Increased Resolution to Discover Heterogeneous Treatment Exposure: Estimating the Effect of Abortion Restrictions

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1 Introduction

On June 24, 2022, the U.S. Supreme Court ruled in Dobbs v. Jackson Women's Health Organization to overturn Roe v. Wade, which had guaranteed women the federal right to abortion. Thirteen states enacted trigger laws that immediately enforced near-total bans on abortion after the ruling, and at least a dozen more have since restricted abortion access to some degree [1]. Studies have shown that abortion bans are associated with higher rates of poverty and lower rates of women in the workforce [2]. In this project, we study the effect of abortion bans on a number of outcome variables that measure aspects on women's health, education, and poverty. However, we also note that the effects of overturning Roe v. Wade are still evolving, and this returning to this project in the future may yield additional insight.

The fundamental problem with studying the causal effect of abortion restrictions is the effect of confounding variables and characteristics of states that chose to ban abortion compared to those that did not. A direct comparison of outcome variables between states that did and did not ban abortion is therefore invalid. Thus, we rely on the parallel trends assumption and the difference-in-differences (DiD) method to generate valid comparisons. This is further described in Sections 2.1 and 3.2.

2 Difference-in-Differences

We briefly describe the basic DiD method as follows. Suppose we have a population n individuals (indexed by i) and $T = 2$ time periods: a pre-treatment and post-treatment period. Consider a binary policy $W_i \in \{0, 1\}$, which splits the population into treatment ($W_i = 1$) and control ($W_i = 0$) groups. Denote the i^{th} individual being untreated as $Y_{it}(0)$ and the i^{th} individual being treated at time $t = 2$ as $Y_{it}(1)$. We want to estimate the average treatment effect of the treated,

$$\tau := E(Y_{i2}(1) - Y_{i2}(0) \mid W_i = 1),$$

but $Y_{i2}(0) \mid W_i = 1$ is unobserved.

2.1 The Parallel Trends Assumption

To address this problem, we can assume *parallel trends*: in the absence of treatment, the difference between groups is constant over time. Equivalently, the difference in the level of the outcome variable over time is equal for both groups:

$$E(Y_{i2}(0) - Y_{i1}(0) \mid W_i = 1) = E(Y_{i2}(0) - Y_{i1}(0) \mid W_i = 0). \tag{1}$$

With the additional no-anticipation assumption, which assumes that the treatment has no effect in the pre-treatment period (implying $Y_{i1}(0) = Y_{i1}(1)$), we can now generate the counterfactual $E(Y_{i2}(0) \mid W_i = 1)$: Rearranging Equation 1 and applying no-anticipation yields

$$E(Y_{i2}(0) \mid W_i = 1) = E(Y_{i1}(1) \mid W_i = 1) + E(Y_{i2}(0) - Y_{i1}(0) \mid W_i = 0), \tag{2}$$

and both terms on the right hand side can be estimated empirically. In words, the counterfactual is the untreated outcome in the pre-treatment period for the treated group, plus the change in time from the control group. This is compared to the post-treatment outcome of the treated group to elucidate any treatment effects.

3 A Multi-Resolution Approach

The main issue is that states that elected to ban abortion differ strongly than states that did not, so the parallel trends assumption may not hold at the state level. In other words, variables such as women's workforce participation rate may naturally differ over time between different states due to confounding variables. However, counties *within states that banned abortion* are much more apt for comparison. But how can we find treatment variation at the county level? The answer lies in the prior access of abortion in a particular county. In this section, we review how treatment exposure is constructed at the county level and the trade-offs of such an approach.

3.1 Data

Myers [3] provides a data set detailing each county's distance to its nearest abortion clinic by month. The data set covers every county in the contiguous United States, and we use the data from every month in 2022. For a county i, define D_i as the change in distance to the nearest clinic from July 2022 and June 2022. This D_i variable captures the overturn of Roe v. Wade, as shown in Figure 1. However, due to the spatial configuration of counties (some being close to state borders, some being more rural), different counties in these abortion ban states experienced different increases in abortion inaccessibility. Figure 2 plots D_i for every county of interest. Figure 3 plots D_i for Wisconsin. Note the strong geographic variation in D_i. The counties on the southern border do not experience much of an increase because they are near enough to Illinois (and therefore Chicago). However, counties in the middle and north experience larger increases. This validates the conjecture that each county did not experience Dobbs in the same way.

Previous literature has used such a measure of treatment exposure within treated states to estimate the effects of Medicare. Finkelstein [4] uses the pre-treatment rates of insurance amongst the elderly as a measure of treatment exposure to medicare, much as we use the pre-treatment distance to an abortion clinic as a measure of treatment exposure to Dobbs.

3.2 Constructing a Binary Treatment Variable

While techniques exist to use a continuous treatment exposure variable, in our exercise of visually comparing parallel trends, it is necessary to construct a binary treatment variable.

