Abortion Legalization and Crime

Aubhik Mazumdar, Yuan Tian

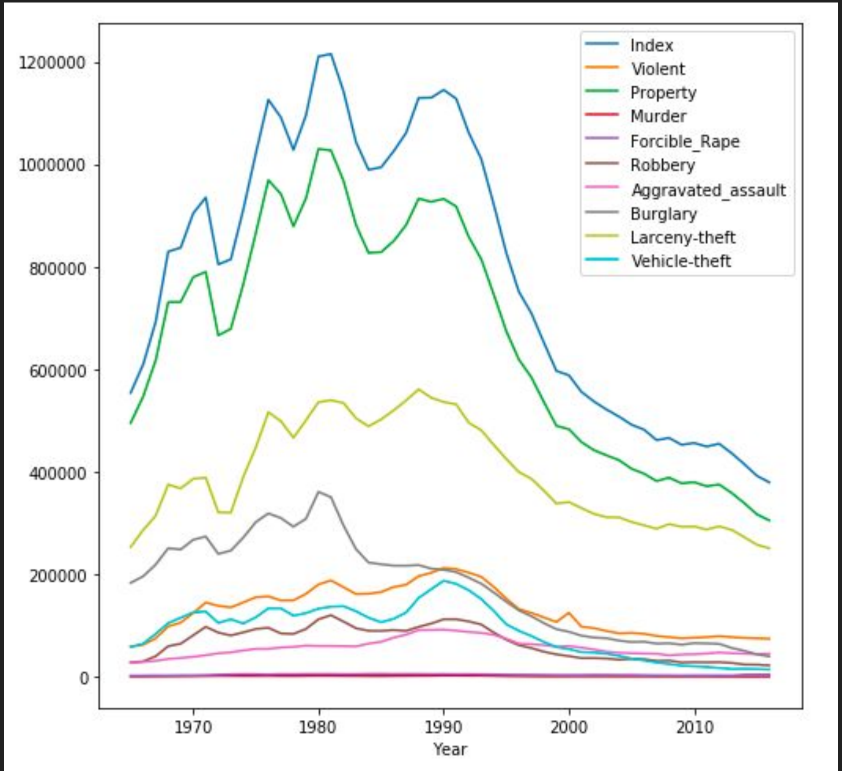
Introduction

- Problem Statement & Hypothesis
- Datasets
- Techniques

Crime Rates by Year

Facts:

- All rates decline after 1990
- People who born in 1973 are 18 yrs old in 1991
- NY legalized abortion in 1973 (Roe vs Wade case in 1972)



Source: Bureau of Justice Statistics (BJS)

Explanation

In the book “freakonomics” the authors argue that the reason for the decline in crime was:

“Abortion legalization meant that parents who thought they were not fit to raise a child could avoid this. This also reduced the number of children who were neglected thus leading them to a life of crime.”

Problem Statement

- Research Topic:

  To determine how the legalization of Abortion affected crime in the US.

- Hypothesis:

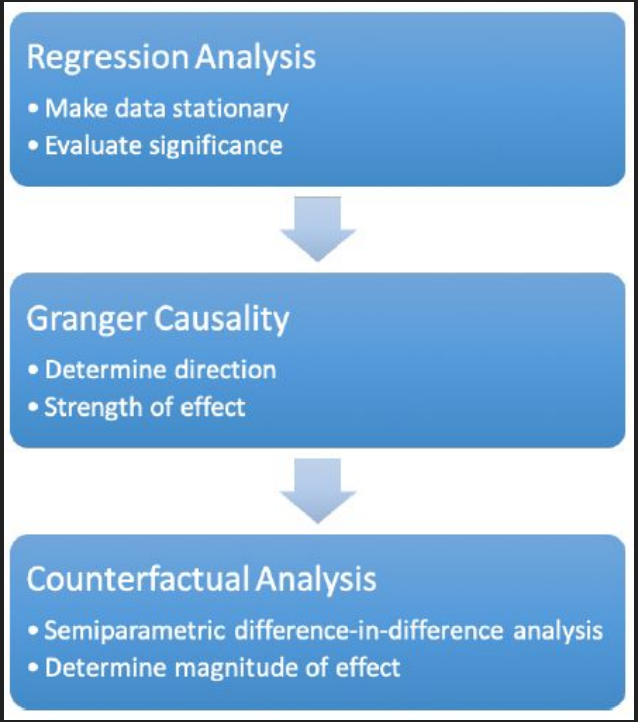
  legalization of abortion contribute to the reduce of crime rates in the US.

