Estimating the causal effects of Krasner's tenure as District Attorney on criminal charges and other outcomes

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Introduction

Elected in November 2017, Philadelphia District Attorney Larry Krasner ran on a platform whose stated top priority was ending mass incarceration in Philadelphia [3]. A self-described progressive DA, Krasner's campaign promised, among other things, to stop prosecuting "insufficient and insignificant cases", to treat addiction as a public safety issue, and to work to stop pursuing extreme sentences [4] [1]. Running for re-election in 2021, Krasner's campaign proclaims a 40% decrease in the county jail population, reductions in sentence length, an end to charging marijuana possession cases, diversion of other drug possession cases to treatment, and a shifting of resources to solving serious crimes, particularly homicides and gun violence. [2]

We carry out an observational study to determine the effect of Krasner's tenure and policies as Philadelphia DA on the number of people charged for different types of offenses. Our primary source of data regarding arrests and charges comes from the Philadelphia District Attorney's Office, and includes counts of arrests and charges by categories of offenses from January 1, 2014 to present. In measuring the outcomes from cases subject to the treatment (being charged by Krasner's office), we restrict our focus to the period from June 1, 2018 (6 months after Krasner's election) to March 15, 2020 (prior to the start of the COVID-19 pandemic in Philadelphia). SAY MORE ABOUT DA SETH WILLIAMS HERE.

Both prior to and over the course of Krasner's tenure, the crime rate across various offenses, measured both by incidents reported by Philadelphia and nearby county police agencies to the FBI's Uniform Crime Reporting (UCR) Program and by police arrests reported by the DA's office, has varied substantially. Since the DA's office only enters the criminal justice process after an arrest has been made, we include arrest counts by date across a variety of offense categories among the covariates that we control over. We argue that the most substantial potential confounders effect the charge counts only through their effect on the number of arrests across various categories and that consequently, by controlling for arrests, we produce estimates of the causal effect of Krasner's tenure as DA on the number of charges brough for various offense types.

Since the arrest counts vary between our control group (offenses charged between January 2014 and June 2017) and treatment group (offenses charged between June 2018 and March 2015), we mitigate potential bias by employing matching as part of our preprocessing prior to estimating causal effects using linear regression. Our results consist of estimates of causal effects (together with confidence intervals) of Krasner's tenure as DA on the number of charges across the following categories: violent, property, drugs, firearms, other, and uncategorized. We adopt these groupings from those reported by the Philadelphia DA's Office and describe a further refinement of which offenses comprise each category in our description of the data below. We state our assumptions, conduct some sensitivity analyses, and conclude with a discussion of future work that could be carried out to improve our causal estimates.

Background on the criminal justice process in Philadelphia

The District Attorney's Office typically only gets involved in a case once an arrest has been made (by Philedelphia Police Department or other agency such that jurisdiction for prosecuting the case falls under

Philadelphia County). At the first stage of this process, the DA's office decides whether to bring charges and what charges to bring. Subsequently, bail is set by a Bail Magistrate, taking into account input from both the DA's office and the attorney for the defense. In some cases, instead of bringing charges, the DA's office can decide to divert a case into one of various diversionary programs. If charges are brought, a case proceeds through the judicial system to an outcome (verdict, guilty plea, dismissal, or withdrawal). One of the DA's many roles in this part of the process is making plea offers. After an outcome, the case proceeds to sentencing. The judge imposes a sentence with recommendations from the DAO. A single case may have many charges, and distinct charges may have different outcomes. Different outcomes subject to sentencing may receive different sentences, and these sentences may be imposed concurrently with others or consecutively.

In this document, we are presently interested in the part of the process that involves charges. Charges for offenses correpond to statutes in the Pennsylvania Criminal Law. The publicly availably data from the DAO that we will be using in our analysis counts only the most serious charge (subject to the most severe sentence) for each case. To help our analysis and interpretability, we group the possible charges into six groups based on the DAO's grouping of these charges on their website. These groups, and the kinds of charges that comprise them, are as follows:

- **Violent charges:** Homicide, Non-fatal shooting, Rape", Robbery with a gun, Robbery (other), Aggravated assault with a gun, Aggravated assault (other), Other assaults, Sexual assaults and other sex offenses
- **Property charges:** Residential burglary, Commercial burglary, Theft of motor vehicle tag, Theft from person, Theft from auto, Retail theft", Theft, Auto theft, Fraud Theft of Services, Embezzlement
- **Drug charges:** Drug possession, Drug sales, DUI
- **Firearms charges:** Illegal firearms possession
- **Other charges:** Prostitution or sex work, Patronizing prostitutes, Threats of violence
- **Uncategorized charges:** All other charges brough by the DAO that do not fall into the categories above.

In the "Exploratory.Rmd" file, we further investigate various frequencies within and between these categories.

The data

Source of data

The data we use in our observational study is publicly available and was downloaded on March 22, 2021 from the District Attorney's Office GitHub repository. [5] Specifically, we use the data frames consisting of counts of charges and of arrests by date, grouped by categories of offenses which are similar, but not identical to the FBI UCR Program categories of Type I and Type II crime.

NEED: more discussion here of how we count. look at DA website.

Our cleaning and preprocessing (described further in the Preprocessing.rmd file) included the following steps:

- Group offenses for charges and arrests into 6 groups (described further below): violent, property, drugs, firearms, other, and uncategorized. Calculate charge and arrest total in each of these categories.
- Subset the charge and arrest data frames on common values of date_value and merge them by date_value, keeping just the totals for each of the 6 categories.
- Filter to include only dates prior to 2017-06-29 and after 2018-06-01. Filter out dates after 2020-03-15 (to exclude judicial actions after the COVID-19 pandemic began effecting the Philadelphia courts). Create a binary treatment variable, assigning it to be fALSE for dates prior to when Krasner took office and TRUE for dates after. This produces the data frame "charges_all"
- We also reshape into a long data frame with columns date_value, type (arrest or chage), group (violent, property, drugs, firearms, other, or uncategorized) and the counts for each combination of the these. This data frame is called "charges_all_long" below.

We read in the resulting datasets and summarise.

```r
charges_all<-read.csv("charges_all.csv", row.names=1)
charges_all_long<-read.csv("charges_all_long.csv", row.names=1)
charges_all$date_value<-as.Date(charges_all$date_value)
charges_all_long$date_value<-as.Date(charges_all_long$date_value)

summary(charges_all)
```

```
##    date_value         arrests_violent arrests_property arrests_drugs
##  Min.   :2014-01-01   Min.   : 5.00   Min.   : 1.00    Min.   :  2.00
##  1st Qu.:2015-06-04   1st Qu.:20.00   1st Qu.:11.00    1st Qu.: 28.00
##  Median :2016-11-05   Median :24.00   Median :15.00    Median : 39.00
##  Mean   :2017-01-15   Mean   :25.39   Mean   :15.98    Mean   : 40.73
##  3rd Qu.:2018-10-11   3rd Qu.:30.00   3rd Qu.:20.00    3rd Qu.: 52.00
##  Max.   :2020-03-14   Max.   :88.00   Max.   :96.00    Max.   :125.00
##  arrests_firearms arrests_other    arrests_uncategorized charges_violent
##  Min.   : 0.000   Min.   : 0.000   Min.   : 3.00         Min.   : 6.00
##  1st Qu.: 2.000   1st Qu.: 1.000   1st Qu.:20.00         1st Qu.:20.00
##  Median : 3.000   Median : 3.000   Median :25.00         Median :25.00
##  Mean   : 3.478   Mean   : 3.565   Mean   :25.01         Mean   :26.24
##  3rd Qu.: 5.000   3rd Qu.: 5.000   3rd Qu.:30.00         3rd Qu.:31.50
##  Max.   :22.000   Max.   :24.000   Max.   :51.00         Max.   :94.00
##  charges_property charges_drugs    charges_firearms charges_other
##  Min.   :  1.00   Min.   :  2.00   Min.   : 0.000   Min.   : 0.000
##  1st Qu.: 11.00   1st Qu.: 26.00   1st Qu.: 2.000   1st Qu.: 1.000
##  Median : 15.00   Median : 38.00   Median : 3.000   Median : 2.000
##  Mean   : 16.46   Mean   : 39.59   Mean   : 3.408   Mean   : 3.195
##  3rd Qu.: 20.00   3rd Qu.: 52.00   3rd Qu.: 5.000   3rd Qu.: 5.000
##  Max.   :147.00   Max.   :114.00   Max.   :17.000   Max.   :38.000
##  charges_uncategorized treatment
##  Min.   : 1.00         Mode :logical
##  1st Qu.: 8.00         FALSE:1275
##  Median :11.00         TRUE :804
##  Mean   :11.84
##  3rd Qu.:15.00
##  Max.   :52.00
```

Observational study design

We set up our observational study such that a single unit consists of a day on which criminal charges in the Philadelphia Municipal Court or Common Pleas court could be brought within a specified range of dates.

