The Effect of Abortion Legalization on Crime in the United States

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***Abstract*— Extensive research has been devoted to studying the cause behind the fall in crime during the 199s but many have resigned their claims after their studies. These studies have concentrated on presumably obvious factors like employment rate and law enforcement. The book Freakonomics however, mentions an interesting causal chain of events, that the authors have argued, makes up for more than 10% of the increase or decrease in the crime rate: Stemming from the national legalization of abortion post 1973. In this paper, we have attempted to validate this claim by applying causal techniques on the same openly-available data sets used by the authors of the book. Our results indicate that their analysis was flawed and premeditated. Additionally, we also calculate the actual effects felt after the legalization of abortion in all states of the United States of America using a difference-in-differences analysis,a causal regression analysis and Granger Causality and find that the magnitude of the effect is negligible.**

I. INTRODUCTION

The study of crime and its causes is one of the most researched topics in the realm of causality. Numerous papers have been published trying to identify links between crime rates and conventional factors like poverty[1], unemployment[2] and prison population size[3] and other unconventional factors like police deployment[4], the presence of medical marijuana dispensaries[5] and Lithium in drinking water[6]. The results of these papers are arguable at the very least. Some have conceded to finding no strength in their hypothesis and others have been criticized for not including all possible interaction variables and confounding factors, of which there is no dearth. This is a testament to just how difficult the task at hand is. The data used also contributes to this difficulty, as in many cases the historical data is inaccurate or incomplete. In cases where the data quality is sufficient, other challenges arise including insufficient granularity and loose definitions that misguide researchers.

On a brighter note, many studies have been conclusive and its authors have received praise for their work including the study mentioned in the book titled Freakonomics [7]. The result of the study was monumental but controversial. In it, they vehemently argue that the legalization of abortion post the Supreme Court case Roe vs Wade [8] led to a drastic decline in crime rates claiming that Legalized abortion appears to account for as much as 50 percent of the recent drop in crime. [9] This study has divided the world of research on this topic with some claiming that the study was flawed [10,11,12] while others supporting the authors claims[13,14,17]. The authors have also gone the extra mile to refute any criticisms of their studies, publishing multiple papers individually targeting the naysayers. [15,16] In a few of these responses they have admitted to making some mistakes and have humbly corrected their techniques. Even after correction though, they have stuck with their original hypothesis but have revised the magnitude of the effect legalized abortion has on crime.

We too will throw our hat in the ring evaluating the effect of legalized abortion on crime in the United States and validating the claims put forth by the rest of the community. Our study has taken a more general approach by studying the variation of crime nationally rather than by state. This ensures 2 things. First, that any idiosyncrasies of the members of a state do not affect the general trend of abortion and crime as proposed by the authors. Second, data for the entire country is much more accurate than at the county level and there is also a forgiveness to errors in the data collected. Conversely, using data of the entire country neglects the fact that abortion was legalized in many states prior to the Roe vs Wade case. Our argument is based on the fact that prior to the case the levels of abortion were pretty stationary but immediately after the legalization i.e 1974, the rates of abortion jumped which signified that the intended effect could be observed. In many cases, a change in rules or an intervention may not take effect immediately but will be seen in a short period after the intervention. We have leveraged and validated this in our study using the data provided.

A serious challenge in proposing causal claims is the necessity of including all the variables that may have an effect on the observed variable. For this, we have first performed a regression analysis including variables that stand as a representation of the economy (Dow Jones Index) and the propensity to commit crime in a given year (incarceration rates). The results of this analysis indicate that abortion is not an insignificant factor and further study would be required. Granger Causality was then used to determine the direction of causation and identify any reverse-causality or simultaneous causation in this case. Finally a difference-in-differences analysis allowed us to calculate the magnitude of the effect legalized abortion had on crime rates in the US.

The rest of this paper describes the methods in more detail and talks about the challenges that were faced and the limitations of our study.

II. Data Sets

For the purpose of our study, we have used openly-available data sets collected by different official agencies. It must be said that the data we have used might not be a 100% accurate representation of the situation present at that time. For example, many divisions of law enforcement started recording and reporting arrest and employment statistics only after the inception of the Uniform Crime Reporting program. The primary sources we have used are the FBIs Uniform Crime Reporting (UCR) program, the Bureau of Justice Statistics and the NYC Open data program.

Most similar studies have analyzed the effects state-wise as each state would have its own effect depending on cohort and environmental factors. We argue that this would not provide a correct representation of the effects in the case of type causality. It is well known that causes at the type level may disappear at the token level thus there could also be cases in which the causes discovered at the token level (state-wise) may disappear at the type level. Additionally, many data sets that have been collected for states are incomplete or incorrect. As mentioned in a research done on the data sets for crime rates, County-level crime data have major gaps, and the imputation schemes for filling in the gaps are inadequate and inconsistent. [36] Crime rates by age were very hard to find for the years of our interest. Many data sets would categorize the offenders as adults or juveniles but few had rates by a single year of age. Imputing methods using the historical levels of offender proportion by age or simply by the population of each age group would lead to more doubts along the way as seen in other studies. Most data sets provided by the FBI were only for the years 1995 to 2014. This was not sufficient for our study as we were trying to examining the effect of an intervention that was made in 1973. Due to this, we had to change our strategy and adopted a counter-factual approach instead of structural equation modelling. We finally used a data set that, after cleaning, had the abortion rate (occurrences per 1000 women) from 1980 - 2014. The regression analysis was also performed on this data.

