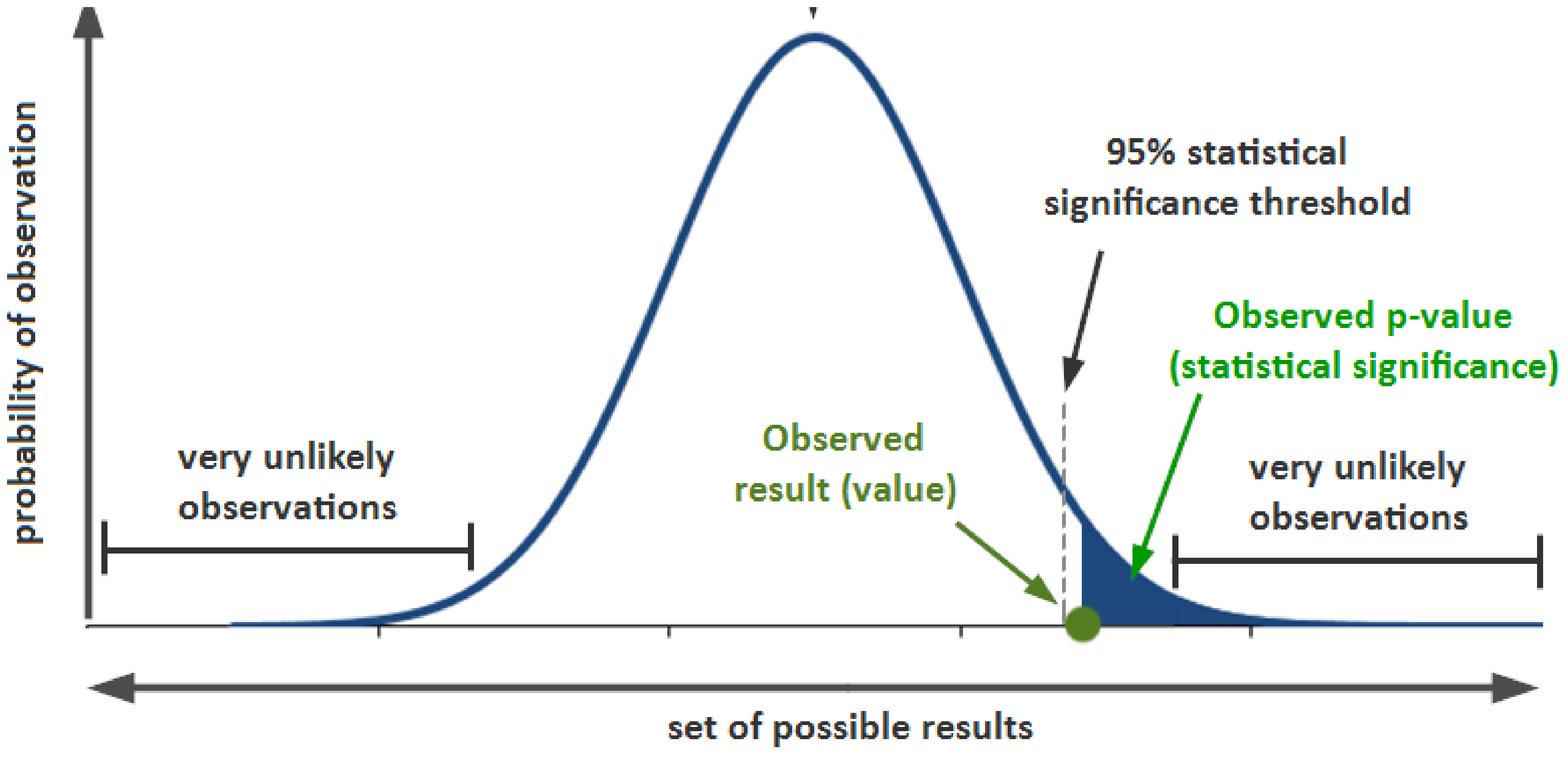
P-values are calculated from the deviation between the observed value and a chosen reference value, given the probability distribution of the statistic, with a greater difference between the two values corresponding to a lower p-value.

