Final Project for PS 531: A Pre-Analysis Plan

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1. Describe a substantive question in social science. What theory are you assessing? Why should anyone care? (2 paragraphs)

My research question is 'What is the effect of corruption punishment information on corruption perceptions?' The theory that this study aims to assess is the contingent self-commitment theory. Originally,Levi (1989) elaborated the concept of contingent self-commitment and defined it as the contingent nature of a commitment to comply with rules in a repeated setting without external coercion. Later, Ostrom (1990) used the concept in her study to propose a potential solution for the 'Tragedy of the commons' problem. Tragedy of the commons is an economics problem in which every individual has an incentive to consume a resource (common-pool resource), but at the expense of every other individual—with no way to exclude anyone from consuming. In the study, Ostrom use the empirical evidence of long lasting common-pool resource (CPR) situations and argues that the repeated games allow participants to design their own contracts in light of the information they have at hand. Essentially, the research emphasizes monitoring and graduated sanctions as the crux information for citizen to develop contingent self-commitment. Ostrom (1990) claims that an information of successful control would stimulate individual members to engage in monitoring process which further consolidates the institution of safeguarding public interest.

In case of corruption, corruption free society which allows effective governance is a common pool resource. A deviant action that harms public interest for private gain is engaging in corruption. Corruption may be viewed as a tragedy of the commons case because an individual has an incentive to break corruption-free society by engaging in corruption at the expense of every other citizen. If Ostrom's contingent self-commitment is valid, a punishment information for corruption may stimulate people to make self-commitment in controlling corruption which may be reflected by the reduce corruption perceptions. Therefore, theoretically, this paper is important for it examines the contingent self-commitment theory. Moreover, previous studies(Winters and Weitz-Shapiro (2013);Boas, Hidalgo, and Melo (2019)) use corruption information which only informs who engaged in corruption in their studies. Unlike the other studies, this research focus on the corruption punishment information which substantively informs public how well their society is functioning in protecting public interest. Thus, this study may have empirical contribution as well by suggesting potential solution for preventing corruption.

2. The study you propose involves learning about a theory by observing certain of its implications. What one or two hypotheses that arise from the theory are you plan-

ning to assess? Why or how does the theory justify your expectations about these hypotheses? (1 or 2 paragraphs)

The study I propose involves learning about a contingent self-commitment theory by observing of its implications. In this study, I aim to test a hypothesis, a corruption punishment information reduces corruption perceptions of the individuals. A contingent self-commitment theory justifies my expectation about the hypothesis because it suggests that a recognition of successful monitoring for unruly action, causing harms to public interest, motivates people to self-engage in further monitoring Ostrom (1990). Consequently, this leads individuals to believe that their society is functioning well in guarding public interest. Given the theory, it is plausible that an information of punishment on corruption may motivate people to make self-commitment in controlling corruption in their society. Further on, such commitment would encourage individuals to perceive that the society is less corrupt. Thus, this study examines the effect of corruption punishment information on corruption perceptions of the individuals. Also, grounding on the theory, I expect to observe the implication that a punishment information would reduce corruption perceptions at an individual level.

3. What data and research design will help you answer this question? Why are you making these choices? (Remember that a statistical model is not a research design.) (2 paragraphs)

My research question is 'what is the effect of corruption punishment information on corruption perceptions?' In order to answer the question and to further obtain a causal inference, this research conducts a survey experiment in South Korea from May 10th to May 18th in 2018. (Although the data was collected in 2018, I did not run any statistical analysis yet.) South Korea experienced the presidential corruption scandal in 2016 and the constitutional court decided to impeach the president in that year. Here, I assume that the fact, corruption occurred, is still evident but the public's memory of exact court sentences for each malefactor faded after two years. This would allow the operation of treatment in the survey context either by reminding or newly informing the corruption punishment information to the participants. A corruption experience in South Korea makes it a good case to examine the contingent self-commitment theory and to test my hypothesis. This is because the corruption scandal was large in scale that it involved incumbent president and the chief executive officer of Korea's top business company, Samsung. More importantly, I was the first time ever in South Korea that the legal accusation was clearly imposed on the culprits for their malfeasance.