Abortion rates data was also needed in our study which we obtained from the Center of Disease Control and Prevention and from researchers who had done prior work in this field. Once again, there were many caveats to this data. First of all, the laws of abortion across the US are different for different states. Prior to the landmark case in 1973 abortion was legal in nearly 20 states like Alaska, Hawaii, Washington State and New York [18]. Secondly, the data collected on abortion rates relied on the clinics themselves. Due to this, the number reported would be far less than the actual number of abortions which could also be carried out by physicians and other unreported entities. Similar to other interventions, they may have a delayed effect especially in the case of a sudden change over a large population. We delved into the data to help us solve this problem and determine the ideal period which we should study to make sure that the

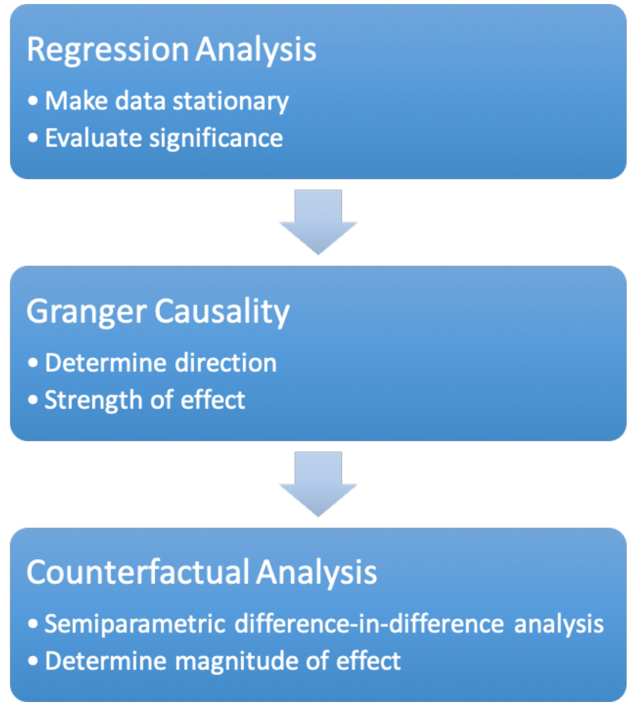

Fig. 1. Analysis process

intervention had had its effect. This turned out to be 1974 rather than 1973 as the rates of abortion spiked, signalling that the effect of legalization was finally felt.

For our regression analysis, we required some more data to judge the actual effect of abortion in the presence of many changing factors - social and enforcement related. The police employment data was obtained from the FBIs Uniform Crime Reports statistics and again is not completely reliable as different divisions joined the program at different times. It is further limited by the time period it covers i.e 2007 to 2017. This data contains the number of police officers employed per 1000 inhabitants. We also needed to include the incarceration rate as a representation for environmental factors like unrest, attitude of the police towards criminals and the attitude of the criminals themselves to answer the question : was the thought of jail deterring citizens from committing a crime? We collected this from multiple sources including the bureau of justice statistics, the NYC open data team and the sentencing project. This contains the number of US residents of all ages in prison or local jail per 100,000 residents from the year 1980 to 2014.

The social factors that were mainly studied are the performance of the economy and environmental situation of citizens at that time. The Dow Jones Index for the years 1980 to 2014 was gathered from the Bloomberg Terminal and adjusted for inflation using the Consumer Price Index (CPI). We chose to use this as an indicator of the performance of the economy as indicated by research. [20]

III. Analysis

As said before, a lot of research has been performed on this topic, some supporting the hypothesis and some refuting it. A common feature in all this research is the fact that they have studied states individually and then have aggregated their data to reach a conclusion which is similar to inferring a type causal effect from a token causal analysis. This, in our opinion, is an incorrect inference approach. Our research focuses more on directly evaluating a type causal effect from the data available. We have thus used national abortion rates, national crime rates and other generalized independent variables in our analysis. We do concede that we will thus lose precision but to test an intervention that ,in theory, affects a country as a unit, we should focus on the country as a unit. Limitations in the data sets have also contributed to this decision.

We have first tested for non-stationary of the time-series in question; mainly the abortion rates per year and the crime rates per year. We then converted any non-stationary series into stationary series by taking the difference between consecutive values. This data was then used in our regression analysis to give us an idea of which variables are significant and affect the rate of crime. A point of note here is that even if a variable is highly significant, it does not mean that it is a causal factor. Further analysis is required to judge it causal which is exactly what we did.

Once we found that abortion rate is indeed a significant variable, we proceeded with the Granger Causality analysis to determine the direction of cause and effect. This helped us avoid possible issues like reverse causality and simultaneous causation. The results were not perfect but strongly indicated that abortion rates were a causal factor in the rate of crime for certain lag values. Finally, to validate this observation, we performed a counter-factual analysis using a difference-in-differences approach to determine the magnitude of the effect abortion rates have as a cause for the increase in crime rates. The next few sections will talk about our analysis in detail.