Mathematically, the p-value is calculated using integral calculus from the area under the probability distribution curve for all values of statistics that are at least as far from the reference value as the observed value is, relative to the total area under the probability distribution curve

HOW TO INTERPRET P-VALUES AND COEFFICIENTS IN REGRESSION ANALYSIS?

P-values and coefficients in regression analysis work together to tell you which relationships in your model are statistically significant and the nature of those relationships. The p-value for each independent variable tests the null hypothesis that the variable has no correlation with the dependent variable. If there is no correlation, there is no association between the changes in the independent variable and the shifts in the dependent variable. In other words, there is insufficient evidence to conclude that there is effect at the population level.

A p-value that is greater than the significance level indicates that there is insufficient evidence in your sample to conclude that a non-zero correlation exists.



EQUATION

For each pollutant $P \in \{PM_{2.5}, PM_{10}\}$ in a city i of country India at time

MODEL 1

$$Air\ Quality_{it}^{p} = \theta_1 Windspeed_{it} + \theta_2 Temperature_{it} + \theta_4 Humidity_{it} + \theta_5 Lockdown_{it}$$

MODEL 2

$$Air\ Quality_{it}^{p} = \theta_1 Windspeed_{it} + \theta_2 Temperature_{it} + \theta_3 (Temperature_{it})^2 + \theta_4 Humidity_{it} + \theta_5 Lockdown_{it}$$

where $Air\ Quality_{it}^{p}$ denotes the Air Quality represented by air pollutant P of the city i of India at time t. $Windspeed_{it}$, $Humidity_{it}$ contributes to the weather effect on Air Quality and $Lockdown$ is the dummy variable.

HYPOTHESIS (EXPECTATION)

Windspeed plays a vital role in atmosphere dilution, high speed favors dispersal of pollutants, which clears the air. Pollutants tend to pile up in calm conditions. Pollution levels due to vehicle emissions are likely to be higher on a low wind day. Hence, we expect the coefficient of windspeed(θ_1) to have a negative relationship with air quality.

Temperature variation with air quality depends on multiple factors, due to which a strong hypothesis can't be made prior. Still considering that more number of months under our observation lie in winter, we hypothesize Temperature(θ_2) to have a positive relationship with air quality.

High humidity increases the water content in the atmosphere, thereby increasing concentration of pollutants ; considering this we expect Humidity(θ_4) to have positive relationship with air quality.

As stricter lockdown measures restrict more internal or international interactions and associated socio-economic activities that rely on such interactions, mostly affecting the manufacturing industry, leading to a dramatic decline in emissions. We expect the coefficient of lockdown(θ_5) to have a negative relationship.

DATA BASE & HYPOTHESIS
AQI

VARIABLES	DATA SOURCE	HYPOTHESIS
LOCKDOWN	DUMMY VARIABLE	NEGATIVE IMPACT
HUMIDITY	CENTRAL POLLUTION CONTROL BOARD (CPCB) DATA	POSITIVE IMPACT
TEMPERATURE	CENTRAL POLLUTION CONTROL BOARD (CPCB) DATA	POSITIVE IMPACT
WINDSPEED	CENTRAL POLLUTION CONTROL BOARD (CPCB) DATA	NEGATIVE IMPACT

RESULTS

RESULTS

GOOGLE MOBILITY (AS PROXY FOR ECONOMIC ACTIVITY)