Figure 4 plots a histogram of D_i. Clearly, there is a large mass of counties in the 0-100 miles range. We take these counties to be untreated and counties above to be treated. That is, treatment $W_i := \mathbb{I}[D_i > 100]$. The 100 mile cutoff is also based in domain knowledge, as previous literature has found effects of larger than 100 mile increases on abortion rates [5].

Figure 5 plots the binary version of the treatment variable. The region in red are counties with $W_i = 1$. Of course, W_i is very geographically correlated since it is defined by a distance measure. Certainly the claim is not that the red counties can be directly compared to the white counties. The hypothesis is that the red counties might experience similar trends in outcome variables of interest as the white counties, and therefore our differences-in-differences strategy can validly identify a treatment effect.

3.3 What Are the Trade-offs?

First, this increases variance. Data at the county level are sparser, and thus while we may get less biased estimates with a more plausible parallel trends assumption, we are left with significantly more variable data. In the data discussed in section 4, the size of the data is cut down by a factor of one hundred once we filter to the county level. This is the classic bias-variance tradeoff.

Second, this approach changes the estimand. We are no longer estimating the effect of banning abortion on an outcome variable Y. We are estimating the effect of differential exposure. In a linear setting, we might get estimates for a one mile increase in distance to an abortion clinic. Interpreting this becomes more difficult, as one's decision to get an abortion is likely non-linear in distance. Furthermore, connecting back to the true highest resolution setting – estimating an individual's decision – becomes harder as well. This is an important point: increasing the resolution gives you access to identification of *a* treatment effect, but not the original one of interest.

However, to see the benefits of "zooming in," it is useful to return to the idealized experiment. If given omnipotence, what would we do? We would flip a coin for each county and completely ban all abortion within it if the coin is heads. We would restrict travel for abortion, etc. The closest we might get to such an experiment in an observational setting is that one county in Wisconsin just happens to be closer to Chicago than another county in a way that is unrelated to the outcomes of interest. Here, we are banking on the variation in distance being plausibly exogenous to trends in the outcome of interest.

4 Results

4.1 Current Population Survey

For this paper, we used the Current Population Survey (CPS), a monthly U.S. labor force survey, to extract information about our outcome variables of interest in the months before and after the overturn of Roe v. Wade. The CPS uses a stratified sampling approach by grouping counties and areas in the U.S. into 2000 sampling units, from which a representative sample of 60000 households is drawn each month. In particular, we looked at the female labor force rate, the rate of any physical or cognitive difficulties faced by female respondents, and the female high school and college education rates. The intuition behind testing these outcome variables was that an abortion ban and increase in distance from abortion centers might affect female respondents' overall wellbeings. For example, an abortion ban could lead to an increase in pregnancy rates among females of working age, which might lead to a decrease in female labor force rate. Additionally, an abortion ban could lead to overall health detriments among females, leading to an increase in the rate of female physical or cognitive difficulties. Thus, in the following section, we investigated the effect of abortion bans at the state level and increases in distance from abortion centers at the county level on these outcome variables.

4.2 Parallel Trend Plots

For each outcome variable, we created parallel trend plots as follows. For 7 to 8 months before and after June 2022 (when Roe v. Wade was overturned), at the state level we found the weighted average of the outcome variable for each state and county using a household-level weight variable provided in the CPS datasets to account for their stratified sampling scheme. Using these weighted averages, we calculated the weighted averages for states and counties that fell into our treatment and control groups (for states, the treatment group was states that had an automatic trigger abortion ban, while for counties the treatment group included those with 100 mile cutoff distance from the closest aborition center as previously described). We then created the typical parallel trend plots at these two resolutions for the outcome variables.

The parallel trend plots at the state and county levels for the previously mentioned outcome variables are in the appendix. Figure 6 shows the plots for female labor force rates, Figure 7 shows the plots for female physical and cognitive difficulty rates, Figure 8 shows the plots for female high school education rates, and Figure 9 shows the plots for female college education rates. For each of the outcome variables, we can draw somewhat similar conclusions. First, our initial hypothesis that the parallel trends assumption would hold more strongly at the county level than at the state level due to the increase in resolution was generally proven false by the plots. At the state level for each outcome variable, the pre-treatment trends for control and treatment groups were generally and consistently parallel to each other, and there was no obvious trend that could be discerned after the treatment policy occurred. At the county level for each outcome variable, the pre-treatment trends for control and treatment groups were also relatively parallel before the treatment policy was put into place, but for some variables (for example, for the female physical and cognitive difficulty rates) the level to which the groups had parallel trends underperformed relatively to the state level plots.

From these plots, we can thus see that increasing the resolution did not always lead to an improvement in the parallel trends assumption. This may have been because of the quality of data used; that is, the CPS data was aggregated to an individual level through the data collection process, and an already county-level dataset might have yielded better results and clearer trends. Additionally, the increase in variance incurred by shifting to a county-level resolution may have led to a decrease in performance for our assumptions at the higher resolution. It is still difficult to make complete judgements on the validity of our hypothesis that the county level would lead to clearer trends, since the amount of aggregation that had to be done to reach the state level may have led to overly successful results for the parallel trends assumption. However, from these initial results, we can still find that the state level analysis did much better than expected with the parallel trends assumption, and the county level analysis did not show any immediate clear trends regarding differences in differences and also did not outperform the state level in the parallel trends assumption.