Datasets

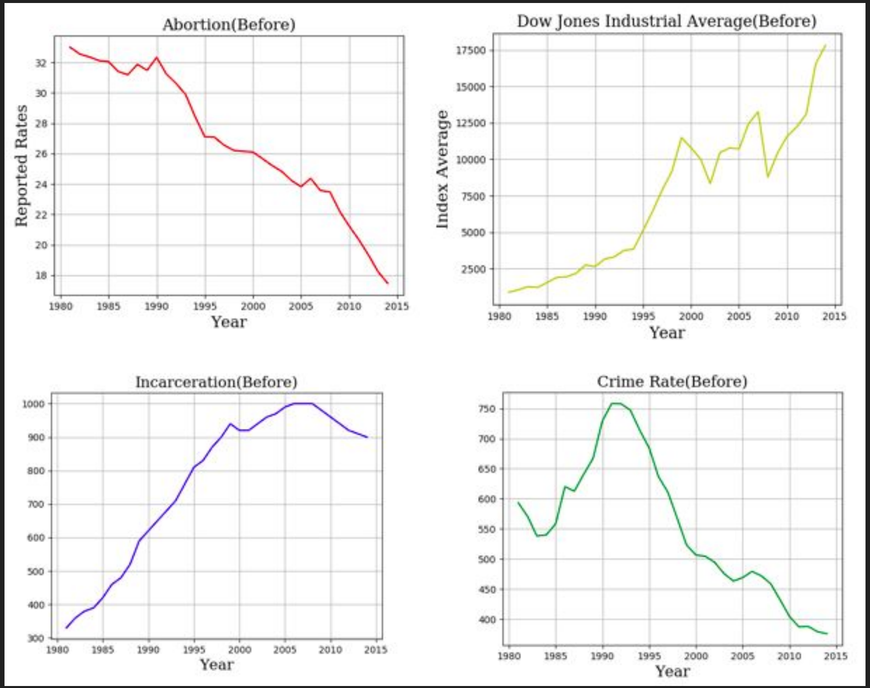
- Features:
  - Abortion Rate (Center of Disease Control and Prevention)
  - Dow Jones Index Average (Bloomberg)
  - Incarceration (Bureau of Justice Statistics)
  - Crime rates (Uniform Crime Reporting Statistics + National Crime Victimization Survey)
- Problems:
  - Insufficient data for NYC? ------ Use nationwide data
  - Stationary or Non-stationary? ---- Statistical Tests