Treatment

Given a unit in our study–a day with with a collection of criminal cases that receive potential charges–we define the treatment to be having the cases that day charged by the DA's office under Krasner. The control is having the cases that day charged by the office of Krasner's predecessor, former DA Seth Williams.

Note that our treatment is defined somewhat narrowly, and in particular, the treatment does not include other actions or conditions during Krasner's tenure as head of the DAO, even those initiated by the DAO. Our treatment is strictly defined whether Krasner's office charges the cases on a given day. See the Assumptions section for further discussion of this.

Also note that we are not studying the causal effect of Krasner himself but the effect of the entire DAO under Krasner's leadership (as opposed to the control of the DAO under Williams' leadership). We view the treatment as binary (see the Discussion section for more on this).

Outcomes

As discussed above, we group offenses into six groups (violent, property, drugs, firearms, other, and uncategorized). Our outcomes of interest are, for each offense type, the number of cases in which a charge of that type was brought as the most serious charge in that case. We measure outcomes as a difference in means between treatment and control group as well as a percent change relative to the control group mean.

Covariates

The number of charges on a given day, by category, is caused by a number of factors: the number of criminal incidents in previous weeks, the number of arrests, policing practices such as gathering of evidence and writing reports, criminal law (local, state, and federal), criminal records of defendants, police department policies, and DA office policy and practice regarding charges. The DAO is the final actor in a complicated process.

For most of the covariates that come prior to the DAO's role in the process, their effect on our outcomes of interest (mean daily charges by offense category) is indirect and goes through the number of arrests. For instance, policy department policies regarding whether to make arrests for a given type of offense and how actively to pursue enforcing it will only effect charges through the number of arrests made for that type of offense. Thus, our covariates consist of daily arrest totals by offense category. By conditioning on these, we remove confounding by many of the factors mentioned above.

Assumptions

We assume stable unit treatment values (SUTVA); that is, we assume that the outcomes of one unit (that is, the count of most serious charges in cases from one day by type) do not vary with the treatments assigned to other units. In other words, given a day, the charge counts from that day do not vary depending on whether the cases from a different day were charged pre or post Krasner's tenure as DA. This assumption could be violated in the case of reoffenders if the past criminal record of a defendant had an effect on the sorts of charges that were brought in their case. We assume that the effect of such instances is negligible, though a data set that contained information on reoffenders would lead to a more refined analysis.

As defined above, we also assume that there is only one form of the treatment. This assumption would be violated if during Krasner's tenure as DA, the DAO changed its policies or practices in charging certain kinds of cases. This would be particularly of concern in the first few months of Krasner's tenure as DA when big changes occured in the DAO (for instance, 31 staffers, including prosecutors, left the DAO in the first week of Krasner's tenure). We address this assumption further and conduct a sensitivity analysis in the Discussion section of this document.

We assume that unobserved confounders have negligible impact on our estimates. Unobserved confounders that are of potential concern are ones that have a direct effect on charge counts that does not pass through arrest counts. These could include quality of policy reports and evidence-gathering, prior criminal records of defendants, defendant demographics, and local, state, or federal policies regarding charges for certain types of offenses. Our data does not allow us to measure many of these. We address how robust our analysis is to their impact through sensitivity analyses in the Discussion section below.

Finally, we assume there is no post-treatment bias; that is, the distribution of arrest counts does not vary with treatment assignment. At first glance, days charged during Krasner's tenure as DA have a different distribution of arrests from days charged prior to Krasner's tenure as DA. However, we recall that our definition of treatment is quite narrow: we say that a unit (day) in our study has received the treatment if the cases on that day were charged by Krasner's office, and a unit has received the control if the cases were charged by Williams' office. In particular, our definition of treatment does not include any actions by the DAO or anyone else that effect arrests: for each individual unit, arrest counts are pre-treatment covariates and are uneffected by the treatment assignment. While the DAO could very well have a causal effect on arrest counts by, for instance, instituting a policy of not charging certain kinds of offenses causing the police not to make arrests for those offenses, this kind of action of the DAO does not fall within our definition of treatment, and so is not measured by our causal estimates. We are simply measuring the effect of Krasner's DAO on charging the arrests they are given. Any other effects of the DAO on charges are outside the scope of our study.

Outline of analysis

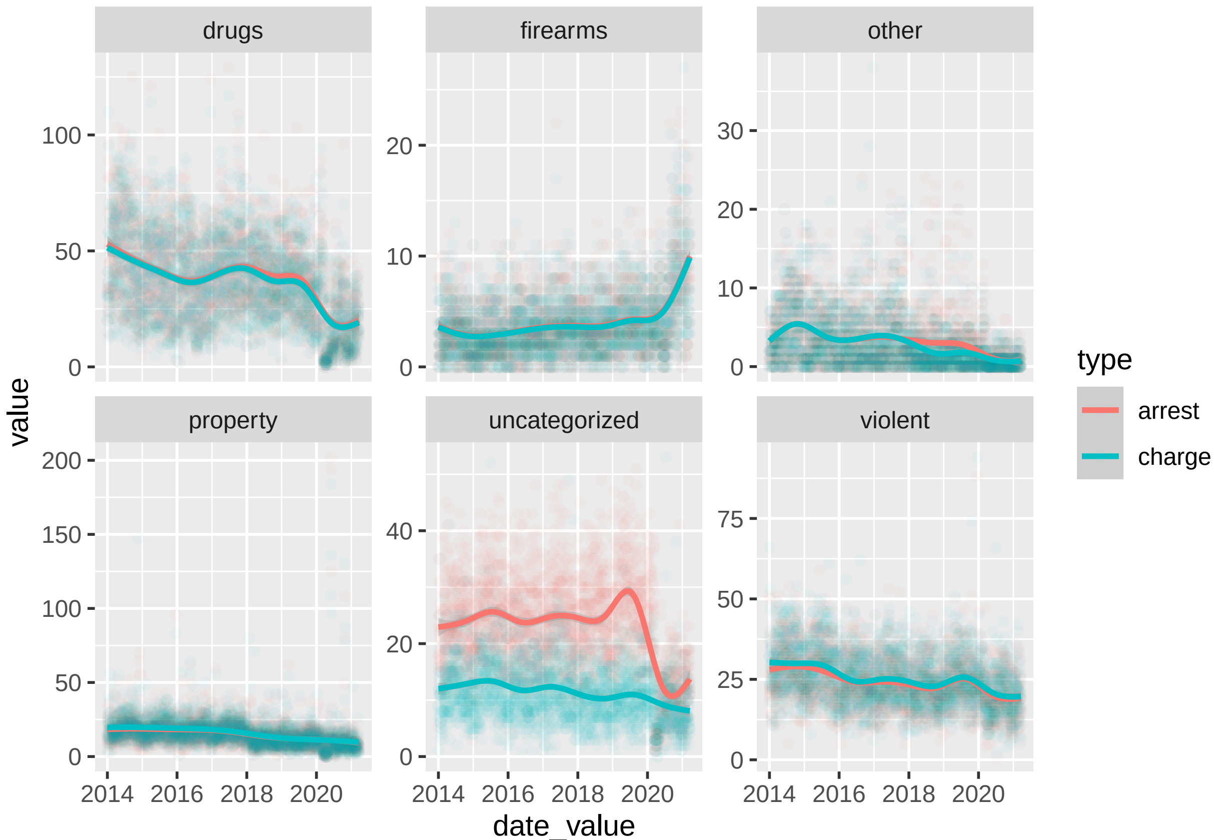
Our method of analysis will be to use a linear regression to estimate the treatment effect on charge counts by type regressing on covariates giving arrest counts by type. In order to ensure that the arrest count covariates are similarly distributed between the treatment and control groups, we implement nearest-neighbor matching with calipers (further discussed below). Upon achieving our desired balance, we fit a linear model to the matched data to estimate the desired causal effects.