In terms of the treatment, the court decision for the punishment, is randomly proposed to the participants through a vignette before they answer the survey questions. Participants in the control group view a vignette which only has the information that a grand scale corruption occurred in Korea. Next, the survey question measures the potential outcome, corruption perceptions, by asking 'How frequently do you expect the use of authority for private gain or personal connection will occur in the future?' Respondents answer the degree of perceived corruption for the future in five-level Likert Scale from '1' indicating definitely more to '5' referring definitely less. The total number of 457 people participated in the survey, and 229 were treated while the 228 were not treated. The data collection process continued until it fulfills the minimum number of 227 responses that fully answered the questions. Overall, the survey experiment design compares the potential outcome of the treated group and the control group and assess if there is an effect of corruption punishment information on corruption perceptions.

4. What are the advantages and disadvantages of this research design to addressing your question? (2 paragraphs discussing **both** advantages and disadvantages of the research design; could be 1 paragraph for advantages and 1 for disadvantages or combined discussion across 2 paragraphs.)

The design of survey experiment has two major advantages in addressing my question. First, survey experiment induces less bias than direct questioning in measuring sensitive attitudes and perceptions. (Blair, Imai, and Zhou (2015);Rosenfeld, Imai, and Shapiro (2016);Lensvelt-Mulders et al. (2005)) Since the outcome variable which the study intends to measure is corruption perceptions, and it is a sensitive issue that respondents often veil their thoughts, survey experiment may provide more valid measurement of corruption than the other types of research designs. Second, survey experiment measures causal relationships by randomly assigning respondents to an experimental condition or a control group. This overcomes the limitation of observational study which often draws correlation instead of causal inference. Thus, in my study, survey experiment is useful because it captures the potential effect of corruption punishment information and the casual inference by randomizing the treatment assignment process.

On the contrary, there are important limitations in using survey experiment. First, a survey experiment may capture the explicit attitude which a respondent is aware of, whereas it would not measure the implicit attitude which is not recognized by the respondent oneself (Nosek (2007)). Also, the possibility of contamination in the process of survey experiment such as, question ordering effect and unidentical interpretation of the terms in the question by the respondents exist. Such limitations may reduce the validity of the measured perceptions of corruption in this study. Second, survey experiment may involve confounding, information equivalence problem, and pre-treatment contamination which may result in bias regarding causal inference (Diaz, Grady, and Kuklinski (2020);Dafoe, Zhang, and Caughey (2018)). Because survey experiment is less conservative in a way to observe counterfactual cases than hard science experiment, the causal inference that a researcher draw may not be valid. This requires a scholar to be cautious about the possible bias in survey experiment, and thus, need to be careful in interpreting the result. Such difficulty applies to this research as well. Unidentified confounding variables, unidentical interpretation of the question and the pre-treatment effect outside of the survey context may interrupt accurate observation of the causal relationship between corruption punishment information and corruption perceptions.

5. Describe your measures and any indices you construct. (1 paragraph)

In terms of the outcome variable the survey question that asks, 'How frequently do you expect the use of authority for private gain or personal connection will occur in the future?' measures corruption perceptions. The responses ranges within the five-level Likert Scale from '1' indicating definitely more to '5' referring definitely less. Hence, higher the number, survey participant believe society would be less corrupt in in the future. When it comes to the explanatory variable, the treatment is the stimulus in the survey which is a detailed written information how each accused culprit ended up with final legal sentences, or punishments.