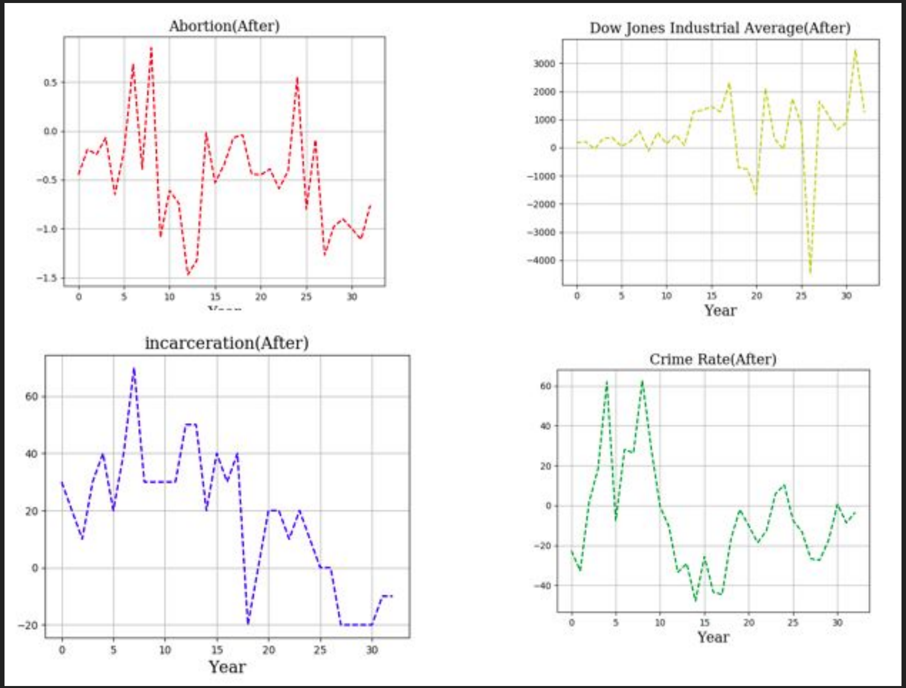
Techniques

1. Stationary conversion - Yuan
2. Linear Regression - Yuan
3. Granger Causality - Aubhik
4. Counterfactual Analysis - Aubhik



TECHNIQUE 1: Stationary conversion





Statistical Test Result: Trend Stationary - Detrend by differencing method

TECHNIQUE 2: Linear Regression

- Normalization is still needed
- Use MATLAB and SAS

```
>> Model
Model =
Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                    Estimate        SE          tStat        pValue
                   __________    ________    __________    _______

    (Intercept)    8.9658e-18    0.030266    2.9623e-16          1
    x1               0.036012     0.11155       0.32284    0.74922
    x2               -0.12443     0.14244      -0.87353     0.3898
    x3              -0.078681     0.13824      -0.56914     0.5738

Number of observations: 32, Error degrees of freedom: 28
Root Mean Squared Error: 0.171
R-squared: 0.0732,  Adjusted R-Squared -0.0261
F-statistic vs. constant model: 0.737, p-value = 0.539
```

TECHNIQUE 2: Linear Regression

- A better result in SAS

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	3	24.05390	8.01797	26.89	<.0001
Error	30	8.94610	0.29820		
Corrected Total	33	33.00000			

Root MSE	0.54608	R-Square	0.7289
Dependent Mean	8.88178E-16	Adj R-Sq	0.7018
Coeff Var	6.148314E16		

Parameter Estimates					
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	1.84042E-15	0.09365	0.00	1.0000
ABORTION	1	0.73538	0.33050	2.23	0.0337
DOWJONES	1	-0.62842	0.35702	-1.76	0.0886
INCARCERATION	1	0.64438	0.19372	3.33	0.0023

TECHNIQUE 2: Linear Regression

- Conclusion:

  We are still not 100% sure about the significance of abortion but it is definitely not insignificant….

  Thus, we need to study it further using Causal inference techniques

TECHNIQUE 3: Granger Causality

- Tested the direction for the cause and the effect by using Granger Causality
- Results were not ideal
- Tested for other variables and got similar results

GRANGER CAUSALITY RESULTS FOR ABORTION RATE & CRIME RATE

LAG	F-value(absolute)	P-value
1	11.036	0.0023
2	3.179	0.0575
3	5.061	0.0073
4	4.840	0.0063
5	3.329	0.0264
6	2.121	0.1112
7	3.475	0.0283
8	3.102	0.0557
9	2.708	0.1189
10	2.264	0.2716