Summary of trends in the data

Before we conduct our analysis, we begin by presenting some summaries of our data. First, we show the counts for charges and arrests by type. For this chart, we use a version of the charges_all_long data frame in which the dates between 2017-06-29 and 2018-01-01 and the dates after 2020-03-25 have not been excluded.

```
all_dates_long<-read.csv("charges_all_long_full.csv", row.names=1)
all_dates_long$date_value<-as.Date(all_dates_long$date_value)

ggplot(data=all_dates_long, aes(x=date_value, y=value, col=type))+
  geom_point(alpha=0.03)+
  geom_smooth()+
  facet_wrap(~group, scale="free_y")
```

```
## `geom_smooth()` using method = 'gam' and formula 'y ~ s(x, bs = "cs")'
```



WRITE MORE ABOUT THE DROP IN UNCATEGORIZED–COMPARE TO CATEGORIES OF PART I and PART II CRIME.

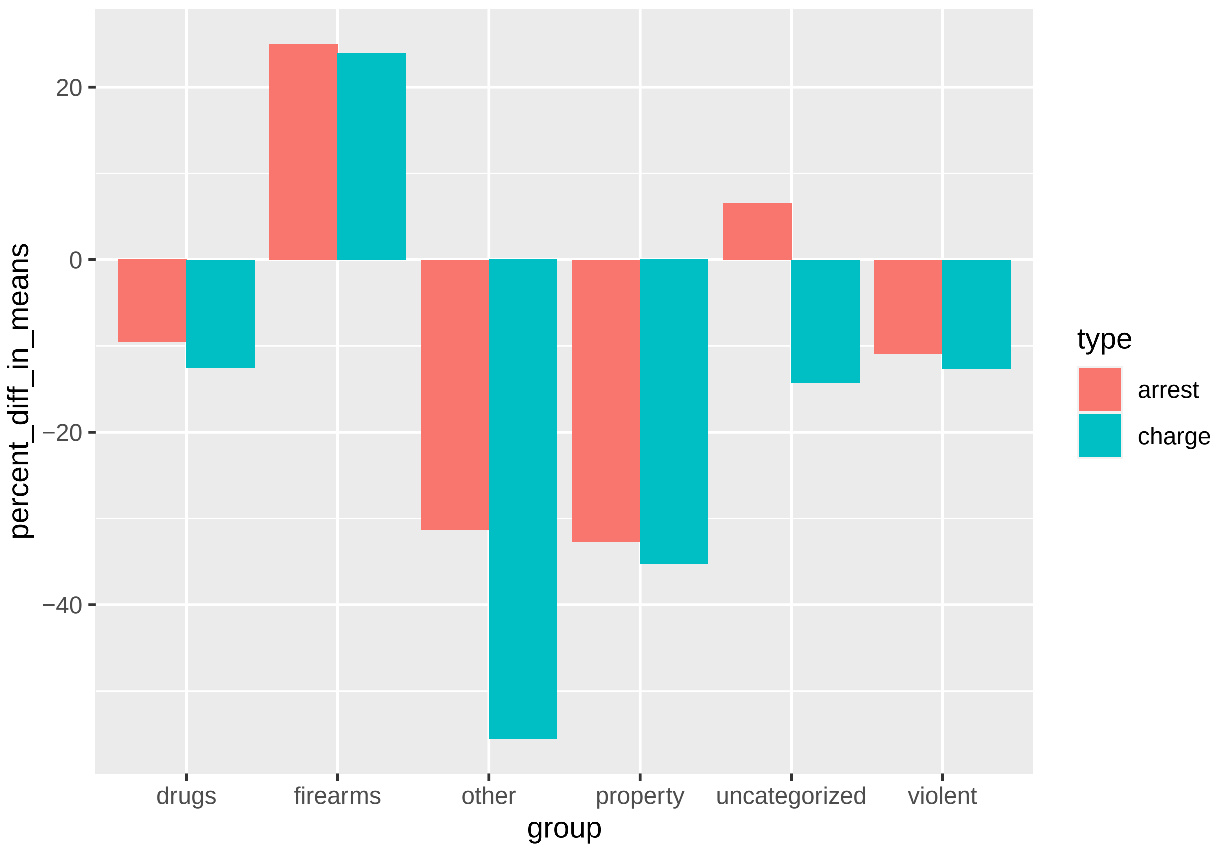
Next, we restrict our focus to the time periods of our control group (2014-01-01 to 2017-06-29) and our treatment group (2018-01-01 to 2020-03-15) and show the control and treatment means for arrests and charges by type, along with the percent in change from the control mean.

```
charges_all_long$treatment<-charges_all_long$date_value>="2018-01-01"
means<-charges_all_long %>%
  group_by(treatment, type, group) %>%
  summarise(mean=mean(value)) %>%
  dcast(group+type~treatment, value.var="mean")

colnames(means)[3:4]<-c("control", "treatment")
means$diff_in_means<-means$treatment-means$control
means$percent_diff_in_means<-100*means$diff_in_means/means$control
##differences in means of charges
charge_diffs<-means %>%
  filter(type=="charge") %>%
  select("group", "diff_in_means", "percent_diff_in_means")

charge_diffs
```

```
##          group diff_in_means percent_diff_in_means
## 1        drugs     -5.203693             -12.50911
## 2     firearms      0.746456              23.93089
## 3        other     -2.259318             -55.52488
## 4     property     -6.717053             -35.25250
```

```
## 5 uncategorized     -1.782953              -14.23460
## 6       violent     -3.501361              -12.68970
```

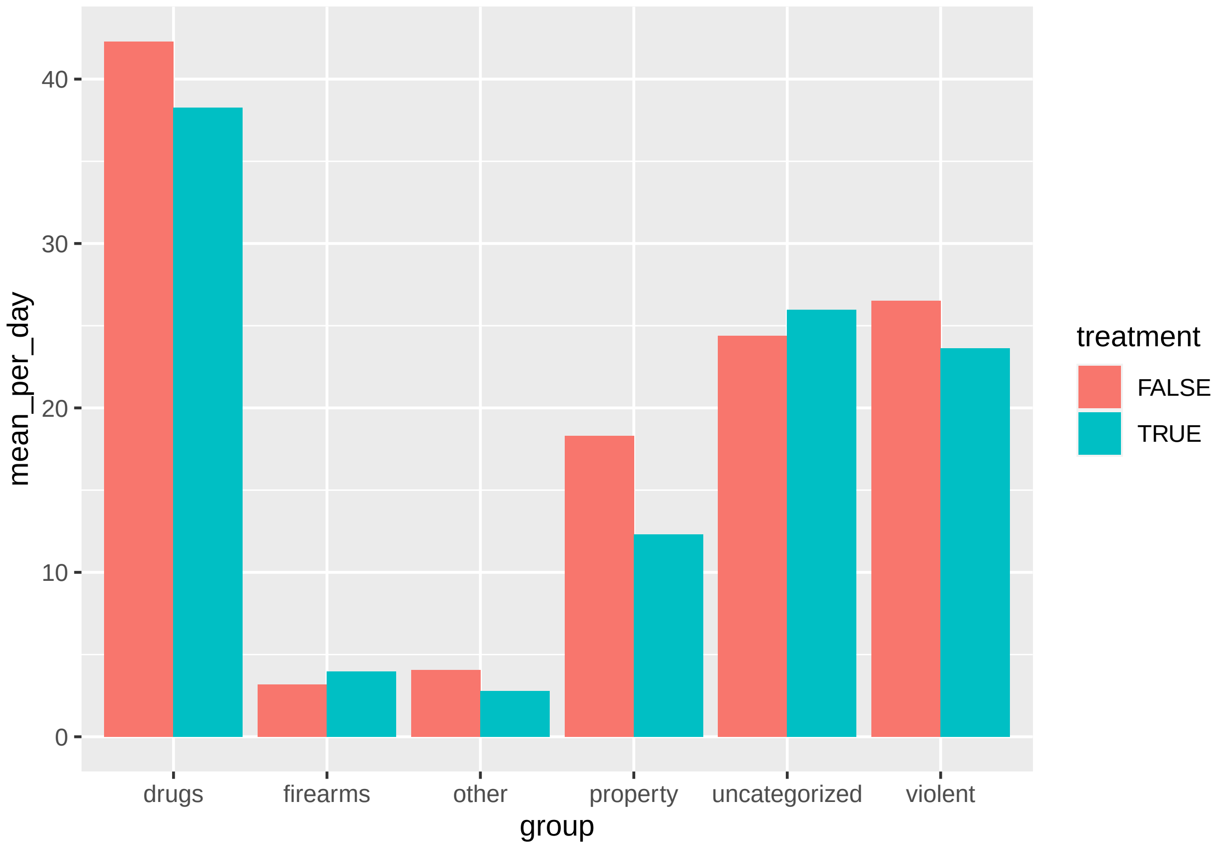
```
ggplot(data=means, aes(x=group, y=percent_diff_in_means, fill=type))+
  geom_bar(position="dodge", stat="identity")
```