Robust OLS Regression
Applied on Google Mobility Parameters

VARIABLES	(1) Retail & Recreation	(2) Grocery & Pharmacy	(3) Parks	(4) Transit Stations	(5) Work Places	(6) Residentials
Total Cases	42.45***	-10.27***	53.24***	19.82***	-7.60*	1.63
	(2.466)	(3.110)	(3.225)	(1.916)	(4.059)	(1.433)
Total Deaths	-36.76***	-4.21	-25.36***	-22.75***	-18.86***	8.12***
	(2.918)	(4.010)	(2.958)	(2.304)	(3.505)	(1.256)
Total Recovery	-4.69	14.23***	-23.15***	3.25	21.73***	-7.94***
	(2.968)	(3.405)	(4.088)	(2.286)	(4.584)	(1.640)
Lockdown Stringency	-0.87***	-1.01***	-0.90***	-0.91***	-0.55***	0.26***
	(0.055)	(0.064)	(0.078)	(0.044)	(0.088)	(0.029)
Constant	-142.20***	64.63***	-49.87***	-55.30***	15.41	-3.00
	(9.543)	(11.882)	(9.865)	(7.134)	(12.220)	(4.383)
Observations	393	393	393	393	393	393
R-squared	0.935	0.881	0.753	0.925	0.694	0.824

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

RESULTS

AIR QUALITY INDEX PM10

	Panel Analysis			
	(1)	(2)	(3)	(4)
VARIABLES	Model 1 Fixed Effects	Model 1 Random Effects	Model 2 Fixed Effects	Model 2 Random Effects
Lockdown	-10.13***	-10.18***	-7.21**	-7.31**
	(3.717)	(3.705)	(3.466)	(3.459)
Humidity	-0.17**	-0.17**	-0.43***	-0.43***
	(0.075)	(0.075)	(0.076)	(0.076)
Wind Speed	-21.52***	-20.78***	-24.63***	-23.96***
	(3.556)	(3.504)	(3.321)	(3.286)
Temperature	-0.34	-0.36	5.41***	5.31***
	(0.222)	(0.220)	(0.716)	(0.714)
Temperature Square			-0.15***	-0.15***
			(0.018)	(0.018)
Constant	96.50***	95.97***	72.89***	72.58***
	(5.303)	(8.916)	(5.670)	(9.784)
Observations	441	441	441	441
R-squared	0.198		0.311	
Number of City_grp	8	8	8	8