GRANGER CAUSALITY RESULTS FOR CRIME RATE & ABORTION RATE

LAG	F-value(absolute)	p-value
1	0.010	0.9181
2	0.067	0.9351
3	1.482	0.2443
4	1.465	0.2481
5	1.038	0.4252
6	2.152	0.1070
7	1.637	0.2160
8	2.753	0.0763
9	1.948	0.2148
10	1.524	0.4025

TECHNIQUE: Counterfactual Analysis

- Semi-parametric difference in differences approach
- Terrible drawing incoming..
- Country-wide data, crimes by age

$$M = \begin{array}{c c} & \begin{array}{cccccc} 18 & 19 & 20 & 21 & 22 & 23 \end{array} \\ \begin{array}{c} Before \\ After \end{array} & \begin{pmatrix} d_{1,1} & d_{1,2} & d_{1,3} & d_{1,4} & d_{1,5} & d_{1,6} \\ d_{2,1} & d_{2,2} & d_{2,3} & d_{2,4} & d_{2,5} & d_{2,6} \end{pmatrix} \end{array}$$

Fig. 6. Matrix for the initial values

$$\forall i \in [0, 24 - a_1]$$

$$difference_{1,i} = \frac{C_{y_2,a_2+i} - C_{y_1,a_1+i}}{C_{y_1,a_1+i}}$$

$$difference_{2,i} = \frac{C_{y_4,a_2+i} - C_{y_3,a_1+i}}{C_{y_3,a_1+i}}$$

Results

MATRIX 1: y_1 = 1990

a_1	Before	After	Difference
18	-0.06122298	-0.06549603	0.00427305
19	-0.06043459	-0.07568391	0.01524932
20	-0.05348453	-0.07452501	0.02104047
21	-0.06015527	-0.06952223	0.00936695
22	-0.05343184	-0.06730351	0.01387168
23	-0.06620941	-0.07644202	0.01023261

AVERAGE TREATMENT VALUES

Matrix	Year	TE
1	1990	0.0123
2	1991	-0.0459
3	1992	-0.0288
4	1993	-0.0292
5	1994	-0.0256
6	1995	0.033
Average Treatment Effect		-0.0066

$$delta_j = \frac{\sum_i^{len(matrix^j)} (matrix^j_{0,i} - matrix^j_{1,i})}{len(matrix^j)}$$

$$\text{average treatment effect (ATE)} = mean(delta)$$

Future Work

- Structural Equation modelling can be applied if we have the right data
- Better counterfactuals may exist
  - Australia, Russia
- Carry out this experiment in a controlled environment where abortion is still illegal.
- Apply this technique on other laws. Eg. Gun control

What we have learned about Causality?

- Granger Causality is a compass not a navigator
- Counterfactuals are hard to find
- Extremely valuable!

VS Machine Learning?

- Answering why something happens and not just when
- Maybe robots should be taught causality instead of simple pattern matching

“All the impressive achievements of deep learning amount to just curve fitting,” - Judea Pearl

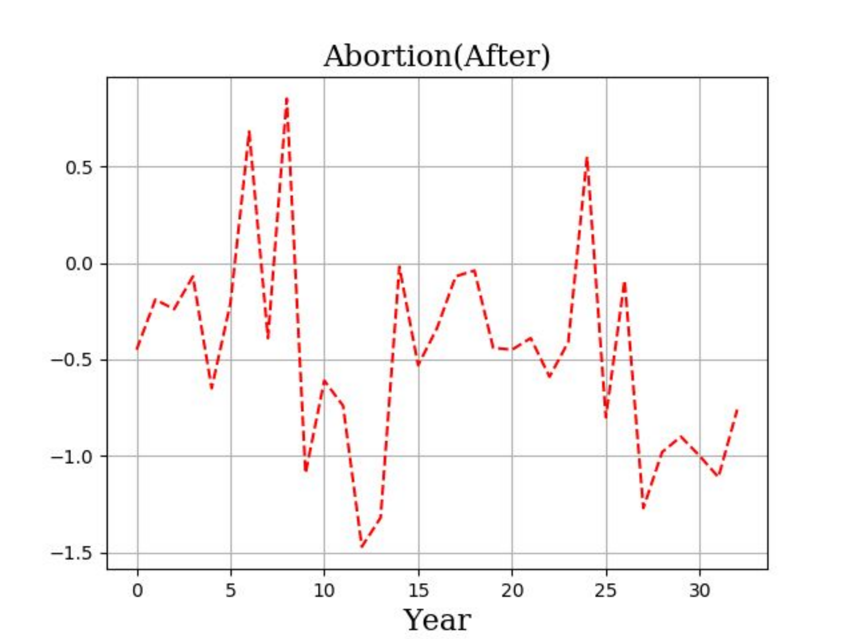
CODE AVAILABLE HERE - *https://github.com/Det2sial/CausalInference*