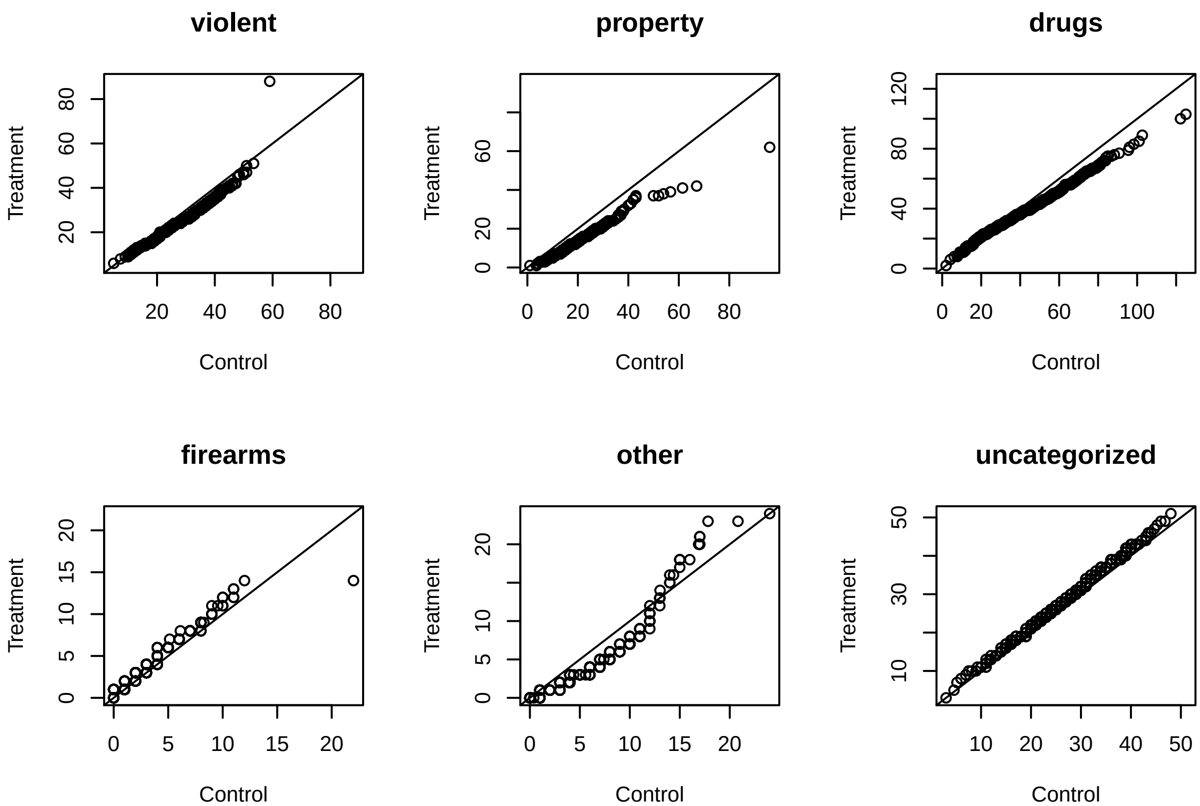
Matching

Our causal effect estimates will come from fitting a linear model, controlling for arrest count covariates for each of our six types of offenses. Before fitting the model, in this section we employ matching to account for imbalance of covariates in our treatment and control groups. First, here is a plot of the distributions of mean arrest counts by type, along with a QQ plot for each plot:

```
arrest_count_sum<-charges_all_long %>%
  filter(type=="arrest") %>%
  group_by(group, treatment) %>%
  summarise(mean_per_day=mean(value))

ggplot(data=arrest_count_sum, aes(x=group, y=mean_per_day, fill=treatment))+
  geom_bar(position="dodge", stat="identity")
```




```r
##Construct data with empirical quantiles for control and treatment groups

par(mfrow=c(2,3))
for (g in unique(charges_all_long$group))
{
  x<-filter(charges_all_long, type=="arrest", group==g, !treatment)$value
  y<-filter(charges_all_long, type=="arrest", group==g, treatment)$value
  qqplot(x, y, main=g,
  xlab="Control",
  ylab="Treatment",
  xlim=c(min(x, y), max(x, y)),
  ylim=c(min(x, y), max(x, y)))
  abline(0,1)
}
```




```
#mtext("QQ plots for mean daily arrest counts by offense group", outer=TRUE,side=3,line=0, cex=1.5)
```

We see imbalance for some of the arrest types, particularly property, drugs, and other.

To address this imbalance, we implementing matching on propensity scores. Following [6] and appealing to the "propensity score tautology", our sole concern is achieving balance on the covariates, and so whatever matching method we implement that yields our desired level of balance will do the job. We experimented with a variety of matching methods (further detailed in the "Matching.Rmd" document), and we found there to be somewhat of a tradeoff between sample sizes of matched data and balance. For example, using subclassification matching with 6 classes, we were able to get good balance, but at the expense of one of the subclasses having as few as 19 control units.

We ended up settling on variable ratio nearest-neighbor matching with calipers of size 0.1 (standard deviations of the propensity scores within which to draw matches). Since the higher end of the propensity score distribution was overrepresented in the treatment group, the price we paid for our balance was about 31% of our treated observations going unmatched. DISCUSSION WHY THIS IS OK. We conduct further sensitivity analyses and argue that our analysis is robust to this choice in the Discussion section below.

