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Causal Analysis of Police Interventions in Domestic Violence: An Instrumental Variable Approach

Part A.

1.

(a) What do you understand by counterfactuals in the context of causal inference? Explain through an example.

In a casual inference scenario, a counterfactual is a hypothetical scenario in which a representation is what would have happened if a particular treatment had not occurred. For example, if we take an example of a new level job training on a group of people if that helps in increasing the mean and median salary of a group after the training. The factual outcome is the income of the people who participated in the training. The counterfactual outcome is the income of those same participants if they had *not* participated in the program.

(b) What do you understand by endogeneity? Can you draw causal inference in the presence of endogeneity? Why?

Endogeneity occurs when a x variable is correlated with the error term of the OLS regression model. This leads to a bias and inconsistency estimation of the casual effect. The reason for this is the omitted variable bias, simulation bias and error in measurement.

2.

(a) Under what assumptions can one use regression to make valid causal inference?
Zero conditional mean: The error term's expected value, conditional on the predictors, is zero.
Exogeneity: The predictors are uncorrelated with the error term (no endogeneity).
Linearity: The relationship between the predictors and the outcome is linear.
Homoscedasticity: The error term has constant variance.
No multicollinearity: Predictors are not perfectly correlated.

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(b) Explain omitted variable bias and bad controls through examples from the real-world.

When a variable that may or may not affect the outcome of the y variable is omitted from the regression model is known as the omitted variable. Including a control variable that is itself an outcome of the treatment variable can introduce bias by blocking a causal pathway or creating a spurious association and this phenomenon is known as bad controls.

3.

(a) What are the assumptions of Differences-in-difference regression models? What is the difference between DiD model and Staggered DiD model?

Differences-in-differences regression models are based on a few important assumptions, with the most important being the parallel trends assumption. This means that if there was no treatment, the treated and control groups would have followed similar trends over time. It also assumes there are no spillover effects from the treatment group to the control group, and that the groups stay consistent over time. A regular DiD model looks at one point in time when the treatment happens for everyone in the treated group. On the other hand, a staggered DiD model is used when different groups get treatment at different times.

(b) What are the common pitfalls of DiD models?

Common pitfalls of Differences-in-Differences models include several issues that can lead to biased or misleading results if not properly addressed. One major pitfall is violating the parallel trends assumption, which is the core requirement for DiD to produce valid causal estimates that is if the treatment and control groups were already on different paths before the treatment, the results may reflect those differences rather than the impact of the treatment.

4.

(a) Can matching methods such as Propensity Score Matching (PSM) address the problem of endogeneity? When is PSM useful in making causal inference?

Propensity Score Matching can address endogeneity stemming from observed confounding variables, but it cannot be correct for unobserved confounders. PSM is valuable when treatment assignment is non-random, relying on observed characteristics; it creates comparable treatment and control groups by matching individuals with similar propensity scores

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(b) Explain the assumptions of matching methods in your own words.
Matching methods try to make the treated and untreated groups as similar as possible based on stuff we can see and measure. We're assuming that once they look the same on those things, any differences in what happens to them are because of the treatment, not hidden differences we missed. Plus, we need enough people in both groups who are similar, so we can find matches.

5.

(a) Describe instrumental variable method (2 Stage Least Square regression) in your words. Can the use of instrumental variable method address the issue of endogeneity? Why?
The instrumental variable (IV) method using 2 Stage Least Squares helps fix endogeneity by using an external variable that affects the treatment but not the outcome directly. It works only if the instrument is valid, meaning it’s strongly related to the treatment and not linked to the error term. So yes, IV can address endogeneity, but only with a good instrument.

(b) What are the pitfalls of IV method?
The IV method can fail if the instrument is weak or not truly exogenous. It also gives less precise estimates and only captures local effects, not the average impact on the whole population. Finding a good instrument is often the biggest challenge.

