

Final Paper Assessment DD design

This research aims to investigate the impact of a program introduced by a state child support agency that offers intensive case management services to non-custodial parents (NCPs) at selected local child support sites across the state. To evaluate the effectiveness of the program, the study will compare the employment rates of NCPs and single mothers, as well as the percentage of NCPs with child support debt. The study will also use evidence to verify that the Difference in Differences (DD) research design is suitable for this research and meets the necessary assumptions.

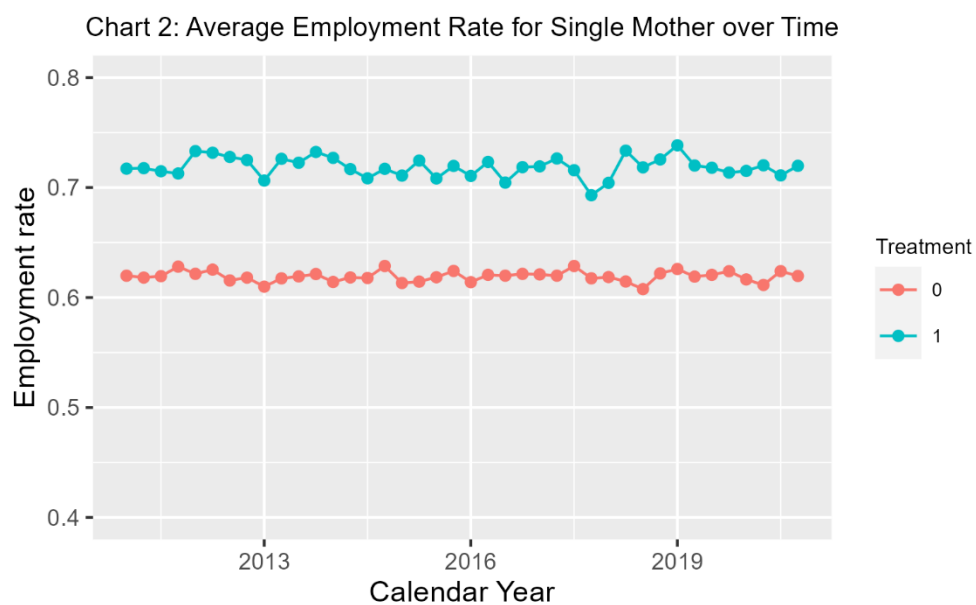
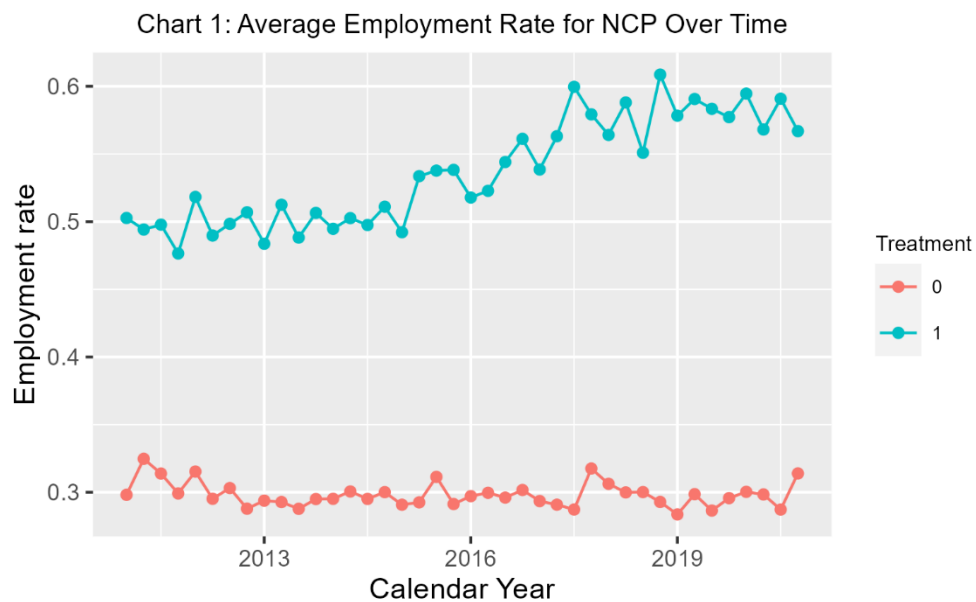
The intuition behind using the Diff-in-Diff research design is that in this case, the treatment refers to the child support agency's program that provides intensive case management services to NCPs in selected local child support sites. The site that received the program is the treatment group, while the site that did not receive the program is the control group. By comparing the employment rate for NCPs and single mothers, as well as the fraction of NCPs owing child support debt, in the treatment and control group before and after treatment, we can measure the causal effects of the treatment. Since the treatment was introduced at varying dates across 13 different quarters from 2014 to 2016, we assume that the timing of the treatment is random. Additionally, we assume that any differences between the treatment and the control group are stable over time prior to treatment.