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

RESULTS

HAUSMAN TEST

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. hausman fe re
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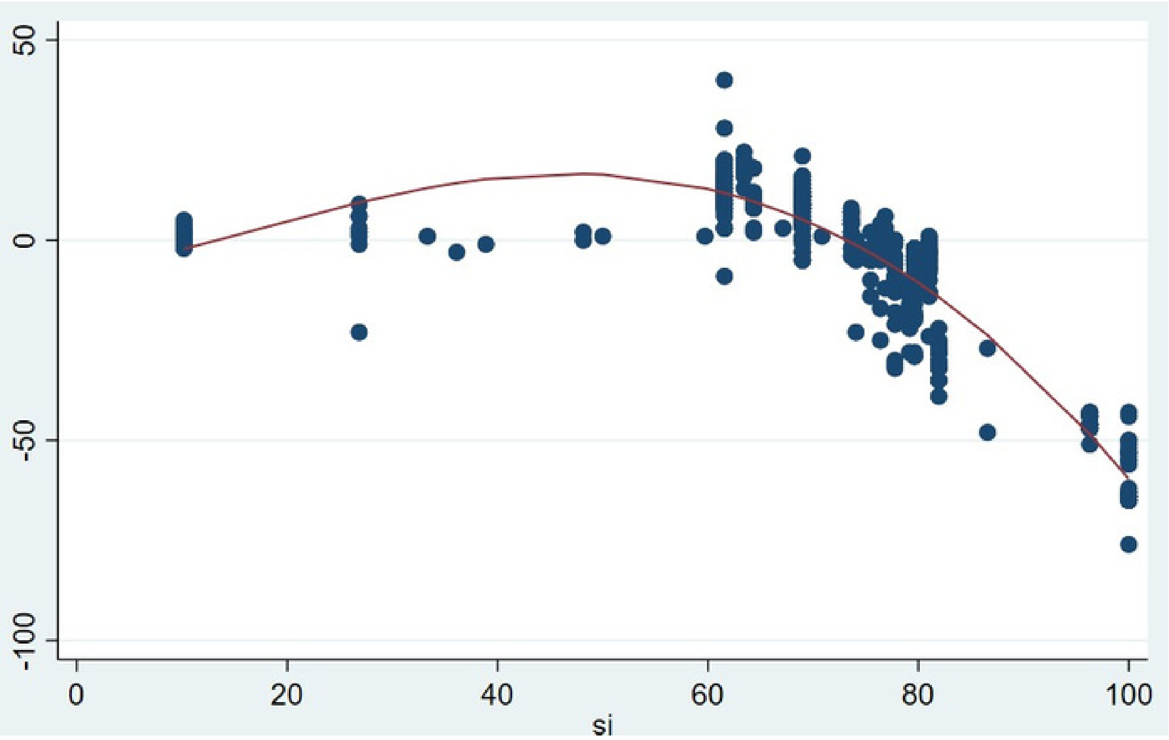
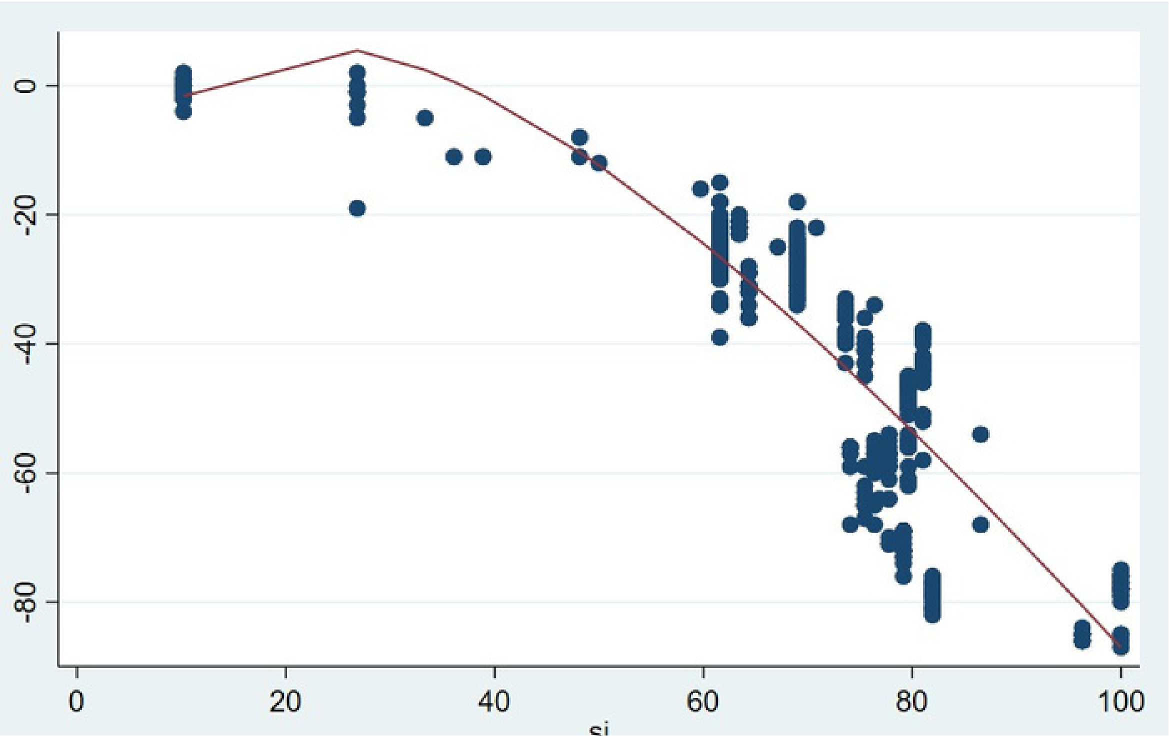
	Coefficients (b) fe	Coefficients (B) re	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
lockdown	-7.21306	-7.305845	.0927851	.2211205
humidity	-.433086	-.4279305	-.0051555	.0078728
wind_speed	-24.63451	-23.96418	-.6703267	.4797064
temp	5.40973	5.31336	.0963693	.0596537
temp2	-.1518632	-.1496293	-.0022339	.001499

```
                           b = consistent under Ho and Ha; obtained from xtreg
            B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                  chi2(5) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =        3.28
                Prob>chi2 =      0.6565
```