6. Use data to make the case that your research design allows you to interpret observed quantities (like observed data comparisons or parameters of models fit to data) as theoretically relevant and clear: (Most people will only have to do either 6.1 and 6.2 **or** 6.3 and 6.4 here depending on whether you have a randomized design or an observational design).

   i. **If you are using an randomized study design**, explain how the experiment will help you make the case for interpretable comparisons. What counter arguments and/or weaknesses of your approach might you expect? (For example, how will you think about Hawthorne effects or alternative explanations of your results arising from crticisms of your measurement and conceptualization strategy or missing data problems.) (1 paragraph)

The survey experiment will help me make the case for interpretable comparisons by randomly assigning treatment, the stimulus information of corruption punishment, to the survey participants. This way, we can compare the outcome of the treated group and the control group in order to measure the effect of the treatment and to make causal implication. In this randomized study design, potential counter argument exists. One might argue that experimental setting may modify respondents' behavior causing Hawthorne effect and interrupt the measurement process. A possible leeway in this study is that the experiment was an online survey and collected the responses anonymously. Some others might argue that the treatment in the survey experiment setting does not actually measures the effect of corruption punishment information but the framing effect of the survey. This criticism is valid because it is true that social scientists cannot infuse manipulated information to the participants of an experiment for ethical reasons. Nevertheless, randomization is difficult under an observational study and thus, scholars intend to approach, as if experiment setting, for achieving causal inference through randomization process in exchange of less accurate and valid measurement. Still others may concern the missing data problem in the study. However, there will be no missingness in treatment in this experimental setting and the collected dataset indicates no missingness in the outcome variable as well. Ultimately, survey experiment is not a panacea to make a causal inference nor allows perfect measurement of the treatment effect. Therefore, I should be careful in interpreting the result of survey experiment and be aware of the potential biasness in testing the hypothesis.

ii. **If you are using a randomized study design**, explain how you will know that your randomization and/or other aspects of your design turned out as they should (for example, you might explain about randomization tests here). (1 paragraph)

I will know that my randomization turned out as it should be by checking the balance of treatment and control group of the survey experiment using a statistical tool, 'Xbalance'. Xbalance tests conditional independence of the treatment variable and the covariates within strata by calculating standardized mean differences along each covariate with and without the stratification. (see detailed information on https://www.rdocumentation.org/packages/

RItools/versions/0.1-17/topics/xBalance) The result of xbalance shows that p-value (0.878) is greater than 0.05. This indicates that there is not enough evidence to support the difference in background variables of the treated and control group.

% latex table generated in R 4.0.5 by xtable 1.8-4 package % Wed May 19 02:21:11 2021

	treatment=0	treatment=1	adj.diff	adj.diff.null.sd	std.diff	z
sex	1.50	1.51	0.01	0.05	0.01	0.14
age_quart	3.54	3.52	-0.02	0.16	-0.01	-0.12
residence	5.90	5.54	-0.37	0.39	-0.09	-0.94
party_affiliation	3.93	3.94	0.01	0.26	0.00	0.05
pol_ideo	2.75	2.78	0.03	0.08	0.03	0.34
edu	3.15	3.20	0.05	0.11	0.04	0.47
income	3.83	3.60	-0.23	0.21	-0.10	-1.11

7. Explain your plans for any missing data or extreme outcome or covariate values you may encounter when you get the real data (or perhaps you have the background data but not the real outcomes, so you can explain your plans for such data issues in that case here too). (1 or 2 paragraphs)

Missingness in data may happen regarding outcome, treatment and covariate variables, respectively. First, the collected dataset indicates that there are no missing values in both outcome and treatment variable. Also, missingness in covariates is not a critical issue in this study because it only focuses on the effect of the treatment on the outcome variable. The expected structural model in this paper does not consider the background variables. Next, it is unlikely that the data would have an extreme outcome value because the survey response ranges from 1 to 5 measured in ordinal scale.