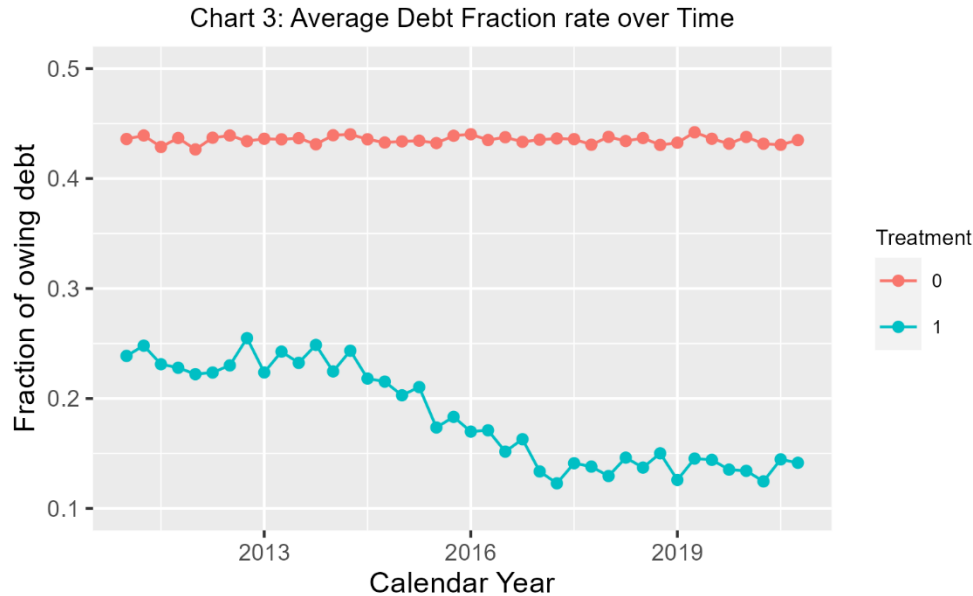
One of the crucial assumptions to estimate the causal impacts of the program is that the treatment and control groups have similar and stable outcomes before the treatment. It is important to avoid spillover effects so that the program only affects those who received the treatment, and the control group's outcomes remain unchanged. This ensures that any changes in outcomes observed after the treatment can be attributed to the treatment itself. Additionally, the

treatment should be exogenous, meaning there should be no observable or unobservable confounding variables that could affect the outcome. These assumptions are necessary for a valid causal interpretation of the program's impacts.

In this study, the panel data collected over multiple calendar quarters consists of 7440 observations and 8 variables. In order to see if there were parallel and stable changes in outcomes, I plotted the average employment rate and debt fraction over calendar quarters for both the treatment and control groups. Chart 1 displays the average employment rate for NCPs across quarters, indicating that those who received the treatment had higher employment rates than those who did not. Prior to the treatment, the change between the two groups was constant and stable. After the treatment, however, a growing gap emerged, suggesting that the treatment had a positive effect on the employment rate for NCPs, which is consistent with the assumptions of the DD design.

