Final Project

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Outline

1. treatments' effect on output (OLS)
2. treatments' effect on output (Double Lasso)
3. IPW estimation with logit
4. CATE estimation (patient characteristics)
5. Mediation model with lasso

1 OLS replication

I re-do OLS with both traditional standard error and robust standard error. Here are results using R and result from original paper:

TABLE 1 OLS WITH STATA AND R

	Postpartum hemorrhage (1)	Preeclampsia (2)	Sepsis (3)	Neonatal death (4)
	Original OLS with STATA			
Input Incentive	**-0.0845**	0.0573	0.0371	0.0032
(SE)	(0.0284)	(0.0434)	(0.0253)	(0.0051)
p-value	0.012	0.185	0.437	0.605
Output Incentive	-0.0741	0.0612	0.0209	0.0079
(SE)	(0.0294)	(0.0329)	(0.0224)	(0.0067)
p-value	0.7209	0.9235	0.3127	0.2881
	OLS with R			
Input Incentive	**-0.2631**	0.0253	**-0.1816**	0.0064
(SE)	(0.0441)	(0.0383)	(0.02803)	(0.0044)
p-value	<0.001	0.509	<0.001	0.144
Output Incentive	**-0.2291**	**-0.12**	**0.0431**	**0.002**
(SE)	(0.011)	(0.01)	0.0086	(0.0015)
p-value	<0.001	<0.001	<0.001	0.182

The significant coefficients (at 5% significance level) are marked red. The regressions in TABLE 1 all adopt robust standard error, including district and enumerator fixed effects and household- and provider-level controls. The control variables I use is the same in the original paper, yet the regression results has seismic differences. In the original result, two treatments only have effect on postpartum hemorrhage. Yet, in my results, they also have influence on the other three outcome variables. What's more, the coefficients of two are far from the same. The two reasons I can find for this difference is the way two software handling collinearity. Stata only drop a small portion of variables while R drops a large amount of provider dummies. Even though, such dramatic difference indicates that there are other potential problem with command or method which I fail to discover.

2 Double Lasso (treatment effect on output)

The comparison of treatment effect estimation using OLS in the orginal paper and using double lasso is shown in TABLE 2.

TABLE 2 TREATMENT EFFECT BY DOUBLE LASSO

	Postpartum hemorrhage	Preeclampsia	Sepsis	Neonatal death
	(1)	(2)	(3)	(4)
Input Incentive	**-0.0689**	0.0184	0.0047	**-0.0076**
p-value	<0.001	0.292	0.67	0.054
Output Incentive	0.0275	0.0062	0.0079	0.00523
p-value	0.125	0.685	0.427	0.2126

As shown in TABLE 2, the double lasso results are similar to OLS result in the original paper, the input incentive decreases incidence rate of postpartum hemorrhage by 6.89%; it also has influence on neonatal death, yet less significant. While output incentive has no significant effect on any of these four outcomes.

3 IPW estimation with logit

Because the treatments are randomly assigned, the propensity score should be around 0.5. However,when calculating propensity score with second-degree flexible logit, 842 observations get a score higher than 0.8 or below 0.2. Adopting normal first-degree logit would generate propensity scores around 0.5, but the two forms generate little difference in the following analysis, I still adopt flexible logit calculating IPW estimation. Because the IPW command does not allow missing value, only 1518 observations out of 2895 are used in this section. I perform a regression to check whether in the sub-sample is correlated with other variables in the data set. Regressing treatment assignments on control variables and provider dummy variables, I found most of the significant variables are provider fixed effect, only a few of control variables are significant. I could argue that whether in the subset is not correlated with most control variables. Even they are correlated, due to unconfoundness assumption, IPW is not biased after incorporating control variabls and fixed effect in the estimation. The result is shown in TABLE 3.

TABLE 3 IPW ESTIMATION WITH LOGIT

	Postpartum hemorrhage	Preeclampsia	Sepsis	Neonatal death
	(1)	(2)	(3)	(4)
Input Incentive	**-0.115**	-0.067	0.0087	-0.003
(SE)	0.05	0.04	0.0169	0.0023
Output Incentive	**0.216**	**0.402**	0.177	0.0076
(SE)	0.045	0.15	0.091	0.0185

Throughout three different approaches, only two results are consistent: First, only postpartum hemorrhage react significantly to treatments, especially input incentive; second, the two treatments hardly generate effect on the other three outcome variables (at least no robust). The data I use changed slightly throughout these method due to command limitation, but if the treatment effect is robust enough, small changes in observations should not stir a huge change. I also perform double lasso and IPW estimation using my experimental data. The result is not very different from standard OLS regression.