8. What statistical tests do you plan to use? Explain why you chose these tests and any decision making criteria you will use upon seeing the results of the tests. You should also engage with the problem of multiple testing here if you are going to show the results of more than one test. (Recall that confidence intervals and hypothesis tests convey more or less the same information. So a confidence interval is a form of testing.) (1 paragraph)

I am going to use robust linear regression to test my hypothesis. There are two major reasons for using this statistical test. First, this research is interested in finding a causal inference of corruption punishment information on corruption perceptions. Mainly, the study aims to examine the effect of punishment information on the potential outcome. The permutation testing involved in the linear regression suggest how much evidence the research design provide about a causal claim. Therefore, in testing the hypothesis, I examine p-value using robust linear regression analysis which describes the relationship between the observed test statistic and the distribution of possible hypotheses given null effect. Although the permutation testing does not provide exact effect size of the treatment, it reflects if the observed data we have provide sufficient evidence to reject the null hypothesis. Second, robust linear regression allows us not to assume homoskedasticity of the standard error which leads to over fitting problem in terms of outlier or extreme and influential observations. Although, robust linear regression model does not control for covariates, it can increase the precision of the estimation. Thus, once the distribution of the test statistics based on the central limit theorem and the design with the heteroskedasticity-consistent standard error is made, I will check the *p*-value and the confidence interval to find out the probability of seeing the observed estimate more extreme given that the null hypothesis is true. The following table refers to th robust linear regression of corruption perceptions on treatment.

% latex table generated in R 4.0.5 by xtable 1.8-4 package % Wed May 19 02:21:11 2021

	Estimate	Std. Error	t value	Pr(>|t|)	CI Lower	CI Upper	DF
(Intercept)	3.04	0.10	31.79	0.00	2.85	3.22	455.00
treatment	-0.08	0.13	-0.59	0.55	-0.34	0.18	455.00

9. Explain how you will judge the performance of those tests. Will you only use simple false positive rate and power? Or do you need to add family-wise error rate? false discovery rate? Or something else? Explain why you made this choice. (1 paragraph)

I will judge the performance of the tests by simulating the design. Because I am testing a single hypothesis the adjustment to control the error rates is not required. Also, family-wise error rate and false discovery rate that needs to be considered in multiple hypothesis testing is not necessary in this study. To be more specific, I intend to run a simulation and calculate the probability of rejecting a null hypothesis when the true effects are 0 (false positive rate). A good test should have low false positive error rate. In other words, the proportion of small *p*-values should be no larger than *alpha* (level of the test). Also, through the simulation, this paper will calculate the power of the test which indicates the probability to detect the effect when the true effect is not 0. In terms of power, a good hypothesis test should have high statistical power.

10. Show and explain how your test performs in regards those properties (at least you will show false positive rate and power). (2–4 paragraphs)

```
myvarest <- function(data){
variance_diff <- with(data,var(Y[Z==1]) - var(Y[Z==0]))
df <- data.frame(estimate=variance_diff)
return(df)
}

design <-
  declare_model(data = pap) +
  declare_potential_outcomes(Y~ fakeC)+  ##assuming true null effect
  declare_assignment(treatment) +
  declare_measurement(Y = reveal_outcomes(Y ~ Z)) +
  declare_inquiry(ATE=mean(Y_Z_1 - Y_Z_0))+
  declare_inquiry(VATE=var(Y_Z_1) - var(Y_Z_0))+
  declare_estimator(Y ~ Z , model = lm_robust, label = "ITT", inquiry="ATE")+
  declare_estimator(label = "varest", inquiry="VATE", handler=label_estimator(myvarest))
```

```
##Power(= false positive rate in this case) and Coverage
set.seed(123456)
diag<- diagnose_design(design, sims = 1000)

##false positive rate
set.seed(789789)
sim<- simulate_design(design, sims = 1000)
fpr1<- mean(sim$p.value[sim$estimator_label=="ITT"]<0.1) ##alpha=0.1
fpr2<-mean(sim$p.value[sim$estimator_label=="ITT"]<0.05)  ##alpha=0.05
fpr3<- mean(sim$p.value[sim$estimator_label=="ITT"]<0.01)  ##alpha=0.01
##fpr1
fpr2
##fpr3
```

Research design diagnosis based on 1000 simulations. Diagnosand estimates with bootstrapped standard errors in parentheses (100 replicates).