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Part B

Objective:

The aim of this assignment is to perform an Instrumental Variables (IV) analysis using the MDVE dataset. This dataset includes information on domestic violence incidents and the types of police responses. Through this analysis, students will explore the effectiveness of different police interventions in preventing repeat incidents.

This analysis should be done using either R or Python programming languages. If you plan to use any other programming language, do reach out to the professor.

Dataset:

You will analyze the MDVE dataset, which contains detailed records of domestic violence incidents and the interventions applied (arrest, separation, or advice) by police in Minneapolis. These interventions are the focal point of the IV analysis.

Data Cleaning and Manipulation: 30 points

1. **Load the dataset into your programming environment. Detail any necessary data cleaning and preprocessing steps, such as dealing with missing values or categorizing variables.**

   # Load data

   file_path <- ("C:/Users/91884/Desktop/BAIS/Advance data science/Mid Term/mdve.xlsx")
   data <- read_excel(file_path, sheet = "mdve")
   summary(data)
   str(data)

```
> str(data)
tibble [330 x 22] (S3: tbl_df/tbl/data.frame)
 $ ID      : num [1:330] 3.72e+08 4.41e+08 2.81e+08 6.81e+08 2.32e+08 ...
 $ T_RANDOM: num [1:330] 3 1 1 3 3 1 1 1 3 2 ...
 $ MONTH   : chr [1:330] "5" "5" "5" "7" ...
 $ YEAR    : chr [1:330] "81" "81" "81" "81" ...
 $ CLOCK   : chr [1:330] "125" "515" "1910" "210" ...
 $ TIME    : chr [1:330] "35" "40" "15" "NA" ...
 $ P_REPORT: num [1:330] 1 1 1 0 1 1 1 1 1 0 ...
 $ CCN     : chr [1:330] "83905" "NA" "77252" "NA" ...
 $ V_RACE  : num [1:330] 1 1 3 3 1 2 3 1 1 1 ...
 $ S_RACE  : chr [1:330] "1" "2" "3" "3" ...
 $ V_CHEM  : chr [1:330] "1" "0" "1" "1" ...
 $ S_CHEM  : chr [1:330] "0" "1" "0" "1" ...
 $ S_DMNOR1: chr [1:330] "1" "2" "2" "1" ...
 $ S_DMNOR2: chr [1:330] "1" "2" "2" "2" ...
 $ WEAPON  : chr [1:330] "3" "4" "5" "3" ...
 $ GUNS    : chr [1:330] "1" "1" "1" "1" ...
 $ T_FINAL : num [1:330] 3 1 1 3 3 1 1 1 3 2 ...
 $ REASON1 : chr [1:330] "1" "1" "1" "1" ...
 $ REASON2 : chr [1:330] "1" "1" "1" "1" ...
 $ REASON3 : chr [1:330] "1" "1" "1" "1" ...
 $ REASON4 : chr [1:330] "1" "1" "1" "1" ...
 $ R_RELATE: chr [1:330] "NA" "NA" "NA" "NA" ...
```

   correlation_matrix <- cor(data[c("T_RANDOM", "ID", "P_REPORT", "V_RACE", "T_FINAL")])
   corrplot(correlation_matrix, method = "pie")

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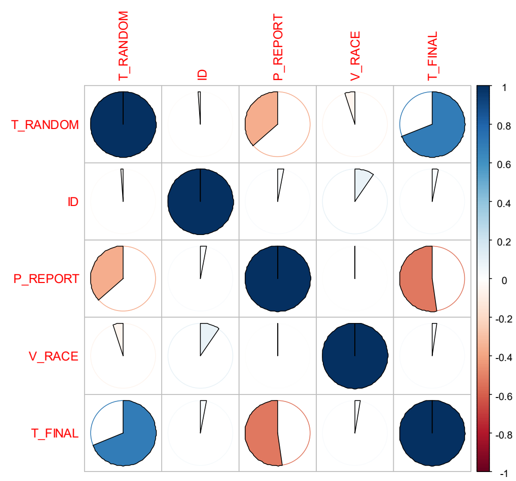
print(correlation_matrix)