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

A. *Stationary Examination*

Stationary data has the property that its mean, variance, covariance and autocorrelation structure is stable with time

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

and do not have trend or periodic effects. When using time series data, before establishing a model to fit the data we have, a stationary examination and processing is necessary if we expect a well-performed result.

1) First data analysis: The easiest way to check for non-stationary data is to plot the current data we have and see if they are stable or not as shown in fig. 2. From the graph we can easily see all four features we used in this research show some upward or downward trends as year goes by. For a stationary series, the trend should not be present in figure, thus, by simply observing the graphs we know a stationary processing is needed here in our research.

2) Statistical tests: We also used some statistic tests to help analyzing the data we have. The common two tests, as we listed below, are Augmented Dickey Fuller Test (ADF) and Kwiatkowski-Phillips-Schmidt-Shin Test (KPSS). They both have their advantages in stationary examination.

3) ADF test: ADF is more popular and commonly used as a unit root test for stationary. The problem is, the type I error rate often occurs in ADF Test though it can handle complex models and widely used. Here we use constant no

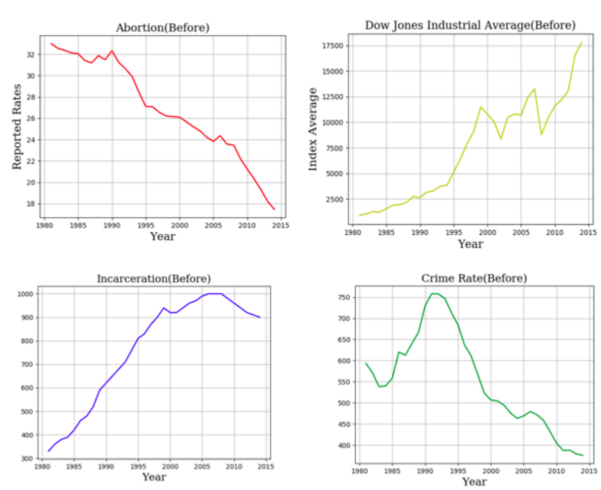

Fig. 2. Non-stationary data plots

trend formula, which is shown in equation 1.where α is the constant called drift, β is the coefficient on a time series, δ is the coefficient for the focus of testing, n is the lag order of the first-differences autoregressive process and ϵ is an independent identically distributed residual term.

$$\Delta y_t = \alpha + \delta y_{t-1} + \sum_{i=1}^{n} \beta_i \Delta y_{t-i} + \epsilon_t \tag{1}$$

- Null Hypothesis (H_0): data series is non-stationary (has unit root,$\delta = 0$)
- Alternative Hypothesis (H_a): data series is stationary or trend-stationary. ($\delta < 0$)

4) Analysis: In table x we can see the test statistics for abortion rate, Down Jones Index Average, incarceration rate, crime rate in ADF test is 1.6780, -0.1516, -2.1849, -0.9739 which is larger than critical value at 90% (10%), 95% (5%) and 99% (1%) confidence intervals, and this means the H_0 should be accepted. P-value is 0.9981, 0.9440, 0.2117, 0.7834 which is larger than significant level , and this also tells us the null hypothesis (H_0) holds. Therefore, all features needs to be stationary.

5) KPSS (Kwiatkowski-Phillips-Schmidt-Shin) Test: This test tells us whether a time series is stationary with a linear trend or nonstationary (trend stationary). KPSS applies to those timeseries that have a trend in their plots. The vector e is the vector of residuals on the time series and S is the sum of residuals and σ^2 is the estimate of the variance of the residuals

$$KPSS = n^{-2} \sum_{i=1}^{n} \frac{S_t}{\sigma^2} \tag{2}$$

$$e = (e_1, e_2, ..., e_n) \tag{3}$$

$$S_t = \sum_{i=1}^{n} e_i \tag{4}$$

- Null Hypothesis (H_0): The data trend is stationary
- Alternative Hypothesis (H_a): The data series has a unit root(non-stationary)

6) Analysis: In table we can see the test statistics for abortion, Dow jones, Incarceration in KPSS test is 0.4496, 0.4407, 0.3973 which is larger than critical value at 99% (1%) confidence intervals, and this means the H0 should be rejected. For critical value at 95%, 90%, the null hypothesis should be accepted. P-value is 0.0558, 0.0596, 0.0783, 0.1000 which is larger or equal than significant level (α = 10%,5%,1%), and this also tells us the null hypothesis holds. Therefore, all features with trend are stationary.

7) Cases discussion:

- Case 1: Both tests are non-stationary
- Case 2: Both tests are stationary
- Case 3: ADF is non-stationary and KPSS is stationary
- Case 4: ADF is stationary and KPSS is non-stationary

Case 3 is trend stationary. The data series has no unit root but its trend is stationary. Once the trend is removed the result series will be strict stationary, which means the mean and variance and covariance in this data series are not a

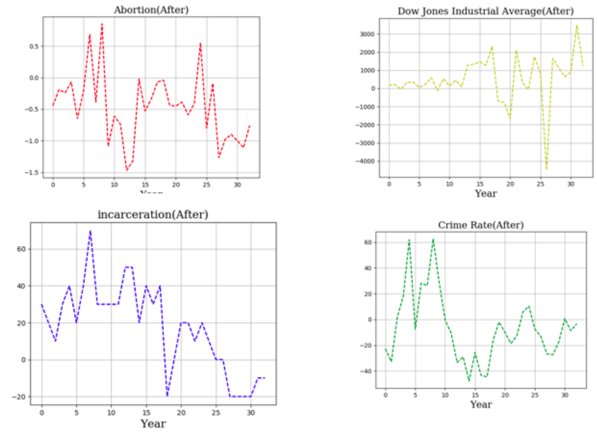

Fig. 3. Stationary data plots

function of time. Case 4 is difference stationary. We should use differencing to make series stationary. Therefore, we are facing the case 3, where all features are trend stationary.