Chart 2 shows the average employment rate for single mothers, where we observe that the program did not affect the control group since the trend of the two groups appears to be similar, with only a slight difference of about 0.1. This satisfies the assumption that the control group is not affected by the treatment. In Chart 3, we observe the average fraction of NCPs owing debt over time. The site that did not receive treatment shows a constant trend over quarters, while the treatment group shows a decreasing fraction of NCPs owing debt, indicating that the decrease in debt fraction is due to the treatment effect.





To better understand the treatment effect on employment rates, I created a variable for time since treatment to observe the outcomes of treated NCP and treated single mothers. Chart 4 displays the average employment rate for treated NCPs over time since treatment. It is evident that the employment rate was consistent in the years preceding the treatment, but there was a significant increase following the intervention. This suggests that the observed change in employment rate is primarily attributable to the treatment effect, which aligns with the assumptions of the DD design. To make a comparison, I also plotted the change in the control group. Chart 5 shows the average employment rate of treated single mothers, which remained constant until the end of the observation period when it experienced a significant increase. This further supports our assumption that the control group's outcomes were stable and unaffected by the treatment. Lastly, Chart 6 shows the average fraction of NCPs owing child support debt. Prior to treatment, there was little change in outcome, but after the treatment, the average fraction showed a clear decrease. This confirms that treated NCPs owing debt were negatively impacted by the treatment.