2. **Explore the variables included in the dataset and its selection with the rationale and Find out the Instrumental Variable from the data and justify why this is an appropriate choice for an instrumental variable in your analysis.**

Predictor table:

Predictor	Effect	Rationale
DV: Health		
T_RANDOM	+/-	Type of police intervention may affect how safe or supported someone feels, influencing health.
P_REPORT	+/-	Whether someone reported the incident could be linked to stress or empowerment, affecting health.
V_RACE	+/-	Victim's race may be related to different experiences with support systems or health risks.
S_RACE	+/-	Suspect's race might reflect systemic differences in how cases are handled, influencing victim health.
V_CHEM	+/-	Victim's chemical use could directly impact their physical and mental health.
S_CHEM	+/-	Suspect's chemical use may lead to more severe incidents, affecting victim health.
S_DMNOR1	+/-	Past behavior or legal history of suspect could signal patterns that increase health risks.
S_DMNOR2	+/-	Similar to S_DMNOR1, could reflect behavioral patterns that affect safety or stress levels.
GUNS	+/-	Presence of guns can escalate violence and trauma, potentially harming health.
REASON1	+/-	The main reason for the incident might signal severity or type of trauma affecting health.
R_RELATE	+/-	The nature of the relationship may influence emotional or physical harm experienced.
Excluded: CLOCK, TIME, CCN, WEAPON, T_FINAL, REASON2, REASON3, REASON4, MONTH_YEAR		

3. **Compute and present descriptive statistics for key variables, paying special attention to the frequency of repeat incidents across different intervention groups.s**

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4.

 # If T_FINAL looks like it reflects repeated offenses (e.g., >1, or coded as yes/no)
repeat_summary <- data %>%
group_by(T_RANDOM, T_FINAL) %>%
summarise(count = n()) %>%
*mutate(percentage = round(100 * count / sum(count), 1))*

print(repeat_summary)

 # Cross-tabs with race
repeat_vrace <- table(data$V_RACE, data$T_FINAL)
print(repeat_vrace)

repeat_srace <- table(data$S_RACE, data$T_FINAL)

print(repeat_srace)

```
> table(data$T_FINAL)

  1   2   3   4
136  89  89  16
> table(data$P_REPORT)

  0   1
136 194
> # If T_FINAL looks like it reflects repeated offenses (e.g., >1, or coded as yes/no)
> repeat_summary <- data %>%
+   group_by(T_RANDOM, T_FINAL) %>%
+   summarise(count = n()) %>%
+   mutate(percentage = round(100 * count / sum(count), 1))
`summarise()` has grouped output by 'T_RANDOM'. You can override using the `.groups` argument.
> print(repeat_summary)
# A tibble: 11 x 4
# Groups:   T_RANDOM [3]
   T_RANDOM T_FINAL count percentage
   <fct>      <dbl> <int>      <dbl>
 1 1              1    91       97.8
 2 1              3     1        1.1
 3 1              4     1        1.1
 4 2              1    19       17.3
 5 2              2    84       76.4
 6 2              3     5        4.5
 7 2              4     2        1.8
 8 3              1    26       20.5
 9 3              2     5        3.9
10 3              3    83       65.4
11 3              4    13       10.2
> # Cross-tabs with race
> repeat_vrace <- table(data$V_RACE, data$T_FINAL)
> print(repeat_vrace)

     1  2  3  4
  1 77 57 49  8
  2 31 18 23  4
  3 26 11 16  3
  4  0  1  0  0
  5  2  1  0  1
  6  0  1  1  0
> repeat_srace <- table(data$S_RACE, data$T_FINAL)
> print(repeat_srace)

      1  2  3  4
  1  60 48 35  4
  2  49 28 34  6
  3  24 10 14  3
  4   0  1  1  0
  5   2  1  3  2
  6   0  0  1  0
  7   0  0  1  0
  NA  1  1  0  1
> T_FINAL
```