8) Stationary Process: In this step, our aim is to remove the trend in data we have. We will use differencing method, we calculate the differences to detrend data. Fig. 3 show us the results of converting the non-stationary data to stationary data. Before using the data though, we will still need to normalize it.

B. Regression Model

1) First Model: linear: The formula for the first model is shown in equation 5. x_1 represents the abortion rate, x_2 represents the Dow Jones Index and x_3 represents the rate of incarceration.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \epsilon \tag{5}$$

The p-values in first LR model examine the null hypothesis H_0 that there is no effect on the corresponding row feature and in other words, the coefficient should be zero. Set the common statistic significant value to be 0.05, and compare with p value, we found that none of these features coefficient should remain in this model. For t value we have, the closer it to zero, the more likely there is no significant difference between predictors and response variable, which means H_0 is true.

TABLE V
RESULT FOR LINEAR REGRESSION MODEL

	Coefficients	Standard Error	t-statistic	P value
β_0	8.9658e-18	0.030266	2.96233e-16	1
β_1	0.036012	0.11155	0.32284	0.74922
β_2	-0.12443	0.14244	-0.87353	0.3898
β_3	-0.078681	0.13824	-0.56914	0.5738

2) Second Regression Model: quadratic: The formula for the model is shown in equation 6. The p-values in the second model are still too large for common significant level 0.005

but some rows are better than model 1.

$$y = \sum_{i=1}^{3} \beta_i x_i + \beta_{13} x_1 x_3 + \beta 11 x_1^2 + \beta_{22} x_2^2 + \beta_{33} x_3^2 + \epsilon \quad (6)$$

TABLE VI

RESULT FOR LINEAR REGRESSION MODEL(QUADRATIC)

	Coefficients	Standard Error	t-statistic	P value
β_0	-0.057056	0.065566	-0.87021	0.39358
β_1	0.033332	0.12092	0.27564	0.7854
β_2	-0.19545	0.15912	-1.2283	0.23232
β_3	-0.053268	0.2387	-0.22316	0.82547
β_{12}	-1.1568	0.76759	-1.5071	0.14601
β_{13}	0.44467	0.92644	0.47998	0.63598
β_{23}	-1.2112	0.86576	-1.399	0.17576
β_{11}	-0.2281	0.56288	-0.40523	0.68922
β_{22}	-0.98563	0.76322	1.2914	0.20997
β_{33}	0.49607	0.53797	0.92211	0.36648

C. Granger Causality

As seen from the results of the Linear Regression model, abortion rates are significant. This does not mean that higher abortion rates are a cause for crime rates increasing/decreasing but it cannot be ruled out. To actually judge whether it is a cause, we need to extend our analysis using tools like Granger Causality analysis. Granger Causality is a misnomer as it does not really confirm a causal relationship but rather confirms the direction of effect for 2 or more variables i.e does X cause Y or Y cause X. The formula for Granger Causality below can be translated to make it more relevant to our case. Is the probability of a change in crime rates affected by a change in abortion rates?

$$P(X_1(t+1)|W^*(t)) \neq P(X_1(t+1)|W^*(t)\text{-}X_2^*(t)) \quad (7)$$

1) Data: Our analysis was performed using the values of abortion rates and crime rates from the years 1980-2014. We did not wish to include values from previous years to avoid reducing the power of the analysis while also avoiding issues that are intrinsic to the data itself. The abortion rates were represented in the number of reported abortions per every 1000 women. We tested the crime rates for each age and achieved a similar value for every age. The tables shown below are for 18 year old offenders.

2) Procedure & Discussion: In equation 7, x_1 represents the rate of crime and x_2 represents the rate of abortion while W would represent all the other variables/factors that may affect the relationship. Thus we are trying to judge how much the probability of x_1 at time t+1 would be affected if we did not have knowledge of x_2 at time t. If the probability is not equal as suggested by the equation, that would mean that abortion rate does give us some information about the change in crime rates. The next step would be to verify that the direction of the cause-effect relationship is as we expect. For this, we compare the F-test values for x_2 Granger Causes x_1 and x_1 Granger Causes x_2 over multiple lags. Multiple lags are used to verify that the effect persists over a period of time and not just for a few periods. This is shown in table 1.