4 CATE estimation (patient characteristics)

Two important variables among those whose importance are above mean value are new mother's age and their previous pregnancy times. These variables are strongly related to mother's health condition and treatment effects. The mean values of previous pregnancy number and mother's age are 1.92 and 24.1 separately. Due to lack of detailed information about other important variables selected by CATE methods, the analysis is restricted to these two variables in this section. The result is shown in TABLE 4.

TABLE 4 CATE ESTIMATION BY PATIENT'S TRAITS

	Previous Pregnancy		New Mother's age		
	<2	>=2	<24	>=24	pregenancy>=2 & age>=24
Input Incentive	-0.052	**-0.098**	-0.023	**-0.113**	**-0.117**
(SE)	0.069	0.049	0.061	0.042	0.058
p-value	0.454	0.046	0.708	0.007	0.046
	Previous Pregnancy		New Mother's age		
	<2	>=2	<24	>=24	pregnancy<2 & age>=24
Output Incentive	**-0.127**	-0.001	**-0.131**	-0.021	**-0.203**
(SE)	0.062	0.05	0.054	0.051	0.065
p-value	0.038	0.979	0.015	0.679	0.002

From TABLE 4, it's clear that for older mother who has over 2 pregnancies, the input incentive treatment works well, while for younger mothers who has one or none pregnancy before, output incentive generate more benefit for them. Such heterogeneous is worth exploring further as it's vital for policy maker to understand which sub group benefit from which kind of treatment. And the mechanisms behind this interesting result can not be revealed fully by this data set.

5 Mediation model with lasso

In this section, I perform a mediation analysis with lasso. Previous study about the combination of mediation model and LASSO concentrate on the scenario where the potential mediators are of large dimension (Ye et al., 2021; Schaid and Sinnwell, 2020). But there are four channels of particular interest in this paper, which transforms the motivation of using LASSO in mediation model from finding right mediators to selecting proper control variables for estimations in the traditional mediation analysis. According to the original paper, the decreasing incidence of postpartum hemorrhage attributes to the increasing input related to this certain kind of disease. The authors offered OLS regression in the paper to prove treatments does enhance four kinds of related input. But they didn't test the link between those four inputs and outcome variable. I propose a mediation model to verify their argument. The procedure of a traditional mediation model with LASSO is as follows:

1. Regress mediator on treatment (LASSO)
2. Regress mediator on treatment with control variables selected in step 1 (OLS)
3. Regress outcome on mediator (LASSO)
4. Regress outcome on treatments and mediator with control variables selected in step 1 and step 3 (OLS)

TABLE 5 MEDIATION MODEL WITH LASSO

	coefficient	standard error	p-value
Input incentive & Mediator1			
Indirect effect			
Input Incentive-mediator1 (step 2)	**0.84**	0.001	0.001
mediator1-outcome (step 4)	0.14	0.116	0.23
Direct effect			
Input Incentive-outcome (step 4)	**-0.425**	0.045	0.001

	coefficient	standard error	p-value
Output incentive & Mediator1			
Indirect effect			
Output Incentive-mediator1 (step 2)	**0.625**	0.001	0.001
mediator1-outcome (step 4)	0.14	0.116	0.23
Direct effect			
Output Incentive-outcome (step 4)	**-0.228**	0.008	0.001
Input incentive & Mediator2			
Indirect effect			
Input Incentive-mediator1 (step 2)	0.13	0.078	0.095
mediator2-outcome (step 4)	**0.133**	0.023	0.001
Direct effect			
Input Incentive-outcome (step 4)	**-0.689**	0.058	0.001
Output incentive & Mediator2			
Indirect effect			
Output Incentive-mediator2 (step 2)	**-0.866**	0.024	0.001
mediator2-outcome (step 4)	**0.133**	0.023	0.001
Direct effect			
Output Incentive-outcome (step 4)	**-0.433**	0.026	0.001
Input incentive & Mediator3			
Indirect effect			
Input Incentive-mediator3 (step 2)	**0.917**	0.045	0.001
mediator3-outcome (step 4)	**0.087**	0.03	0.004
Direct effect			
Input Incentive-outcome (step 4)	**-0.92**	0.055	0.001
Output incentive & Mediator3			
Indirect effect			
Output Incentive-mediator3 (step 2)	**0.022**	0.006	0.001
mediator3-outcome (step 4)	**0.087**	0.03	0.004
Direct effect			
Output Incentive-outcome (step 4)	**-0.144**	0.019	0.001
Input incentive & Mediator4			
Indirect effect			
Input Incentive-mediator4 (step 2)	-0.327	0.105	0.143
mediator4-outcome (step 4)	0.016	0.036	0.643
Direct effect			
Input Incentive-outcome (step 4)	0.05	0.066	0.447
Output incentive & Mediator4			
Indirect effect			
Output Incentive-mediator4 (step 2)	-0.4	0.144	0.144
mediator4-outcome (step 4)	0.016	0.036	0.643
Direct effect			
Output Incentive-outcome (step 4)	**0.41**	0.034	0.001