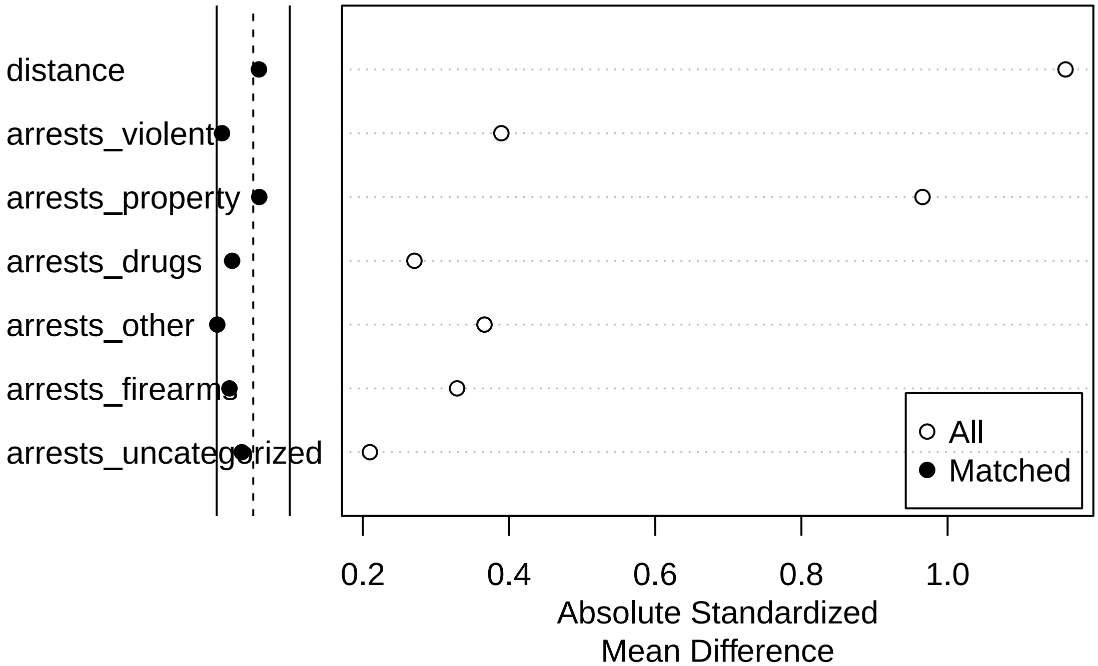
Here we print the summary of our matching method and a few plots that demonstrate balance.

```
mcal1.out<-matchit(treatment~arrests_violent+arrests_property+arrests_drugs+arrests_other+arrests_firea
scal1.out <- summary(mcal1.out, standardize = TRUE)
scal1.out
```

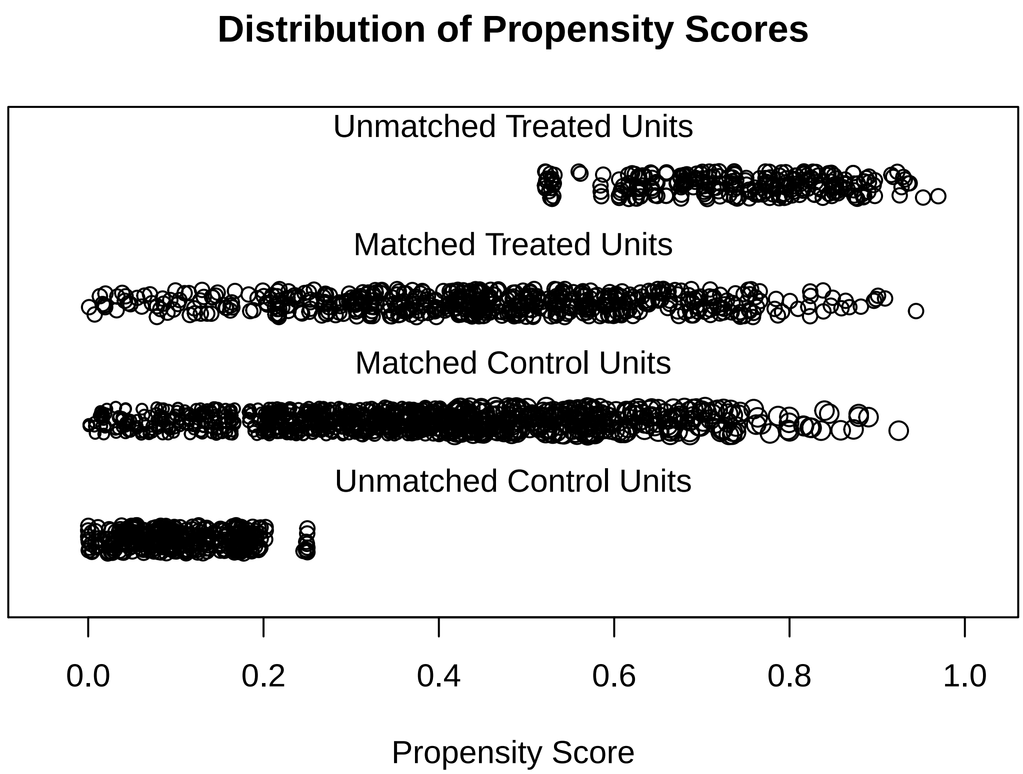
```
##
## Call:
## matchit(formula = treatment ~ arrests_violent + arrests_property +
##     arrests_drugs + arrests_other + arrests_firearms + arrests_uncategorized,
##     data = charges_all, method = "nearest", caliper = 0.1, ratio = 1275/804,
##     min.controls = 1, max.controls = 3)
##
```

```
## Summary of Balance for All Data:
##                        Means Treated Means Control Std. Mean Diff. Var. Ratio
## distance                      0.5432        0.2880          1.1614     1.2204
## arrests_violent              23.6231       26.5059         -0.3895     0.8310
## arrests_property             12.3122       18.3004         -0.9657     0.6218
## arrests_drugs                38.2624       42.2847         -0.2705     0.6301
## arrests_other                 2.7873        4.0549         -0.3664     0.8886
## arrests_firearms              3.9639        3.1710          0.3289     1.1302
## arrests_uncategorized        25.9801       24.3937          0.2096     1.1008
##                        eCDF Mean eCDF Max
## distance                  0.3013   0.4819
## arrests_violent           0.0585   0.1692
## arrests_property          0.1113   0.3838
## arrests_drugs             0.0445   0.1427
## arrests_other             0.0573   0.1924
## arrests_firearms          0.0500   0.1591
## arrests_uncategorized     0.0330   0.0988
##
##
## Summary of Balance for Matched Data:
##                        Means Treated Means Control Std. Mean Diff. Var. Ratio
## distance                      0.4517        0.4390          0.0578     1.0869
## arrests_violent              24.5154       24.4619          0.0072     1.0359
## arrests_property             13.9673       14.3285         -0.0582     1.2431
## arrests_drugs                39.5608       39.2465          0.0211     0.7711
## arrests_other                 3.1924        3.1951         -0.0008     1.4480
## arrests_firearms              3.5590        3.6010         -0.0174     0.7509
## arrests_uncategorized        25.2686       25.0091          0.0343     0.9290
##                        eCDF Mean eCDF Max Std. Pair Dist.
## distance                  0.0136   0.0563          0.0416
## arrests_violent           0.0096   0.0387          1.0887
## arrests_property          0.0117   0.0538          0.6803
## arrests_drugs             0.0210   0.0696          1.2609
## arrests_other             0.0173   0.0466          1.0641
## arrests_firearms          0.0134   0.0517          0.9621
## arrests_uncategorized     0.0084   0.0321          1.0662
##
## Percent Balance Improvement:
##                        Std. Mean Diff. Var. Ratio eCDF Mean eCDF Max
## distance                          95.0       58.2      95.5     88.3
## arrests_violent                   98.1       81.0      83.6     77.1
## arrests_property                  94.0       54.2      89.4     86.0
## arrests_drugs                     92.2       43.7      52.9     51.3
## arrests_other                     99.8     -213.5      69.8     75.8
## arrests_firearms                  94.7     -134.0      73.2     67.5
## arrests_uncategorized             83.6       23.4      74.7     67.5
##
## Sample Sizes:
##                Control Treated
## All            1275.       804
## Matched (ESS)   733.04     551
## Matched         920.       551
## Unmatched       355.       253
## Discarded         0.         0
```