TABLE VII

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

The results of the Granger test for x_1 causes x_2 i.e rate of crime affects the rate of abortion are shown in table 2. In our case, we have tested for 10 different lags with the null hypothesis stating the first variable does not Granger Cause the second variable. The F-test values report the variation of the data or the dispersion. A far more important statistic would be the p-value that tells us the strength of our claim-whether we can reject the null hypothesis or not. As we can see, the p-values in table 1 are much lower than those in table 2. From table 1 we can say that we can reject the null hypothesis that crime rates do not depend on abortion rates. Similarly, from table 2, we cannot reject the null hypothesis with much confidence as the p-values are high and so the abortion rate does not depend on the crime rate. This means that the crime rates do not affect the abortion rate in any way eliminating the possibility of reverse causation. Say for example, if a high proportion of murders were involving pregnant women, the rate of abortion might have taken a toll. This test also eliminates the possibility of simultaneous causation as for different lags, we are seeing similar p-values and f-values. Interestingly, in the case of the 1st lag, the F-value statistic is extremely high. We estimate that is due to the fact that the effects of changes in rates of abortion and changes in the rate of crime are not felt immediately but rather after a year strengthening our assumption that the effects of the legalization of abortion in 1973 would only be felt in 1974.

We have now got a sense of direction about the interaction between the rate of crime and the rate of abortion. now say that the rate of crime depends on the rate of abortion and not the other way around. This still does not mean that an increase in the rate of abortion causes a decrease in the rate of crime in the country. Further analysis is still necessary.

3) Limitations: As said before, our sampling size is small compared to other studies. This is because we have considered the values for an entire year instead of individual states and quarters. We have also tested for the other significant variables from our regression model and found that the incarceration rate and the Dow Jones index also Granger Causes crime rates. This result is not unexpected as many factors can be involved in affecting crime rates. Further,

TABLE VIII

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

it justifies the extension of our analysis using the counter-factual approach presented in the next section.

D. Counter-factual Approach

The results from our Granger causality analysis indicate that the crime rates are not independent of the rate of abortion but to actually find out the magnitude of the effect we have to extend our analysis. We use a counter-factual approach to do this.

We will be using a semiparametric difference-in-difference estimator to compare the difference in rates of crime in the populations that were exposed and not exposed to legalized abortion. The first period represents the situation in which abortion was not legal all over the US. The second situation represents the situation in which the intervention has been performed i.e abortion has been legalized. During our analysis we have to control for situational effects as well as cohort effects. For example, there was a major change in the attitude of the police towards gun possession which contributed to the decrease in crime rates [21]. Along with this, the 1980s experienced a high rise in the consumption of crack-cocaine, raising the levels of crime far above the usual. Naturally, once this abated it also reduced the crime rates and brought it back to normal [22]. This may mean that the legalization of abortion could be a spurious cause rather than an actual one. In the next few sections we will detail the steps performed to assess the magnitude of the actual effect of the legalization of abortion on crime rates.

1) Data: For the purpose of this analysis we do not require much data but what we do require has to be extremely specific and accurate. We have used a data set which contains the crimes committed per year by individuals of specific ages. We gathered this data through the National Crime Victimization Survey provided reports. These are first hand reports from victims rather than the police and contain data with a high level of granularity which was required for our study. The offenders age,sex, and race are also provided along with details of the crime including the location, victim-offender relationship and physical/economic consequences. It has details of crimes committed between 1973-2016 and is thought to be much more accurate than reports generated by law-enforcement agencies.

2) Procedure: A difference-in-differences analysis is a very intuitive and simple technique that can be used to judge the effect of an intervention in time-series data. Unfortunately, this technique requires a lot of assumptions that are rarely seen in real-world data. One such assumption is that the values of the observed variable before and after the intervention, if the intervention had not taken place, should follow a parallel path.

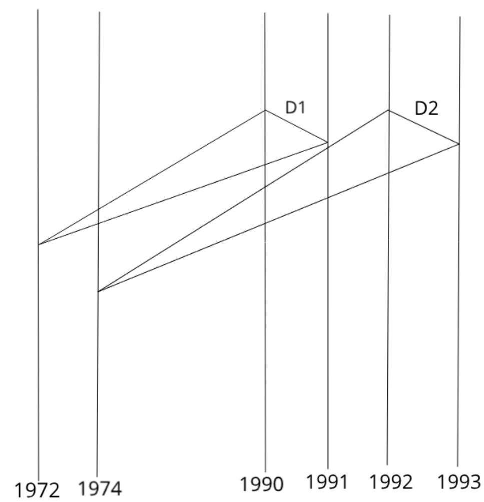

Fig. 4. Semi-parametric difference-in-difference approach

To overcome this issue, we have used semiparametric difference-in-differences estimators instead of the basic estimators [23] as the above assumption was not true in our data. The crime rate can be affected by many factors like gun control, rise in the use of drugs, changes in laws and police enforcement which we henceforth refer to as environmental factors. Cohort effects will also vary in different periods. A few of these include the state of the economy, the minimum wage levels and unforeseen events like natural disasters and riots.

The semiparametric approach allows us to relax this assumption while comparing populations of the 2 different time periods we are interested in. Instead of simply comparing the difference in crime rates in populations where abortion was legal and where it was not, we first need to remove all the environmental and cohort effects in our populations, after which we can compare them. Fig. 4 explains the idea behind this.