Design Label Inquiry Label Estimator Label Term N Sims Bias RMSE Power design ATE ITT Z 1000 -0.00 0.14 0.06 (0.00) (0.00) (0.01) design VATE varest 1000 -0.00 0.16 NA (0.00) (0.00) NA Coverage Mean Estimate SD Estimate Mean Se Type S Rate Mean Inquiry 0.94 -0.00 0.14 0.13 1.00 0.00 (0.01) (0.00) (0.00) (0.00) (0.00) (0.00) NA -0.00 0.16 NA NA 0.00 NA (0.00) (0.00) NA NA (0.00)

Inquiry Label	Estimator Label	Bias	RMSE	Power	Coverage	Mean Estimate	SD Estimate	Mean Se	Type S Rate	Mean Inquiry
ATE	ITT	-0.00	0.14	0.06	0.94	-0.00	0.14	0.13	1.00	0.00
		(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
VATE	varest	-0.00	0.16	NA	NA	-0.00	0.16	NA	NA	0.00
		(0.00)	(0.00)	NA	NA	(0.00)	(0.00)	NA	NA	(0.00)

I will use declare design and diagnose design to assess the test performance of the robust linear regression in testing my hypothesis. First, I plan to diagnose false positive rates by the simulation of true null effect of 1000 times. False positive rate indicates the probability of rejecting a null hypothesis when the true effect of the treatment is 0. The simulated design of the robust linear regression of the fake data indicates that the probability of rejecting a null hypothesis given the true null effect is 0.06. This is not lower than the nominal level of Type 1 Errors, $alpha = 0.05$. This suggest that the false positive rate is higher than the level of confidence interval (0.05), and this reflects that the test performance is moderate or low.

```
##power (assuming true effect not null)

design2  <-
```

```r
  declare_model(data = pap) +
  declare_potential_outcomes(Y~ fakeC+ (-1)*Z)+
  declare_assignment(treatment) +
  declare_measurement(Y = reveal_outcomes(Y ~ Z)) +
  declare_inquiry(ATE=mean(Y_Z_1 - Y_Z_0))+
  declare_inquiry(VATE=var(Y_Z_1) - var(Y_Z_0))+
  declare_estimator(Y ~ Z , model = lm_robust, label = "ITT", inquiry="ATE")+
  declare_estimator(label = "varest", inquiry="VATE", handler=label_estimator(myvarest))

set.seed(1234567)
diag2<- diagnose_design(design2, sims = 1000)
diag2
```

Research design diagnosis based on 1000 simulations. Diagnosand estimates with bootstrapped standard errors in parentheses (100 replicates).

Design Label Inquiry Label Estimator Label Term N Sims Bias RMSE Power design2 ATE ITT Z 1000 0.00 0.13 1.00 (0.00) (0.00) (0.00) design2 VATE varest 1000 -0.01 0.16 NA (0.00) (0.00) NA Coverage Mean Estimate SD Estimate Mean Se Type S Rate Mean Inquiry 0.95 -1.00 0.13 0.13 0.00 -1.00 (0.01) (0.00) (0.00) (0.00) (0.00) (0.00) NA -0.01 0.16 NA NA 0.00 NA (0.00) (0.00) NA NA (0.00)

Inquiry Label	Estimator Label	Bias	RMSE	Power	Coverage	Mean Estimate	SD Estimate	Mean Se	Type S Rate	Mean Inquiry
ATE	ITT	0.00	0.13	1.00	0.95	-1.00	0.13	0.13	0.00	-1.00
		(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
VATE	varest	-0.01	0.16	NA	NA	-0.01	0.16	NA	NA	0.00
		(0.00)	(0.00)	NA	NA	(0.00)	(0.00)	NA	NA	(0.00)