Descriptive summary of repeat incidents across different intervention groups (T_RANDOM), using T_FINAL as the proxy for repeat behavior. From the table, we see that in intervention group 1, most cases (91 out of 93) had a T_FINAL value of 1, suggesting a very low frequency of repeat incidents. In contrast, groups 2 and 3 show more variation, with higher T_FINAL values (2, 3, 4), indicating more frequent repeat incidents. The cross-tabulations with V_RACE and S_RACE show how repeat incidents (as measured by T_FINAL) vary by victim and suspect ethnicity. For example, victim race 1 has a relatively even spread across all T_FINAL values, whereas race 5 mostly had T_FINAL value 1, suggesting fewer repeat outcomes.

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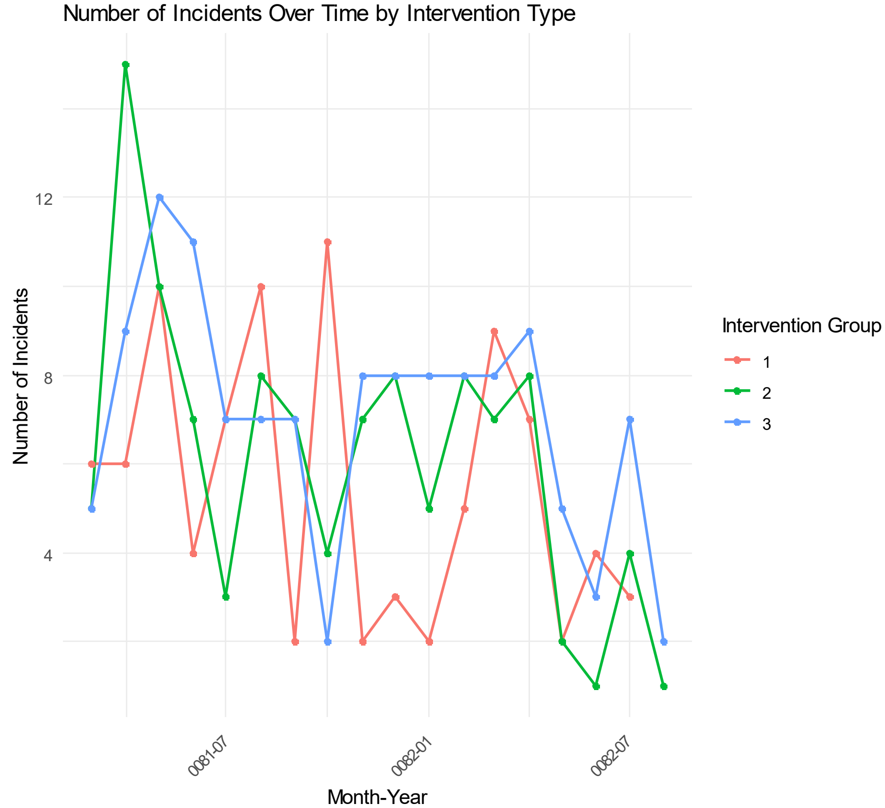
5. **Generate a line chart showing the number of incidents over time, segmented by the type of police intervention. Mark any significant changes or trends you observe.**



Analysis:

Conduct a Two-Stage Least Squares (2SLS) regression.

model_2sls <- ivreg(P_REPORT ~ T_FINAL + V_RACE + S_RACE +

V_CHEM + S_CHEM + S_DMNOR1 + S_DMNOR2 + WEAPON + GUNS +
REASON1 + REASON2 + REASON3 + REASON4 + R_RELATE |
T_RANDOM + V_RACE + S_RACE + V_CHEM + S_CHEM + S_DMNOR1 + S_DMNOR2 +
WEAPON + GUNS + REASON1 + REASON2 + REASON3 + REASON4 + R_RELATE,

data = data)