Using our prior knowledge about the fact that the effects of the legalization of abortion were felt after a year of its implementation, we chose to use the year 1972 as the control year and the year 1974 as the treatment year. Since 18 and 19 year old subjects are the highest offenders we set that as our starting ages. 18 year old subjects born in 1972 would be 18 in 1990 and 19 in 1991. We first calculate the difference in crime rates of 18 year old offenders in 1990 and 19 year old offenders in 1991. This represents the population that was not exposed to legalized abortion.

$$y_1 \in [1990, 1997]$$

$$y_2 \in [1991, 1998]$$
$$a_1 = y_1 - 1972 \quad (8)$$
$$a_2 = a_1 + 1$$

For the other group we needed for comparison, we had to study the years 1992 and 1993. We calculated the difference in crime rates for 18 year old subjects in 1992 and 19 year old subjects in 1993. This would represent the population that had been exposed to legalized abortion.

$$y_3 \in [1992, 1999]$$
$$y_4 \in [1993, 2000]$$

It is important to note here that this does not serve as a perfect counter-factual as many other factors could also have changed between the years 1972 and 1974. Nonetheless, this is the closest approximation to a counter-factual that we have. Other countries with similar populations and interventions could also be used but very few possess the high quality of data available in the United States.

Since we wanted to observe the same population, our semiparametric approach calculated the difference in the crime rates between 18 and 19 year old offenders exposed to legalized abortion and 18 and 19 year old offenders not exposed to legalized abortion. We did this for all members of populations from the ages 18 to 24. We ignored minors as the rate of crime for their age group is extremely low and would bias our analysis. We could not use ages greater than 24 as the data set did not have specific values by year of age for any age greater than 24. This process is shown in equation 7 and 8, where row 1 of the difference matrix contains the differences for offenders for each age in y_1 and y_2 and row 2 contains the differences for y_3 and y_4.

$$\forall i \in [0, 24 - a_1]$$
$$difference_{1,i} = \frac{C_{y_2,a_2+i} - C_{y_1,a_1+i}}{C_{y_1,a_1+i}} \quad (9)$$
$$difference_{2,i} = \frac{C_{y_4,a_2+i} - C_{y_3,a_1+i}}{C_{y_3,a_1+i}} \quad (10)$$

Once we had these 2 differences, we calculated the difference between these 2 differences, eliminating the different environmental and cohort effects felt by the populations in the 4 years. We are essentially comparing the difference in the rates of crime between 2 populations and observing whether this difference increased or decreased after the legalization of abortion. This would give us a value similar to the average treatment effect as abortion being legal was the only treatment that would be left between these 2 populations. The matrices were created by the procedure described above resulting in a total of 6 matrices, one for each year y_1 between 1990 and 1996 and the corresponding y_2,y_3 and y_4 values. The matrix for the first values is shown in Fig. 5. Each column corresponds to the value of a_1 for that column. The first row represents the population for which abortion was not legal and the second row represents the population for which

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

Fig. 5. Matrix for the initial values

abortion was legal. There were 6 such matrix with different number of columns. The last matrix had only 1 column which was for the years 1995, 1996, 1998 and 1998. The age for these subjects was 23 and 24. The values for the matrices are shown in tables 3 to 8. Using the generated matrices, we calculated the percentage change in the differences and the weighted mean was taken of the values over all the matrices to get the average treatment effect (ATE). The weighted mean was needed as different matrices had a different number of rows and observations. Higher weight should be given to those matrices with more rows.

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

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

3) Results: The average treatment effect is shown in table 9. The treatment effect appears to be extremely low for all years with the average value of -0.014. This can be interpreted as the legalization of abortion having a negative effect of crime but by only a very small amount. The treatment effect for Matrix 6 should be discounted as only one age group was compared in this case and members of that age group naturally tend to commit less crimes as they grow older. As noted in research, "Adults between the ages of 25 and 34 experience the greatest number of arrests compared to other age groups" [24]. This result reflects that the legalization of abortion may have affected the rate of crime but not to the extent proposed by other researchers in the field.

4) Limitations: The method we have used is extremely simple and reproducible. However, a more complex model of this method may provide better results. Our method is susceptible to feeling the effect of general trends in the data as we are only using the crime rates for our analysis. For example, if crime was decreasing in general, our method would return a negative value while comparing other years as well. This though is not the case as we have studied the rate of change and not the difference itself.

IV. RESULTS

The causal chain, proposed by other researchers, and initiated by the legalization of abortion is indeed an interesting explanation for the decrease in crime. Legalization allowed mothers in unfortunate situations an option to postpone motherhood to more favourable time. This meant that there were fewer unwanted children and more children getting the attention they deserved while growing up. Though highly

TABLE IX

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

TABLE X

MATRIX 2: y_1 = 1991

a_1	Before	After	Difference
19	-0.10872849	-0.04892615	-0.05980235
20	-0.09647976	-0.03960327	-0.05687649
21	-0.0860326	-0.0346899	-0.0513427
22	-0.07666807	-0.04434909	-0.03231898
21	-0.08102787	-0.05137537	-0.0296525

TABLE XI

MATRIX 3: y_1 = 1992

a_1	Before	After	Difference
20	-0.07452501	-0.05000586	-0.02451915
21	-0.06952223	-0.03676233	-0.0327599
22	-0.06730351	-0.04346225	-0.02384126
23	-0.07644202	-0.04226371	-0.03417832