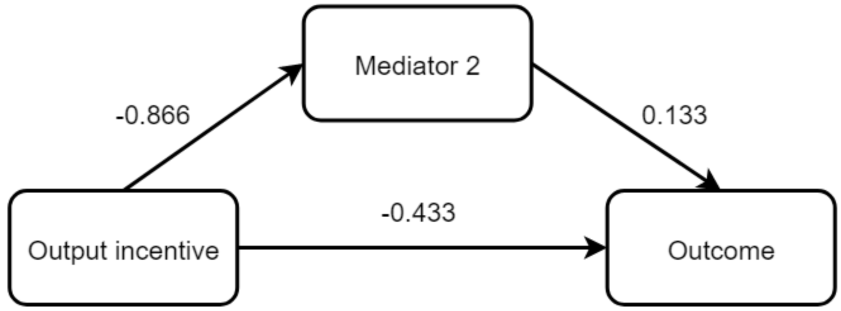

Figure 1. Mediation model 1 (Output incentive & Mediator 2)

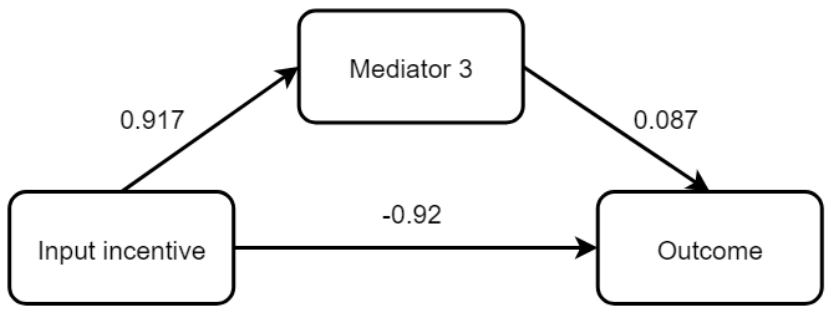

Figure 2. Mediation model 2 (Input incentive & Mediator 3)

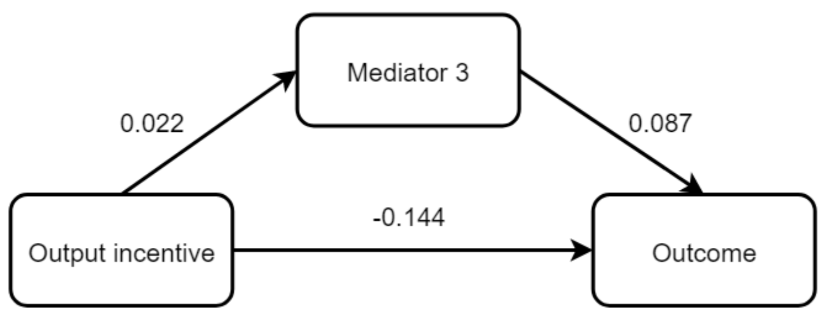

Figure 3. Mediation model 3 (Output incentive & Mediator 3)

In the traditional mediation analysis, a variable is a mediator between treatment and outcome if and only if a mediator is significant in both step 2 and step 4. Here I adopt a similar criterion. There are only 3 combination of mediators and treatments generate valid mediation model, as shown in Table 5. In the logic of original paper, the treatments nudge providers to increase these four specific inputs, therefore decrease the incidence rate, that is the outcome variable. For the combination of output incentive and mediator 2 in Figure 1, the result is contradictory to the author's claim. My result shows a negative effect of this mediator on outcome. However, output incentive does help decrease incidence rate through mediator 2, because it decrease such kind of input. For mediation model 2 and mediation 3, as shown in Figure 2 and Figure 3, though the mediation effect does exist, the sign of the effect is contradictory to author's expectation. Mediator 3 input does go up because of input and output incentive, yet this kind of input would increase the incidence rate. According to the original paper, these intermediate variables (input indicators) comes from previous study and their own validation exercise before the experiment is carried out, yet the validation of these indicators and mediators is worth double check after the experimental data is generated.

References

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