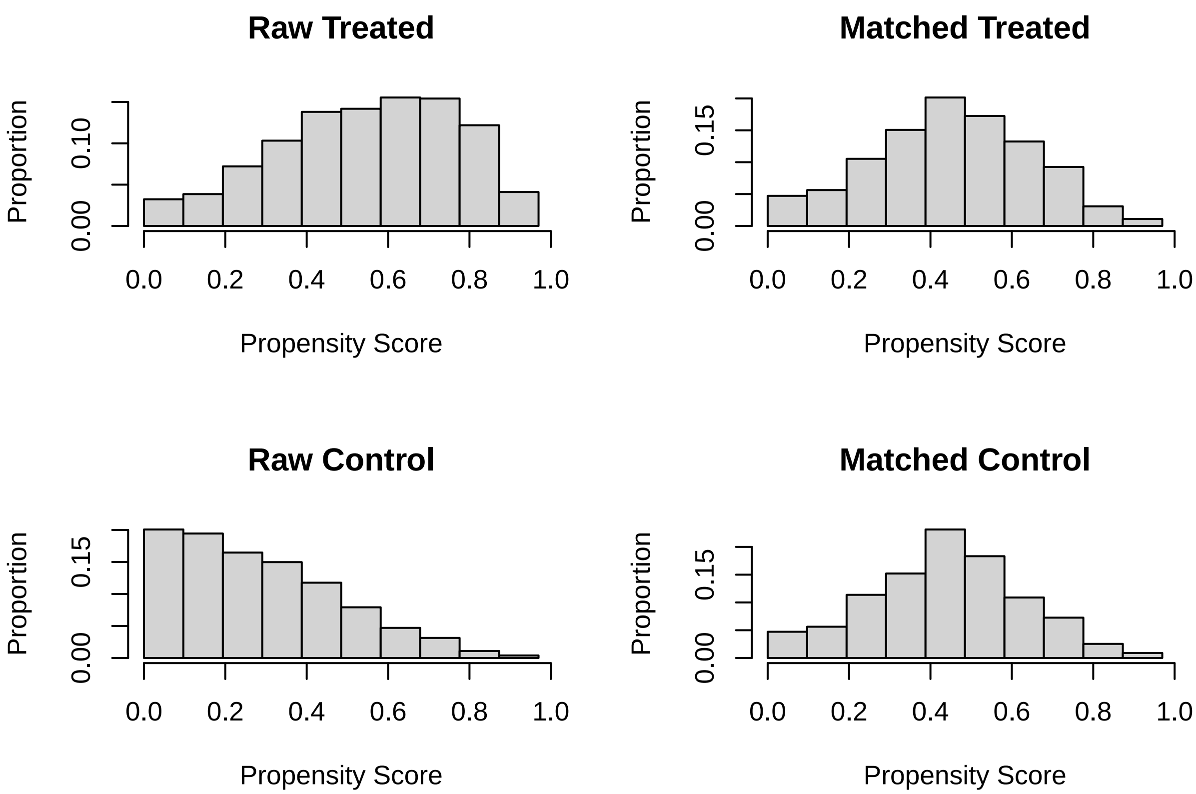
```r
plot(scal1.out)
```



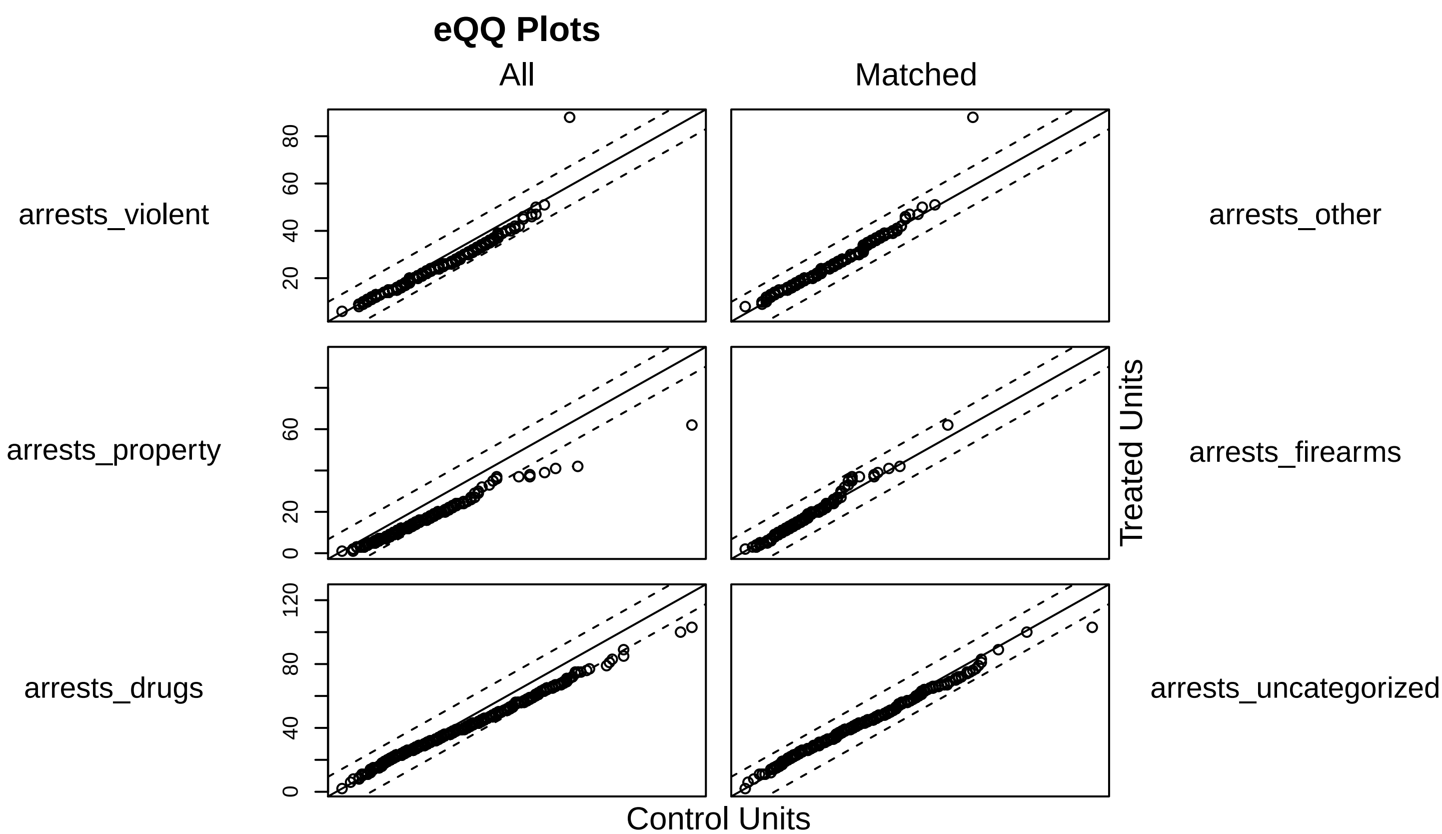

```r
plot(mcal1.out,  type = "jitter", interactive = FALSE)
```




```r
plot(mcal1.out,  type = "hist")
```




```
plot(mcal1.out, type="qq")
```



```r
matched_data2<-match.data(mcal1.out)
```

Fitting a linear model

Now that we have achieved balance between treatment and control groups, we fit a linear model to the data. For each outcome of interest (charge counts for each of the 6 offense groups), we regress on the binary treatment variable and the arrest counts for each of the 6 offense groups.