TABLE XII

MATRIX 3: y_1 = 1993

a_1	Before	After	Difference
21	-0.0346899	-0.06450063	0.02981073
22	-0.04434909	-0.07378913	0.02944004
23	-0.05137537	-0.07972763	0.02835226

TABLE XIII

MATRIX 4: y_1 = 1994

a_1	Before	After	Difference
22	-0.04346225	-0.06982926	0.02636701
23	-0.04226371	-0.0672786	0.0250149

TABLE XIV

MATRIX 5: y_1 = 1995

a_1	Before	After	Difference
23	-0.07972763	-0.1128049	0.03307727

TABLE XV

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

improbable the authors that proposed this hypothesis believe that ”Legalized abortion appears to account for as much as 50 percent of the recent drop in crime.”[9] our study suggests otherwise showing that in the entire country the legalization of abortion has had extremely minor effects on the change in the rate of crime. Our first analysis did show that abortion rates are significant in a regression model that is predicting crime rates but so are other factors like incarceration rate. This allowed us to move onto finding a causal link. Granger Causality was used to determine the direction of the cause effect relationship if any and we did find that the abortion rates do Granger cause a change in crime rates. This did make us hopeful of finding a causal link between the legalization of abortion and crime rates but our final analysis disproved this.

V. DISCUSSION

As in many cases, causal inference has proved to be a hard task in environments that are not controlled. Gaining causal insights from data itself is still a challenge but methods are being improved day by day. We attempted to use an intuitive and simple technique that could be explained to even a layman in the world of causal inference. Our analysis leveraged the data for the country instead of individual states helping us avoid the complications associated with each states individual policies and environments. Analyzing each state individually could have led to different results but historical data for offenders by age is difficult to collect. As mentioned before, each different law enforcement agencies became a part of the collection program at different times. Even so, gathering data that goes 50 years back is a hard task itself.

Our aim in this paper was to first determine whether there is a link between the rate of crime and the rate of abortion and to determine the magnitude of its effect. Our results have indicated that there indeed is a link but the magnitude of its effect is too less to be considered a causal factor.

VI. FUTURE WORK

Other sophisticated techniques like Bayesian Modelling and Structural modelling should be applied to the data sets that we have collected. This would either validate our claims or would lead to new findings. The techniques used by the authors on seminal works in this field should also be applied to country-wide data sets to see if the effect is indeed a type cause or is only present in the certain states that they considered in their studies. As mentioned before, the perfect counter-factual for this case is hard to find but the answer may lie in other countries of equal economic standing who have implemented a similar intervention. A study has been conducted in the United Kingdom tackling the same problem but they have reached the same conclusion as our research; abortion laws do not affect crime rates significantly. Other options may be Australia, Germany and Russia.

REFERENCES

[1] G. O. Young, Synthetic structure of industrial plastics (Book style with paper title and editor), in Plastics, 2nd ed. vol. 3, J. Peters, Ed. New York: McGraw-Hill, 1964, pp. 1564.

[2] PATTERSON, E. B. (1991), POVERTY, INCOME INEQUALITY, AND COMMUNITY CRIME RATES. Criminology, 29: 755-776. doi:10.1111/j.1745-9125.1991.tb01087.x

[3] Cantor, D., & Land, K. C. (1985). Unemployment and Crime Rates in the Post-World War II United States: A Theoretical and Empirical Analysis. American Sociological Review, 50(3), 317. https://doi.org/10.2307/2095542

[4] Levitt, S. D. (1996). The Effect of Prison Population Size on Crime Rates: Evidence from Prison Overcrowding Litigation. The Quarterly Journal of Economics, 111(2), 319351. https://doi.org/10.2307/2946681

[5] Levitt, Steven, D. 2004. "Understanding Why Crime Fell in the 1990s: Four Factors that Explain the Decline and Six that Do Not ." Journal of Economic Perspectives, 18 (1): 163-190.

[6] Kepple, N. J., & Freisthler, B. (2012). Exploring the ecological association between crime and medical marijuana dispensaries. Journal of Studies on Alcohol and Drugs, 73(4), 523530. https://doi.org/10.15288/JSAD.2012.73.523

[7] Schrauzer, G. N., & Shrestha, K. P. (1990). Lithium in drinking water and the incidences of crimes, suicides, and arrests related to drug addictions. Biological Trace Element Research, 25(2), 105113. https://doi.org/10.1007/BF02990271

[8] Levitt, S. D., & Dubner, S. J. (2005). Freakonomics: A rogue economist explores the hidden side of everything. New York: William Morrow.

[9] Roe v. Wade, 410 U.S. 113 (1973).