Chart 4: Average Employment Rate for Treated NCP

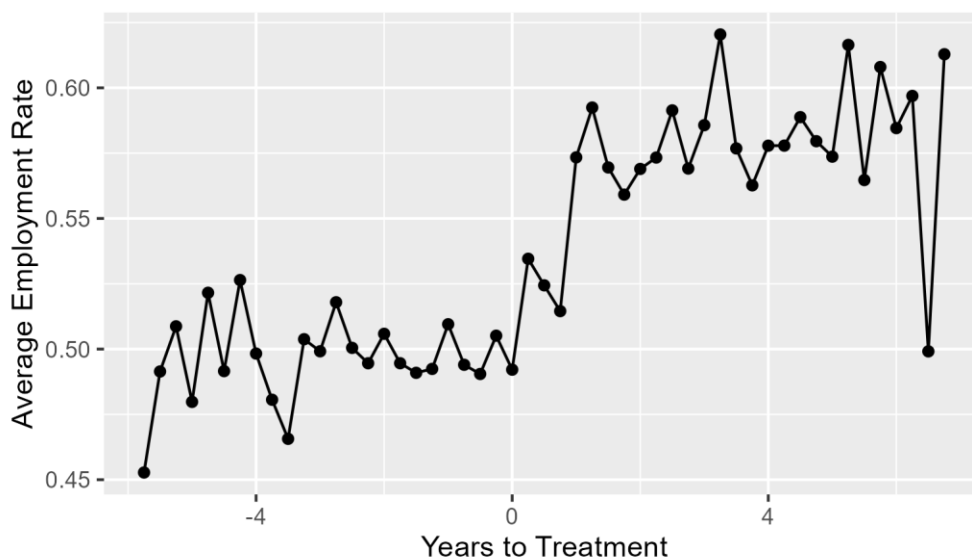
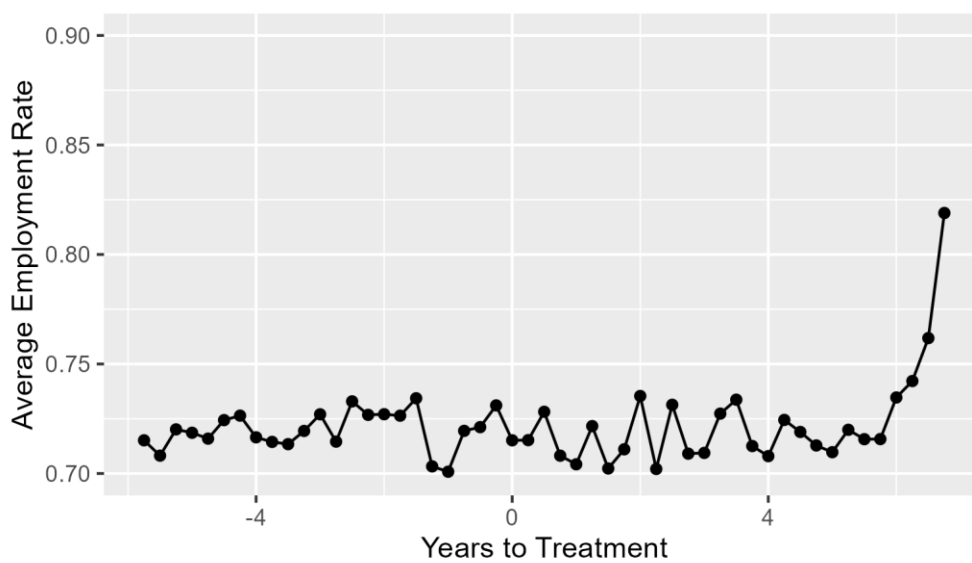
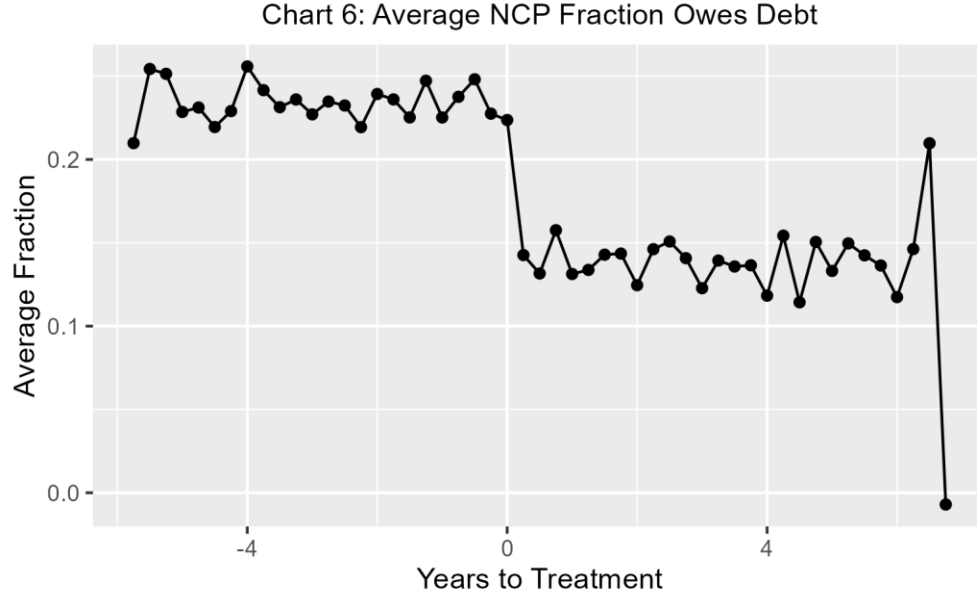


Chart 5: Average Employment Rate of Single Mother for Treated NCP





Then, I applied regression analysis to the entire dataset, which includes both the treatment and control group, in order to estimate the treatment effect. The regression model we employ is specified as follows:

$$y_{in} = \alpha_0 + a_1 n_i + \sum_{k=1} [\delta_k D_{ik}] + \gamma_N + \gamma_s + \gamma_t + error_{it}$$

where y_{in} denote average employment rate for NCP i in year t , n_i denote an indicator for being a treated NCP, D_{ik} denotes an indicator variable for being a treated NCP and having time since treatment = k , γ_N denotes numbers of NCPs fixed effects, γ_s denotes site fixed effects, and γ_t denotes calendar year quarter.

Figure 1 presents the coefficients of the employment rate of treated NCPs over time since treatment. The non-significant outcome before the treatment is in contrast to the statistically significant outcome after the treatment, which suggests a positive treatment effect on the employment rate. To further investigate, we estimate the same regression using the employment rate of treated single mothers as the outcome.