We print the summary of each linear model below.

```r
lm_violent.out<-lm(charges_violent~treatment+arrests_violent+arrests_property+arrests_drugs+arrests_fir
#x.out <- setx(z.out, data = match.data(m.out), fn = NULL, cond = TRUE)
#s.out <- sim(z.out, x = x.out)
summary(lm_violent.out)
```

```
##
## Call:
## lm(formula = charges_violent ~ treatment + arrests_violent +
##     arrests_property + arrests_drugs + arrests_firearms + arrests_other +
##     arrests_uncategorized, data = matched_data2)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -39.165  -4.617  -0.549   4.075  67.559
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)            9.59362    0.85559  11.213  < 2e-16 ***
## treatmentTRUE         -1.63853    0.38494  -4.257 2.21e-05 ***
## arrests_violent        0.53249    0.02490  21.384  < 2e-16 ***
## arrests_property       0.04125    0.03019   1.366  0.17204
## arrests_drugs          0.02994    0.01287   2.326  0.02013 *
## arrests_firearms      -0.09221    0.08413  -1.096  0.27326
## arrests_other          0.16001    0.05885   2.719  0.00663 **
## arrests_uncategorized  0.06408    0.02862   2.239  0.02531 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.996 on 1463 degrees of freedom
## Multiple R-squared:  0.3186, Adjusted R-squared:  0.3153
## F-statistic: 97.72 on 7 and 1463 DF,  p-value: < 2.2e-16
```

```r
lm_property.out<-lm(charges_property~treatment+arrests_violent+arrests_property+arrests_drugs+arrests_f
#x.out <- setx(z.out, data = match.data(m.out), fn = NULL, cond = TRUE)
#s.out <- sim(z.out, x = x.out)
summary(lm_property.out)
```

```
##
## Call:
## lm(formula = charges_property ~ treatment + arrests_violent +
##     arrests_property + arrests_drugs + arrests_firearms + arrests_other +
##     arrests_uncategorized, data = matched_data2)
##
## Residuals:
```

```
##     Min      1Q  Median      3Q     Max
## -24.592  -3.595  -0.865   2.495 128.375
##
## Coefficients:
##                          Estimate Std. Error t value Pr(>|t|)
## (Intercept)              7.404964   0.873176   8.480  < 2e-16 ***
## treatmentTRUE           -2.964401   0.392853  -7.546 7.86e-14 ***
## arrests_violent          0.028109   0.025413   1.106 0.268875
## arrests_property         0.511002   0.030813  16.584  < 2e-16 ***
## arrests_drugs            0.008959   0.013132   0.682 0.495209
## arrests_firearms         0.084886   0.085863   0.989 0.323009
## arrests_other            0.206995   0.060064   3.446 0.000585 ***
## arrests_uncategorized    0.007616   0.029211   0.261 0.794347
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7.14 on 1463 degrees of freedom
## Multiple R-squared:  0.2496, Adjusted R-squared:  0.246
## F-statistic: 69.51 on 7 and 1463 DF,  p-value: < 2.2e-16
```

```
lm_drugs.out<-lm(charges_drugs~treatment+arrests_violent+arrests_property+arrests_drugs+arrests_firearms
#x.out <- setx(z.out, data = match.data(m.out), fn = NULL, cond = TRUE)
#s.out <- sim(z.out, x = x.out)
summary(lm_drugs.out)
```

```
##
## Call:
## lm(formula = charges_drugs ~ treatment + arrests_violent + arrests_property +
##     arrests_drugs + arrests_firearms + arrests_other + arrests_uncategorized,
##     data = matched_data2)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -52.187  -6.793  -0.513   6.180  81.278
##
## Coefficients:
##                         Estimate Std. Error t value Pr(>|t|)
## (Intercept)             10.60379    1.30873   8.102 1.13e-15 ***
## treatmentTRUE           -3.47140    0.58882  -5.896 4.63e-09 ***
## arrests_violent         -0.10307    0.03809  -2.706  0.00689 **
## arrests_property        -0.13375    0.04618  -2.896  0.00383 **
## arrests_drugs            0.81671    0.01968  41.494  < 2e-16 ***
## arrests_firearms         0.07805    0.12869   0.607  0.54427
## arrests_other           -0.07792    0.09002  -0.866  0.38690
## arrests_uncategorized    0.07685    0.04378   1.755  0.07941 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 10.7 on 1463 degrees of freedom
## Multiple R-squared:  0.6365, Adjusted R-squared:  0.6348
## F-statistic:   366 on 7 and 1463 DF,  p-value: < 2.2e-16
```

```
lm_firearms.out<-lm(charges_firearms~treatment+arrests_violent+arrests_property+arrests_drugs+arrests_fi
#x.out <- setx(z.out, data = match.data(m.out), fn = NULL, cond = TRUE)
#s.out <- sim(z.out, x = x.out)
```

```r
summary(lm_firearms.out)
```

```
##
## Call:
## lm(formula = charges_firearms ~ treatment + arrests_violent +
##     arrests_property + arrests_drugs + arrests_firearms + arrests_other +
##     arrests_uncategorized, data = matched_data2)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -9.7864 -1.0336 -0.1855  0.8962 14.3359
##
## Coefficients:
##                         Estimate Std. Error t value Pr(>|t|)
## (Intercept)            0.5660635  0.1998225   2.833  0.00468 **
## treatmentTRUE          0.2494747  0.0899027   2.775  0.00559 **
## arrests_violent       -0.0007096  0.0058156  -0.122  0.90290
## arrests_property      -0.0080548  0.0070515  -1.142  0.25352
## arrests_drugs          0.0164700  0.0030052   5.480 4.99e-08 ***
## arrests_firearms       0.6403571  0.0196494  32.589  < 2e-16 ***
## arrests_other         -0.0121206  0.0137454  -0.882  0.37803
## arrests_uncategorized -0.0001594  0.0066847  -0.024  0.98098
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.634 on 1463 degrees of freedom
## Multiple R-squared:  0.4761, Adjusted R-squared:  0.4735
## F-statistic: 189.9 on 7 and 1463 DF,  p-value: < 2.2e-16
```

```r
lm_other.out<-lm(charges_other~treatment+arrests_violent+arrests_property+arrests_drugs+arrests_firearms
#x.out <- setx(z.out, data = match.data(m.out), fn = NULL, cond = TRUE)
#s.out <- sim(z.out, x = x.out)
summary(lm_other.out)
```

```
##
## Call:
## lm(formula = charges_other ~ treatment + arrests_violent + arrests_property +
##     arrests_drugs + arrests_firearms + arrests_other + arrests_uncategorized,
##     data = matched_data2)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -11.9232  -1.0897  -0.0776   0.8453  11.2408
##
## Coefficients:
##                         Estimate Std. Error t value Pr(>|t|)
## (Intercept)            8.144e-01  2.401e-01   3.392 0.000713 ***
## treatmentTRUE         -1.417e+00  1.080e-01 -13.118  < 2e-16 ***
## arrests_violent        5.569e-03  6.989e-03   0.797 0.425638
## arrests_property       4.930e-05  8.474e-03   0.006 0.995359
## arrests_drugs          8.846e-03  3.611e-03   2.450 0.014420 *
## arrests_firearms       6.420e-03  2.361e-02   0.272 0.785748
## arrests_other          6.488e-01  1.652e-02  39.279  < 2e-16 ***
## arrests_uncategorized -8.317e-05  8.033e-03  -0.010 0.991741
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.964 on 1463 degrees of freedom
## Multiple R-squared:  0.6216, Adjusted R-squared:  0.6198
## F-statistic: 343.3 on 7 and 1463 DF,  p-value: < 2.2e-16
```

```
lm_uncategorized.out<-lm(charges_uncategorized~treatment+arrests_violent+arrests_property+arrests_drugs+
#x.out <- setx(z.out, data = match.data(m.out), fn = NULL, cond = TRUE)
#s.out <- sim(z.out, x = x.out)
summary(lm_uncategorized.out)
```

```
##
## Call:
## lm(formula = charges_uncategorized ~ treatment + arrests_violent +
##     arrests_property + arrests_drugs + arrests_firearms + arrests_other +
##     arrests_uncategorized, data = matched_data2)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -12.3517  -2.7661  -0.1735   2.4598  25.2811
##
## Coefficients:
##                        Estimate Std. Error t value Pr(>|t|)
## (Intercept)            3.918599   0.522517   7.499 1.11e-13 ***
## treatmentTRUE         -2.317618   0.235087  -9.859  < 2e-16 ***
## arrests_violent        0.009724   0.015207   0.639   0.5226
## arrests_property      -0.033801   0.018439  -1.833   0.0670 .
## arrests_drugs          0.015449   0.007858   1.966   0.0495 *
## arrests_firearms       0.106041   0.051381   2.064   0.0392 *
## arrests_other         -0.020480   0.035943  -0.570   0.5689
## arrests_uncategorized  0.322270   0.017480  18.437  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.273 on 1463 degrees of freedom
## Multiple R-squared:  0.2874, Adjusted R-squared:  0.284
## F-statistic: 84.28 on 7 and 1463 DF,  p-value: < 2.2e-16
```