Next, the power of the test reflects a probability to detect the effect when the true effect is not 0. The simulation using declare design reflects that the probability of detecting the effect when the true effect is not 0 is 1. This suggest that hypothesis test of the design performs well in detecting the effect when the true effect is not null. In addition, the coverage probability of a confidence interval is the proportion of including the true effect. In the simulated design of the hypothesis test, coverage probability is both 0.94 when the true effect is null and 0.95 when the true effect is given not null. This suggest that 94% or 95% of the time, the confidence interval includes the true effect of the treatment, corruption punishment information in our case.

11. What statistical estimators do you plan to use? Explain why you chose these estimators. Especially explain what is your target of estimation — what is the estimand? (1 paragraph)

I plan to use two test statistics in order to test my hypothesis. The two test statistics are the mean difference in outcome and the difference in variances of the outcome. The reason for the choice is that my study is mainly interested in the potential outcome given the treatment is assigned. Precisely speaking, the target of estimation is the intend to treat effect and the estimand is the average treatment effect of the corruption punishment information on the individuals corruption perceptions. The other test statistics that I plan to use is the difference in variance. The target of estimation is the variance intend to treat effect. The estimand is the variance treatment effect of the corruption punishment news on individual perceptions of corruption. I use second test statistics because the treatment effect may only exist in the variance of the outcome variable while it does not affect the mean value.

12. Explain how you will judge the performance of those estimators (especially bias and MSE)? (1 paragraph)

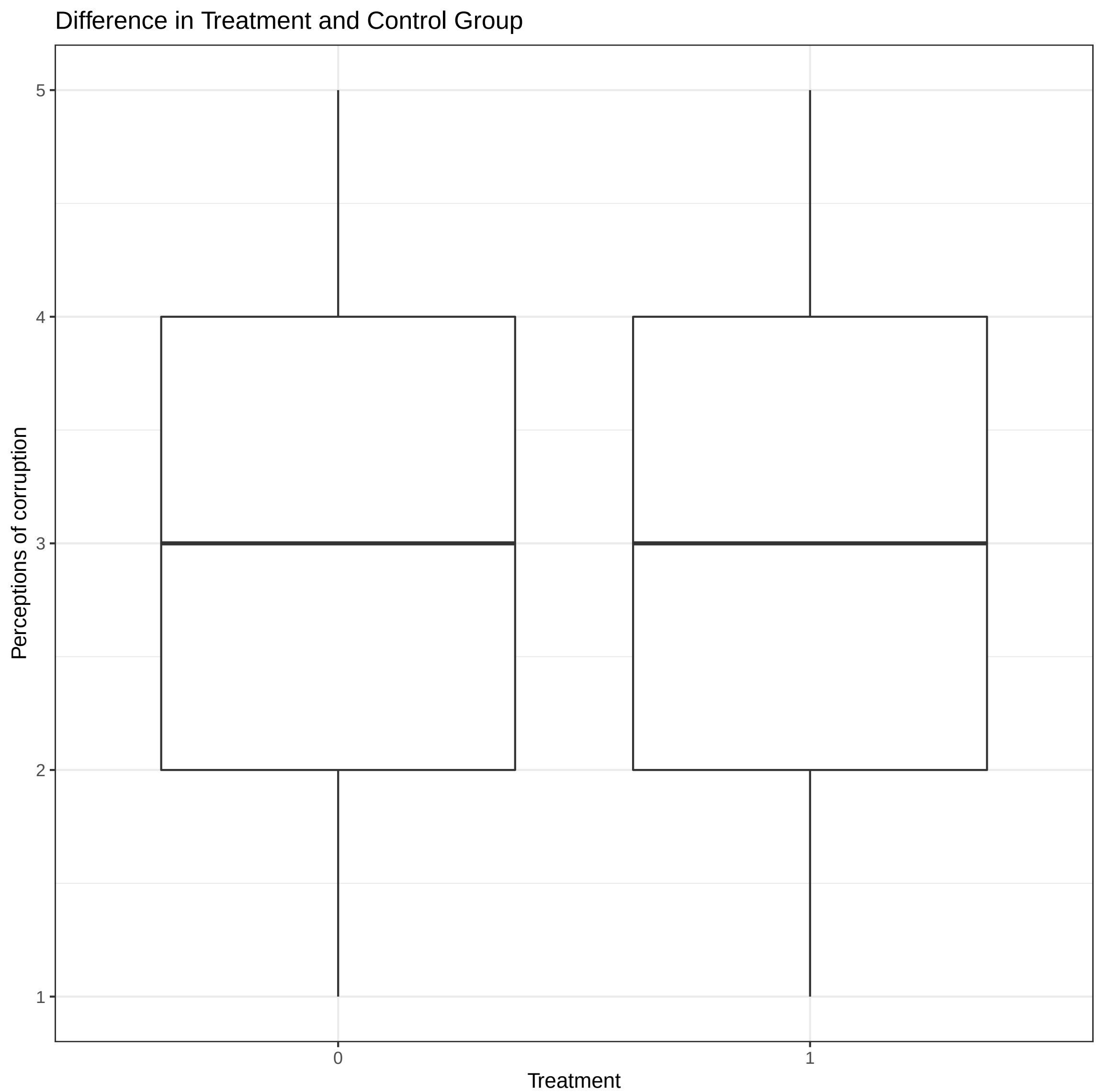
I will judge the performance of the estimators by simulating the design and measure the bias and mean standard error (MSE). A good estimator produces estimates close to the true estimand. Thus, an estimator with small bias reflects precision and good performance of the estimator. Also, a good estimator produces consistent estimate with little variance. MSE reflects the consistency of the estimate. Hence, an estimator with small mean standard error performs better in estimating the treatment effect than other estimators with large MSE. Therefore, by calculating the bias and mean standard error of the simulated models, this study will judge the performance of the estimators.