“Everything should be made as simple as possible, but not simpler.”

- Albert Einstein

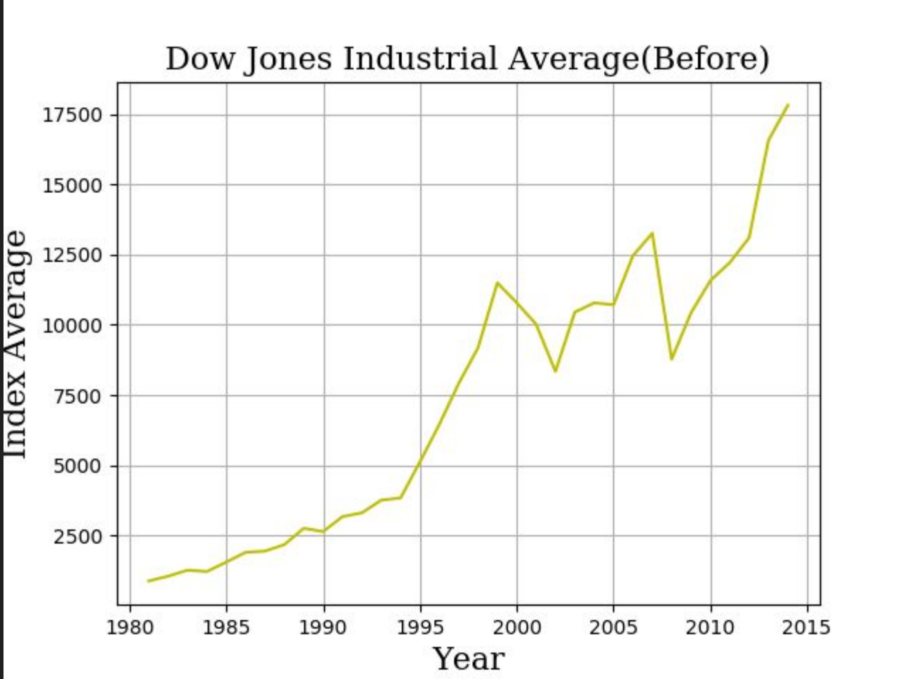
Appendix

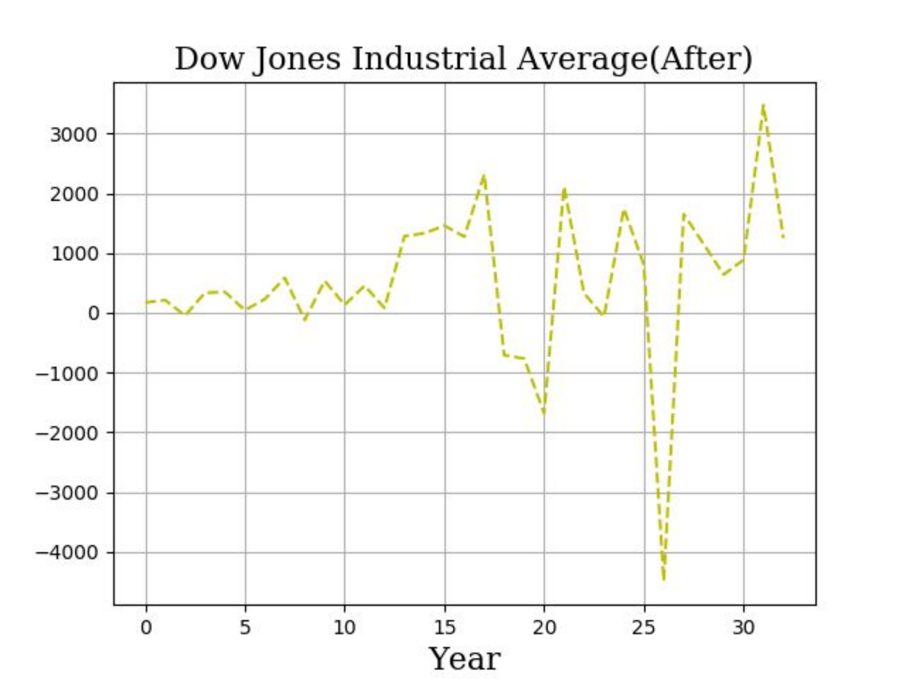
Abortion(Before)