Results: summary of estimated causal effects

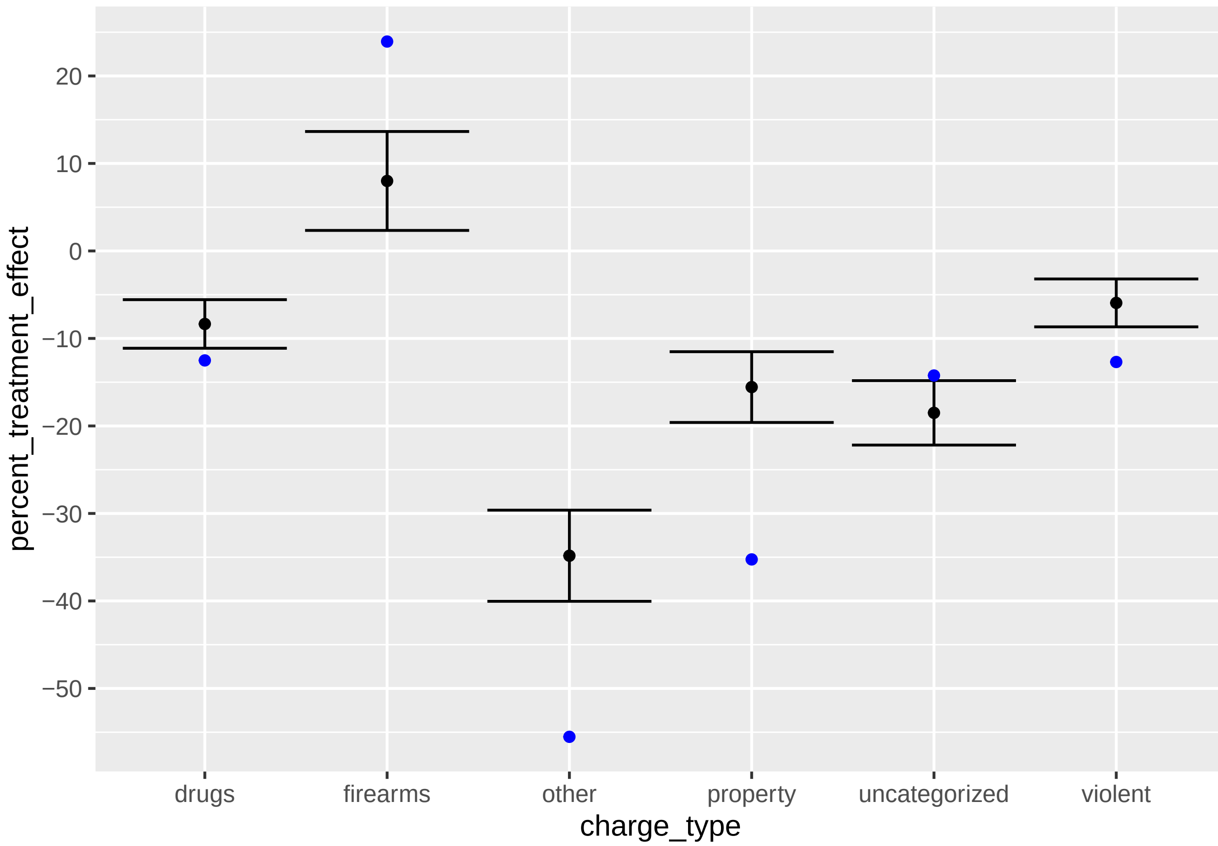
In the table below, we summarise our estimated causal effect for each offense group. We report the mean effect as well as the 95% confidence interval in both absolute counts and as percent change relative to the control mean.

```
charge_type<-c("violent", "property", "drugs", "firearms", "other", "uncategorized")
effect_sum<-as.data.frame(charge_type)
effect_sum[,"treatment_effect"]<-
  rbind(lm_violent.out$coefficients["treatmentTRUE"],
    lm_property.out$coefficients["treatmentTRUE"],
    lm_drugs.out$coefficients["treatmentTRUE"],
    lm_firearms.out$coefficients["treatmentTRUE"],
    lm_other.out$coefficients["treatmentTRUE"],
    lm_uncategorized.out$coefficients["treatmentTRUE"])
```

```r
effect_sum<-cbind(effect_sum,
  rbind(confint(lm_violent.out)["treatmentTRUE",],
    confint(lm_property.out)["treatmentTRUE",],
    confint(lm_drugs.out)["treatmentTRUE",],
    confint(lm_firearms.out)["treatmentTRUE",],
    confint(lm_other.out)["treatmentTRUE",],
    confint(lm_uncategorized.out)["treatmentTRUE",]))

colnames(effect_sum)[3:4]<-c("confmin", "confmax")

effect_sum<-cbind(effect_sum,
                  100*effect_sum[,c("treatment_effect","confmin", "confmax")]/
                    filter(means, type=="charge")[c(6, 4, 1, 2, 3, 5),"control"])

colnames(effect_sum)[5:7]<-c("percent_treatment_effect", "percent_confmin", "percent_confmax")
effect_sum
```

```
##     charge_type treatmentTRUE     confmin    confmax percent_treatment_effect
## 1       violent    -1.6385268 -2.39362098 -0.8834327                -5.938379
## 2      property    -2.9644006 -3.73501604 -2.1937852               -15.557795
## 3         drugs    -3.4713957 -4.62640890 -2.3163826                -8.344859
## 4      firearms     0.2494747  0.07312272  0.4258266                 7.997993
## 5         other    -1.4172731 -1.62920024 -1.2053459               -34.830825
## 6 uncategorized    -2.3176179 -2.77876126 -1.8564745               -18.503211
##   percent_confmin percent_confmax
## 1       -8.675005       -3.201753
## 2      -19.602146      -11.513444
## 3      -11.121385       -5.568332
## 4        2.344266       13.651720
## 5      -40.039135      -29.622515
## 6      -22.184850      -14.821572
```

```r
#charge_diffs

effect_plot<-ggplot()+
  geom_errorbar(data=effect_sum, mapping=aes(x=charge_type, ymin=percent_confmin, ymax=percent_confmax))
  geom_point(data=effect_sum, aes(x=charge_type, y=percent_treatment_effect))+
  scale_y_continuous(breaks=seq(-60,40,10))+
  geom_point(data=charge_diffs, aes(x=group, y=percent_diff_in_means), color="blue")

effect_plot
```



In summary, our mean effect estimates are as follows:

- ***Violent offenses:*** a 5.9% decrease in charges.
- ***Property offenses:*** a 15.6% decrease in charges.
- ***Drug offenses:*** a 8.3% decrease in charges.
- ***Firearms offenses:*** a 8% increase in charges.
- ***Other offenses:*** a 34.8% decrease in charges.
- ***Uncategorized offenses:*** a 18.5% decrease in charges.

In all six categories, we have statistically significant evidence of a nonzero causal effect (a decrease in all categories except firearms offenses). W

Comparing to the point estimates of differences in means (prior to controlling for arrest counts), we observe that none of these estimates fall within our 95% confidence intervals. For violent, property, drug, and other offenses, we find that our estimated causal effect is a smaller decrease than the percent change in means. In the case of uncategorized offenses, our estimated causal effect is a larger decrease than the difference in means. Finally, in the case of firearm offenses, the causal effect we estimate is that of a substantially smaller increase (about 8%) than the simple difference in means (about 24%).

Discussion

Directions for future work

Citations

Stuff to cite: [1] https://web.archive.org/web/20171013182105/https://krasnerforda.com/ [2] https://krasnerforda.com/promises-kept [3] https://ballotpedia.org/Lawrence_Krasner [4] https://www.nytimes.com/2018/10/30/magazine/larry-krasner-philadelphia-district-attorney-progressive.html [5] https://github.com/phillydao/phillydao-public-data/tree/master/docs/data [6] Matching as Nonparametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference, Ho, Imai, King, and Stuart