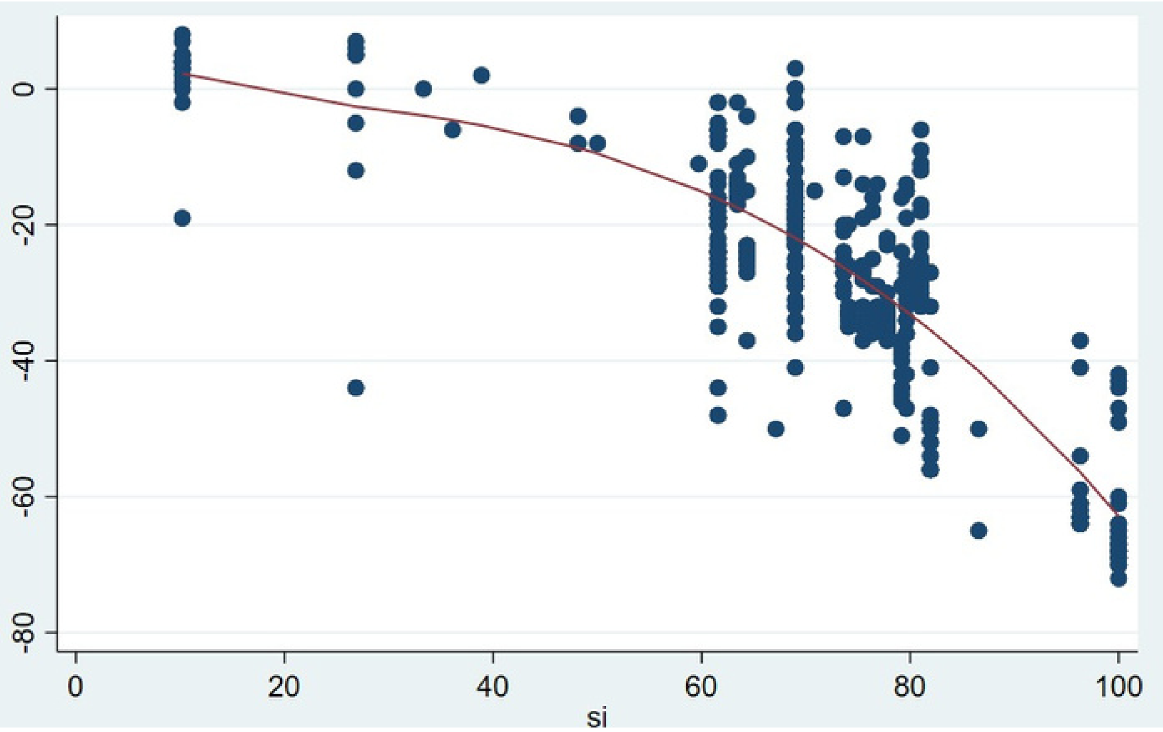
Conclusion



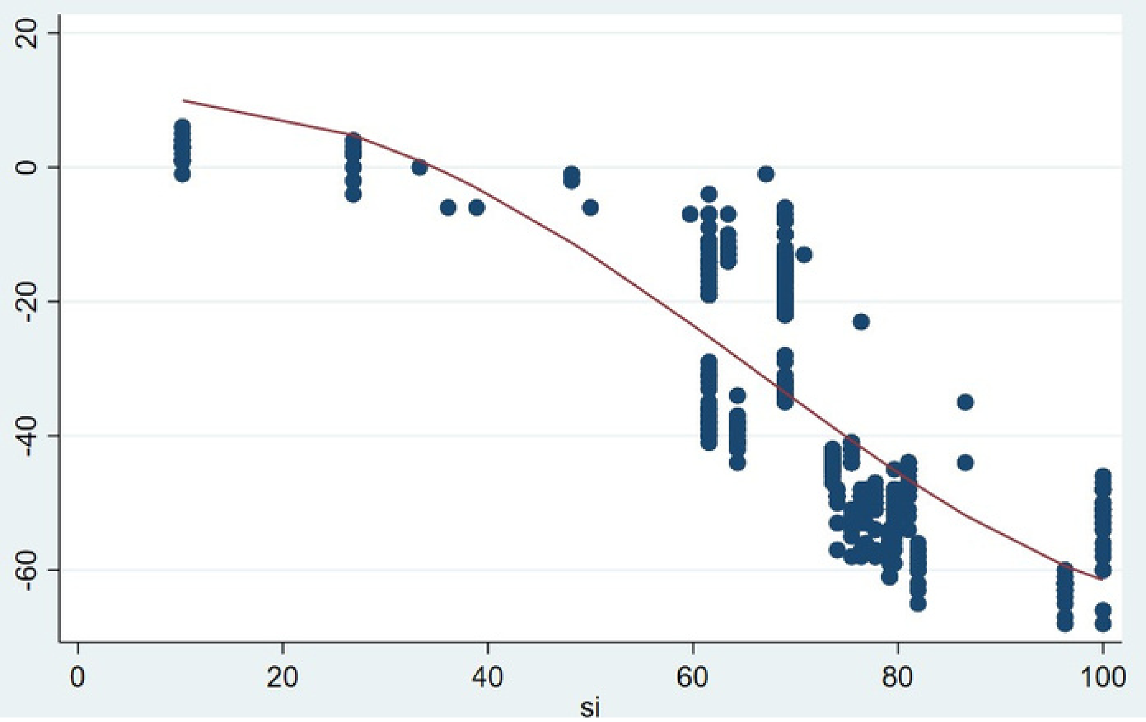
Grocery and Pharmacy



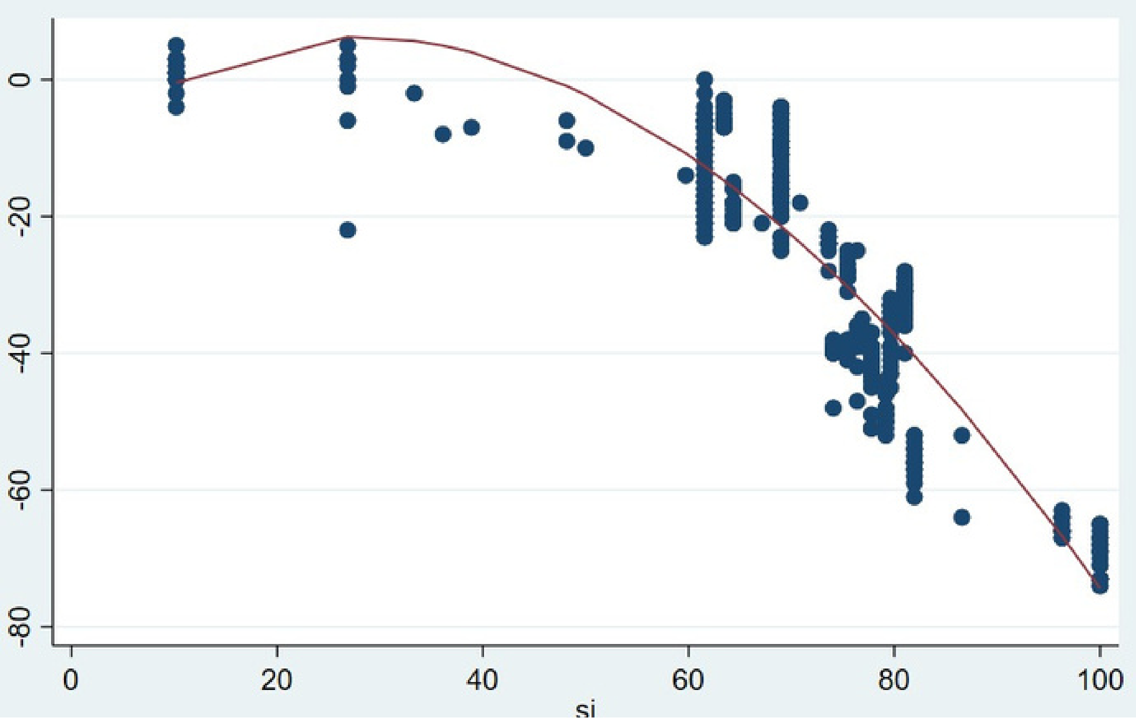
Retail and Recreation



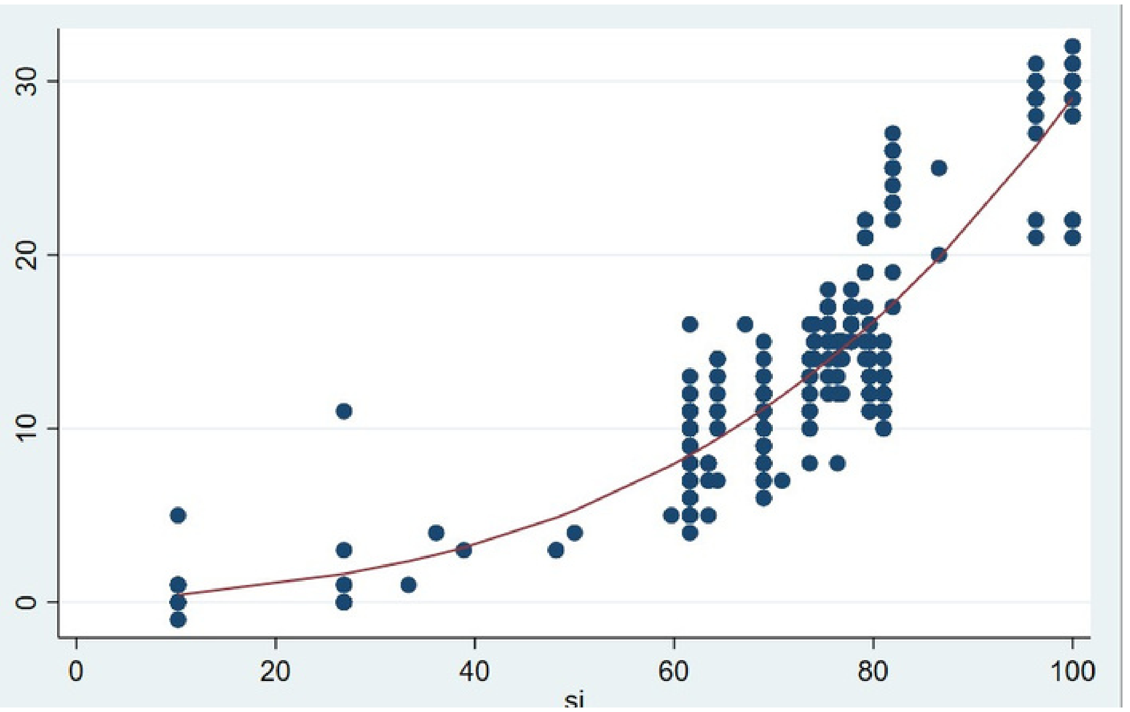
Workplace



Parks



Transit Station



Residential

Tentative Conclusion

We expect to conclude that the stringency index negatively impacts Google Mobility Parameters which led to a decrease in economic activities thereby explaining the fall of the Indian economy in the lockdown period.

We also expect that lockdown favors the Air Quality. The results of this study can provide helpful information regarding the costs and benefits of different air pollution control strategies in the post-pandemic period.