[10] Donohue, J. J., & Levitt, S. D. (2001). The Impact of Legalized Abortion on Crime. The Quarterly Journal of Economics, 116(2), 379420. https://doi.org/10.1162/00335530151144050

[11] Joyce, T. (2004). Did Legalized Abortion Lower Crime? Journal of Human Resources, XXXIX(1), 128. https://doi.org/10.3368/jhr.XXXIX.1.1

[12] Foote, C. L., & Goetz, C. F. (2008). The Impact of Legalized Abortion on Crime: Comment *. Quarterly Journal of Economics, 123(1), 407423. https://doi.org/10.1162/qjec.2008.123.1.407

[13] Joyce, T. (2009). A Simple Test of Abortion and Crime. Review of Economics and Statistics, 91(1), 112123. https://doi.org/10.1162/rest.91.1.112

[14] Marie Muncy, A. (2013). Abortion and Crime. In The Encyclopedia of Criminology and Criminal Justice (pp. 13). Oxford, UK: Blackwell Publishing Ltd. https://doi.org/10.1002/9781118517383.wbeccj517

[15] LOTT, J. R., & WHITLEY, J. (2007). ABORTION AND CRIME: UNWANTED CHILDREN AND OUT-OF-WEDLOCK BIRTHS. Economic Inquiry, 45(2), 304324. https://doi.org/10.1111/j.1465-7295.2006.00040.x

[16] Donohue, J. J., & Levitt, S. D. (2004). Further Evidence that Legalized Abortion Lowered Crime. Journal of Human Resources, XXXIX(1), 2949. https://doi.org/10.3368/jhr.XXXIX.1.29

[17] Donohue, J. J., & Levitt, S. D. (2008). Measurement Error, Legalized Abortion, and the Decline in Crime: A Response to Foote and Goetz *. Quarterly Journal of Economics, 123(1), 425440.https://doi.org/10.1162/qjec.2008.123.1.425

[18] LOTT, J. R., & WHITLEY, J. (2007). ABORTION AND CRIME: UNWANTED CHILDREN AND OUT-OF-WEDLOCK BIRTHS. Economic Inquiry, 45(2), 304324. https://doi.org/10.1111/j.1465-7295.2006.00040.x

[19] Wilson, J. (2013, January 22). Before and after Roe v. Wade. Retrieved from https://www.cnn.com/2013/01/22/health/roe-wade-abortion-timeline/index.html

[20] Surveillance Summary Abortion Surveillance: Preliminary Analysis, 1979-1980 – United States. Retrieved from https://www.cdc.gov/mmwr/preview/mmwrhtml/00001243.htm

[21] Comincioli, B. (1996). The Stock Market As A Leading Indicator: An Application Of Granger Causality. University Avenue Undergraduate Journal of Economics, 1(1). Retrieved from https://digitalcommons.iwu.edu/uauje/vol1/iss1/1

[22] Gius, M. (2014). Gun law and crime. Significance, 11(2), 68. https://doi.org/10.1111/j.1740-9713.2014.00732.x

[23] Grogger, J., & Willis, M. (2000). The Emergence of Crack Cocaine and the Rise in Urban Crime Rates. Review of Economics and Statistics, 82(4), 519529. https://doi.org/10.1162/003465300558957

[24] Abadie, A. (2005). Semiparametric Difference-in-Differences Estimators. The Review of Economic Studies, 72(1), 119. https://doi.org/10.1111/0034-6527.00321

[25] Institute, U. (2001). Risk of Violence Highest for 18- to 24-Year-Olds, Says Urban Institute Study of D.C. Crime. Retrieved from http://webarchive.urban.org/publications/900403.html

[26] Johnston, R. (2018, November). Historical abortion statistics, New York (USA). Retrieved November 2018, from http://www.johnstonsarchive.net/policy/abortion/usa/ab-usa-NY.html

[27] Reproductive Health. (2017, November 16). Retrieved November 10, 2018, from https://www.cdc.gov/reproductivehealth/datastats/abortion.htm

[28] Brownlee, J. (2018, October 18). How to Check if Time Series Data is Stationary with Python. Retrieved November 21, 2018, from https://machinelearningmastery.com/time-series-data-stationary-python/

[29] Unit Root Tests. [online] Freakonometrics. Available at: https://freakonometrics.hypotheses.org/12729 [Accessed 26 Nov. 2018].

[30] DSS - Interpreting Regression Output. [online] Available at: https://dss.princeton.edu/online/help/analysis/interpreting/regression.htm [Accessed 26 Nov. 2018].

[31] Minitab. (2018). How to Interpret Regression Analysis Results: P-values and Coefficients. [online] Blog.minitab.com. Available at: http://blog.minitab.com/blog/adventures-in-statistics-2/how-to-interpret-regression-analysis-results-p-values-and-coefficients [Accessed 26 Nov. 2018]

[32] Iordanova, T. (2018). Introduction To Stationary And Non-Stationary Processes. [online] Investopedia. Available at: https://www.investopedia.com/articles/trading/07/stationary.asp [Accessed 26 Nov. 2018].

[33] Stat.yale.edu. (2018). Linear Regression. [online] Available at: http://www.stat.yale.edu/Courses/1997-98/101/linreg.htm [Accessed 26 Nov. 2018]

[34] Statistics How To. (2018). Stationarity: Definition, Examples, Types - Statistics How To. [online] Available at: https://www.statisticshowto.datasciencecentral.com/stationarity/ [Accessed 26 Nov. 2018].

[35] People.maths.bris.ac.uk.(2018). Time Series Introduction. [online] Available at: https://people.maths.bris.ac.uk/ magpn/Research/LSTS/STSIntro.html [Accessed 26 Nov. 2018].

[36] Maltz, M. D., & Targonski, J. (2002). A Note on the Use of County-Level UCR Data. Journal of Quantitative Criminology, 18(3), 297318. https://doi.org/10.1023/A:1016060020848