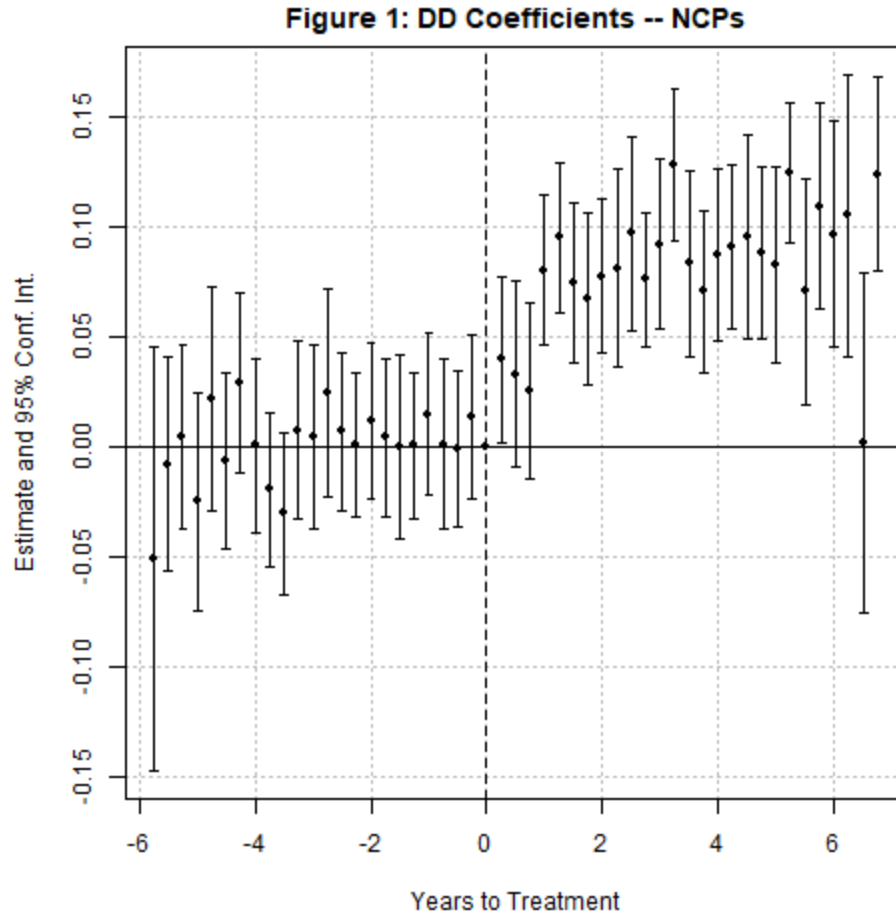


Figure 2 shows that the estimate is not statistically significant over time, which indicates that the control group is not affected by the program. Lastly, we estimate the same regression using the fraction of NCPs who owe child support debt as the outcome. Figure 3 reveals that the coefficient is not statistically significant before treatment but becomes statistically significant after treatment, showing a negative association with the treatment. These results provide robust and compelling evidence that supports our previous analysis and aligns with the DD research design assumption.