13. Show and explain how your estimator performs in regards those properties (at least bias and MSE). (2–4 paragraphs)

This research will simulate the design and estimation process to assess if the estimators in use performs well. Here, I plan to use declare design and diagnose design to make 1000 simulations. I ran the diagnose design using the fake outcome variable. The bias of estimator, the average treatment effect of the corruption punishment information on the potential outcome, perceptions of corruption, is 0 with the standard error of 0.00. Therefore, we may interpret that the ITT estimator in our design is not biased. In terms of the mean standard error, the diagnosis of the design reports the mean standard error of the estimator, 0.13 with the standard error 0.00. This suggest that ITT estimator in this study does not provide consistent estimation in 1000 simulations.

In terms of the variance average treatment effect, the 1000 simulations result in estimator bias -0.01, and standard error 0.00. Although the mean estimate is -0.01, the standard deviation of the estimate is 0.16. Therefore, although the variance average treatment effect may not be a biased estimator with systematic error, it may have weak consistency in estimating the treatment effect.

14. Make one mock figure or table of the kind you plan to make when you use the actual outcome. Interpret the results of the mock analysis as if it were the real analysis. Saying something like, "If the real outcome were as I have simulated it, then the following table/figure would mean such and so about the theory." (1 paragraph)



If the real outcome were as, I have simulated it, then the following figure of box plot would mean that the treatment effect is null both in the potential outcome and in the variance of the outcome. Therefore, the empirical evidence of my study is not consistent with the contingent self-commitment theory. They theory claims that the awareness of corruption punishment information would induce citizen to voluntarily engage in monitoring corruption and reduce the level of corruption perceptions in the future. However, the null effect of the treatment in the boxplot does not support the theoretical account.