Reported Rates
32
30
28
26
24
22
20
18
1980
1985
1990
1995
2000
2005
2010
2015
Year



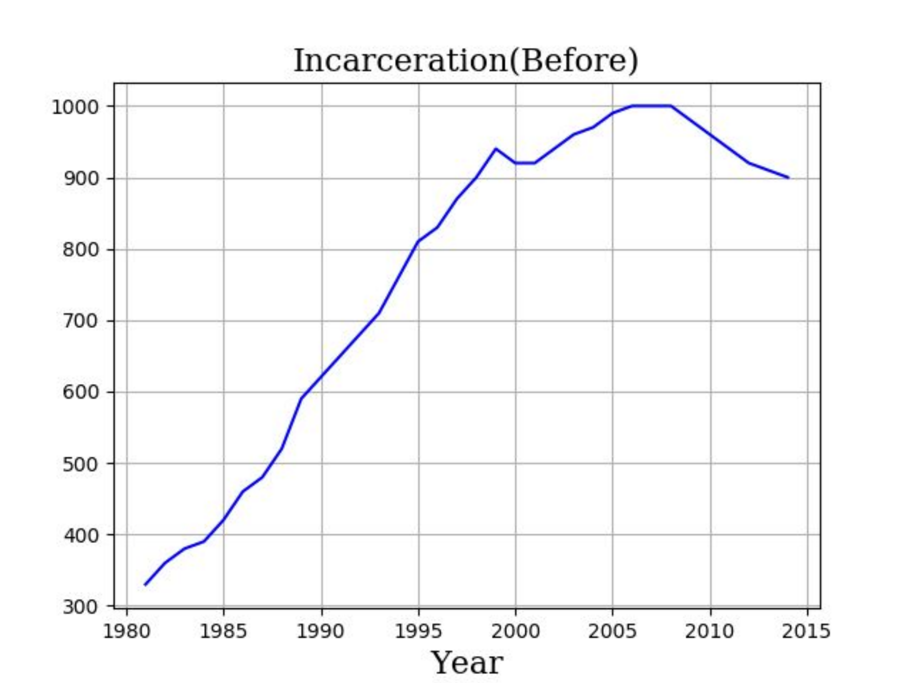
Abortion(After)
0.5
0.0
−0.5
−1.0
−1.5
0
5
10
15
20
25
30
Year