Figure 2: DD Coefficients -- Single Mother

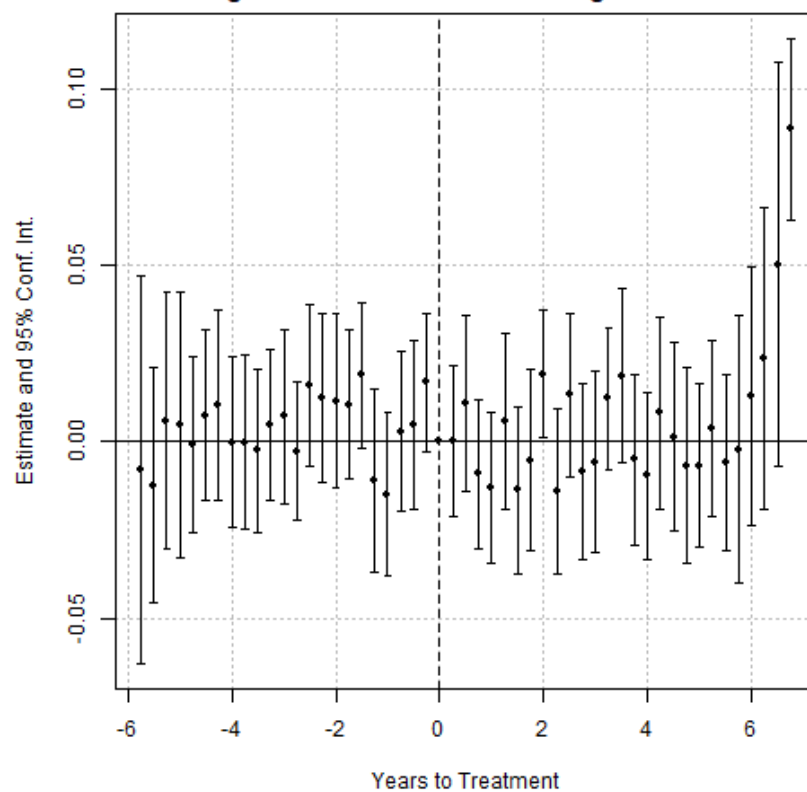
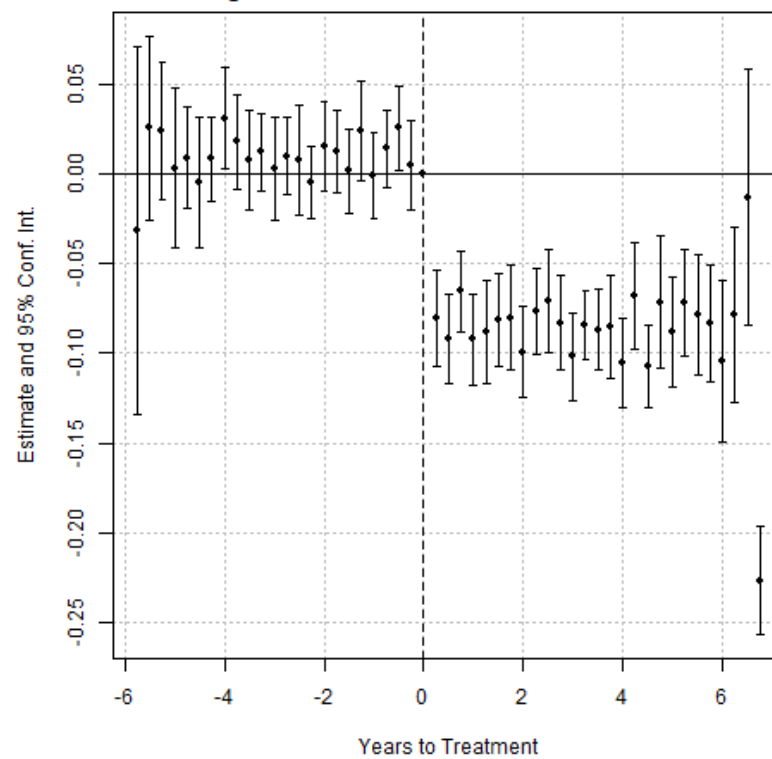


Figure 3: DD Coefficients --Debt Fraction



Using the outcomes of Figure 1 and Figure 3, I also estimated the correlation between the average employment rate of treated NCP and the average debt fraction. The results in the following table show that NCP's employment and fraction owe debt are statistically significant. One percent increase in the employment rate is linked to a 1.28 percent decrease in the NCP fraction that owes child debt.

Table 1: Regression Result of employment rates of NCP and debt fraction

Variable	Estimate	Std. error	t-value	Pr(> t)
nep_emp_rate	0.074	0.005	14.793	< 2.2e-16
nep_wdebt	-0.095	0.003	-35.645	< 2.2e-16

Based on the analysis and results presented, it can be concluded that the Difference-in-Differences design is an appropriate method for evaluating the impact of the treatment on the employment rate of Non-Custodial Parents (NCPs) and the proportion of NCPs with child support debt. The findings suggest that the treatment has a positive effect on the employment rate of NCPs, leading to a reduction in child support debt owed by them.