Appendix

```
library(devtools)
devtools::install_github("viking/r-yaml")
library(RItools)
library(xtable)
library(DeclareDesign)
library(ggplot2)
```

```
library(pillar)
library(knitr)
library(dplyr)

xtable(summary(lm_robust(fakeC~treatment, data= pap))$coef,label="tab:lm_robust Regression"

myvarest <- function(data){
variance_diff <- with(data,var(Y[Z==1]) - var(Y[Z==0]))
df <- data.frame(estimate=variance_diff)
return(df)
}

design <-
  declare_model(data = pap) +
  declare_potential_outcomes(Y~ fakeC)+  ##assuming true null effect
  declare_assignment(treatment) +
  declare_measurement(Y = reveal_outcomes(Y ~ Z)) +
  declare_inquiry(ATE=mean(Y_Z_1 - Y_Z_0))+
  declare_inquiry(VATE=var(Y_Z_1) - var(Y_Z_0))+
  declare_estimator(Y ~ Z , model = lm_robust, label = "ITT", inquiry="ATE")+
  declare_estimator(label = "varest", inquiry="VATE", handler=label_estimator(myvarest))

##Power(= false positive rate in this case) and Coverage
set.seed(123456)
diag<- diagnose_design(design, sims = 1000)

##false positive rate
set.seed(789789)
sim<- simulate_design(design, sims = 1000)
fpr1<- mean(sim$p.value[sim$estimator_label=="ITT"]<0.1) ##alpha=0.1
fpr2<-mean(sim$p.value[sim$estimator_label=="ITT"]<0.05)  ##alpha=0.05
fpr3<- mean(sim$p.value[sim$estimator_label=="ITT"]<0.01)  ##alpha=0.01
##fpr1
fpr2
##fpr3
##power (assuming true effect not null)

design2  <-
  declare_model(data = pap) +
  declare_potential_outcomes(Y~ fakeC+ (-1)*Z)+
  declare_assignment(treatment) +
  declare_measurement(Y = reveal_outcomes(Y ~ Z)) +
  declare_inquiry(ATE=mean(Y_Z_1 - Y_Z_0))+
  declare_inquiry(VATE=var(Y_Z_1) - var(Y_Z_0))+
  declare_estimator(Y ~ Z , model = lm_robust, label = "ITT", inquiry="ATE")+
  declare_estimator(label = "varest", inquiry="VATE", handler=label_estimator(myvarest))
```

```r
set.seed(1234567)
diag2<- diagnose_design(design2, sims = 1000)
diag2

set.seed(1234567)
diag2<- diagnose_design(design2, sims = 1000)
xtable(summary(diag2),label="tab:TrueEffect Diag")


glimpse(pap)

Y<-pap$fakeC
df<-data.frame(
  Z=as.character(pap$treatment),
  y0= min(Y),
  y25=quantile(Y,0.25),
  y50= quantile(Y, 0.5),
  y75= quantile(Y, 0.75),
  y100= max(Y)

)

Boxplot<-ggplot(df, aes(Z,Y)) +
  geom_boxplot(aes(ymin=y0, lower=y25, middle= y50, upper= y75, ymax= y100, stat="identity"
  labs(x= "Treatment", y= "Perceptions of corruption", title="Difference in Treatment and C
  theme_bw()

##another approach
Jitter<- ggplot(df, aes(Z, Y))+
  geom_point(position="jitter")
#Jitter

Boxplot

balcheck<-xBalance(treatment~sex + age_quart + residence + party_affiliation + pol_ideo + e
xtable(summary(lm_robust(fakeC~treatment, data= pap))$coef,label="tab:lm_robust Regression"
kable(summary(diag)[, c(2:3, 6:14)])

kable(summary(diag2)[, c(2:3, 6:14)])
```

github link https://github.com/yeajinrha/PS531_PAP.git

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