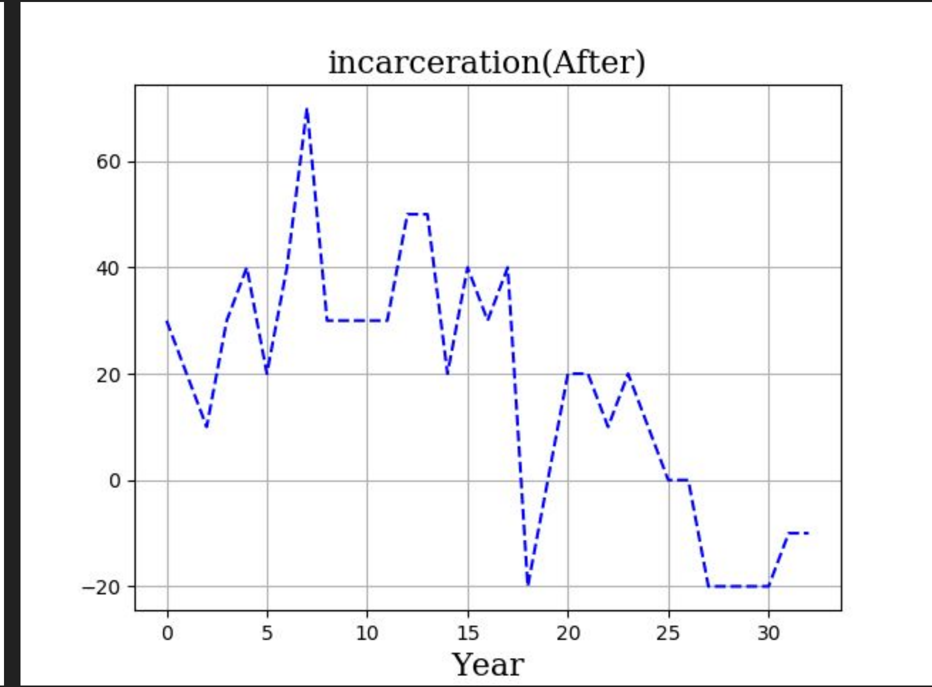
Appendix


Dow Jones Industrial Average(Before)
Index Average
Year
17500
15000
12500
10000
7500
5000
2500
1980
1985
1990
1995
2000
2005
2010
2015

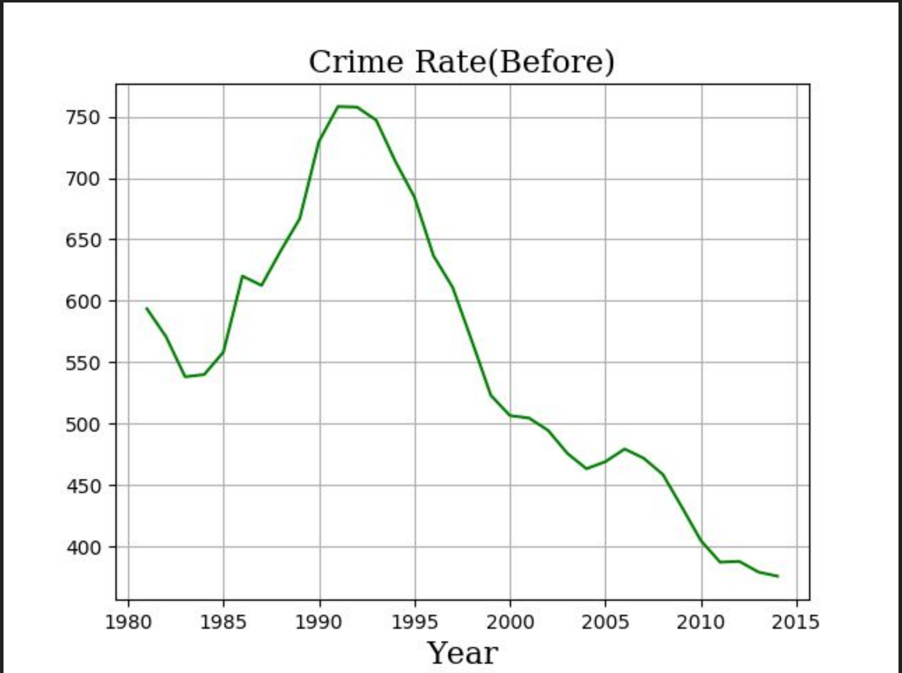

Dow Jones Industrial Average(After)
Year
3000
2000
1000
0
−1000
−2000
−3000
−4000
0
5
10
15
20
25
30