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6. **Evaluate the effectiveness of your chosen instrumental variable. Interpret the results.**

```
Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.54177    0.33340   1.625  0.10530
T_FINAL     -0.31066    0.03970  -7.825 1.07e-13 ***
V_RACE2     -0.06794    0.07662  -0.887  0.37602
V_RACE3     -0.02723    0.09058  -0.301  0.76392
V_RACE4      1.02086    0.85488   1.194  0.23343
V_RACE5     -0.38021    0.25565  -1.487  0.13808
V_RACE6     -0.79745    0.44510  -1.792  0.07428 .
S_RACE2      0.03920    0.07185   0.546  0.58584
S_RACE3      0.05425    0.09457   0.574  0.56672
S_RACE4     -0.18339    0.42855  -0.428  0.66904
S_RACE5      0.33212    0.18668   1.779  0.07631 .
S_RACE6     -0.06131    0.45631  -0.134  0.89321
S_RACE7      1.58132    0.61090   2.589  0.01015 *
S_RACENA     0.10905    0.26345   0.414  0.67926
V_CHEM1      0.04743    0.05677   0.835  0.40419
V_CHEMNA     0.05095    0.24235   0.210  0.83364
S_CHEM1      0.08965    0.05520   1.624  0.10549
S_CHEMNA    -0.22321    0.33890  -0.659  0.51067
S_DMNOR12   -0.00623    0.06114  -0.102  0.91892
S_DMNOR1NA   0.26125    0.17788   1.469  0.14305
S_DMNOR22    0.09187    0.06291   1.460  0.14535
S_DMNOR2NA   0.09906    0.12422   0.797  0.42589
WEAPON3      0.42341    0.30072   1.408  0.16025
WEAPON4      0.39690    0.30643   1.295  0.19632
WEAPON5      0.42677    0.31604   1.350  0.17800
WEAPON6     -0.15232    0.44625  -0.341  0.73310
WEAPON7      0.61774    0.32381   1.908  0.05746 .
WEAPON8      0.38520    0.66202   0.582  0.56114
WEAPONNA    -0.02421    0.52998  -0.046  0.96360
GUNS2       -0.14859    0.16914  -0.878  0.38044
GUNS3       -0.00212    0.11787  -0.018  0.98566
GUNSNA      -0.14311    0.08846  -1.618  0.10686
REASON12    -0.09350    0.17171  -0.545  0.58653
REASON13    -0.40505    0.30719  -1.319  0.18841
REASON14     0.19316    0.24879   0.776  0.43817
REASON15     0.09264    0.16008   0.579  0.56326
REASON16    -0.07570    0.35081  -0.216  0.82932
REASON17     0.20798    0.15220   1.367  0.17288
REASON18     0.20476    0.42383   0.483  0.62939
REASON19     0.27443    0.09530   2.880  0.00429 **
REASON1NA   -0.17803    0.20635  -0.863  0.38901
REASON24     0.40579    0.51794   0.783  0.43401
REASON25    -0.09628    0.48057  -0.200  0.84136
REASON27     0.24273    0.37777   0.643  0.52105
REASON28     0.13732    0.47800   0.287  0.77411
REASON29     0.24775    0.25972   0.954  0.34096
R_RELATE2    0.27439    0.11920   2.302  0.02208 *
R_RELATE4    0.34327    0.32962   1.041  0.29859
R_RELATE5    0.12203    0.12205   1.000  0.31824
R_RELATE6   -0.09978    0.13371  -0.746  0.45614
R_RELATE7   -0.31117    0.43815  -0.710  0.47818
R_RELATENA   0.09330    0.09351   0.998  0.31928
```

The Two-Stage Least Squares (2SLS) regression results show that the variable **T_FINAL** has a strong and statistically significant negative effect on the likelihood of a police report being filed, suggesting that higher final incident severity or outcomes are associated with lower reporting rates. Among the control variables, **S_RACE7**, **REASON19**, and **R_RELATE2** are also statistically significant, indicating that suspect race category 7, a specific reported reason for the incident, and a particular type of relationship between victim and suspect all play meaningful roles in explaining reporting behavior.