Appendix

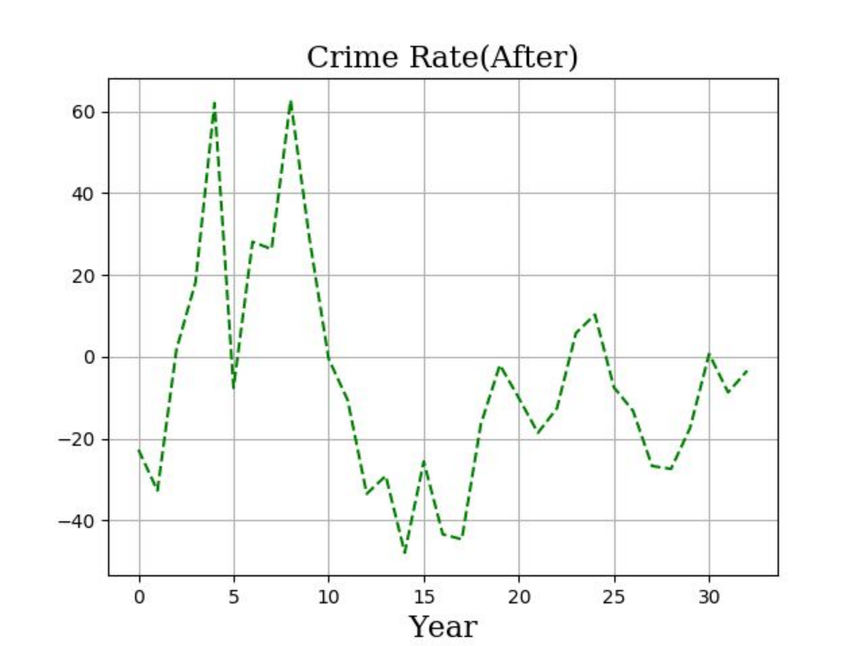

Incarceration(Before)
1000
900
800
700
600
500
400
300
1980
1985
1990
1995
2000
2005
2010
2015
Year


incarceration(After)
60
40
20
0
−20
0
5
10
15
20
25
30
Year

Appendix



Crime Rate(Before)
750
700
650
600
550
500
450
400
1980
1985
1990
1995
2000
2005
2010
2015
Year



Crime Rate(After)
60
40
20
0
−20
−40
0
5
10
15
20
25
30
Year

Appendix

TABLE I

ADF RESULTS FOR ABORTION RATES

	Before	After
Test statistic	1.6780	-4.6622
p-value	0.9981	0.0001
Critical Value (1%)	-3.6461	-3.6535
Critical Value (5%)	-2.9541	-2.9572
Critical Value (10%)	-2.6160	-2.6176

TABLE II

ADF RESULTS FOR DOW JONES INDEX

	Before	After
Test statistic	-0.1516	-2.5718
p-value	0.9440	0.0990
Critical Value (1%)	-3.7377	-3.7377
Critical Value (5%)	-2.9922	-2.9922
Critical Value (10%)	-2.6357	-2.6357

TABLE III

ADF RESULTS FOR INCARCERATION RATES

	Before	After
Test statistic	-2.1849	-2.2808
p-value	0.2117	0.1782
Critical Value (1%)	-3.6535	-3.6535
Critical Value (5%)	-2.9572	-2.9572
Critical Value (10%)	-2.6176	-2.6176

TABLE IV

ADF RESULTS FOR CRIME RATES

	Before	After
Test statistic	-0.9739	-3.4022
p-value	0.7834	0.0109
Critical Value (1%)	-3.6535	-3.7239
Critical Value (5%)	-2.9572	-2.9865
Critical Value (10%)	-2.6176	-2.6328