4.3 Extensions

One area where this paper can be extended is in the construction of a binary treatment variable W_i. This choice is arbitrary, and can greatly affect the treated versus control set of counties. It would be easier to work with D_i directly, as a continuous measure of treatment exposure. A general extension of our framework is the "linear panel model," discussed thoroughly in [6]. Then, we can represent our treatment effect as $\gamma_t D_i$, which linearly enters our model for an outcome Y_i. Here, the γ_t are time-varying coefficients, which allows the model to have dynamic effects of D_i in different time periods. The parallel trends assumption becomes more complicated in this setting, but can be visually checked by observing whether the γ_t coefficients are constant for all t prior to the treatment time.

Next, we also hope to gather further data on the county-by-month level. One serious limitation of our analysis is we are limited to just-released CPS data. This is an individual level survey which we are forced to aggregate at the county level. In the future, more representative and less variable data at the county level will be released. In particular, we are interested in teen birth rates, birth weights, and high school drop out rates for women.

Word Count: 2248

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[3] Caitlin K Myers. County-by-month distances to nearest abortion provider, July 2022.

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5 Appendix

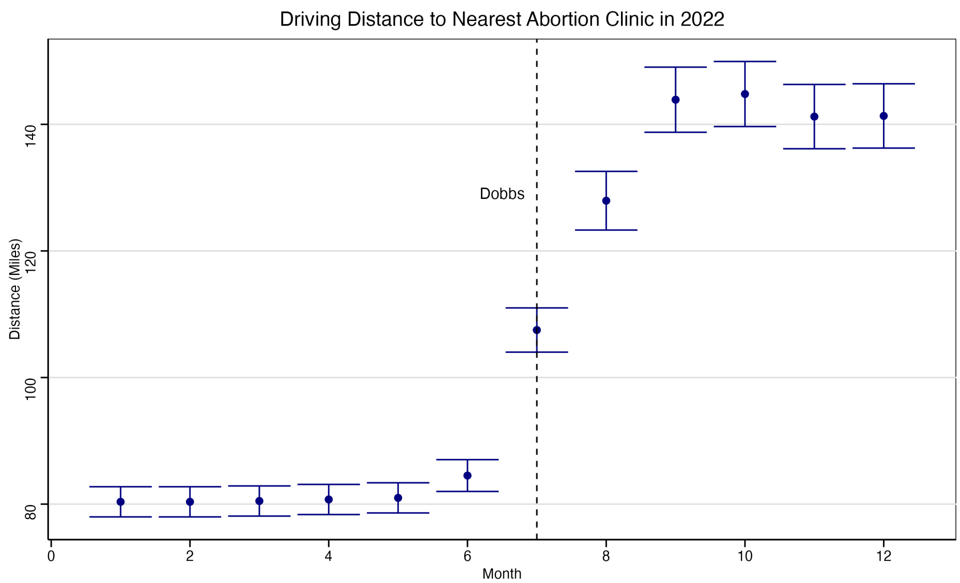

Figure 1: Distance to Nearest Abortion Clinic in 2022

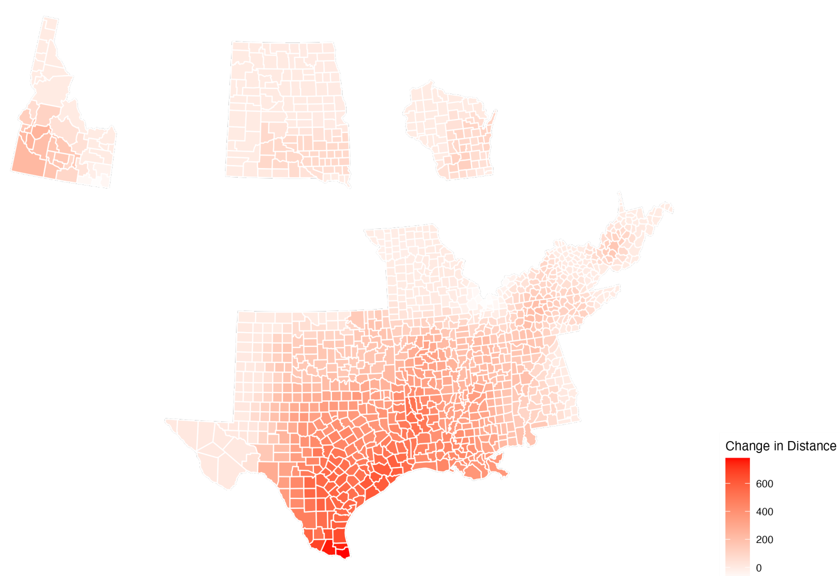

Figure 2: Map of D_i

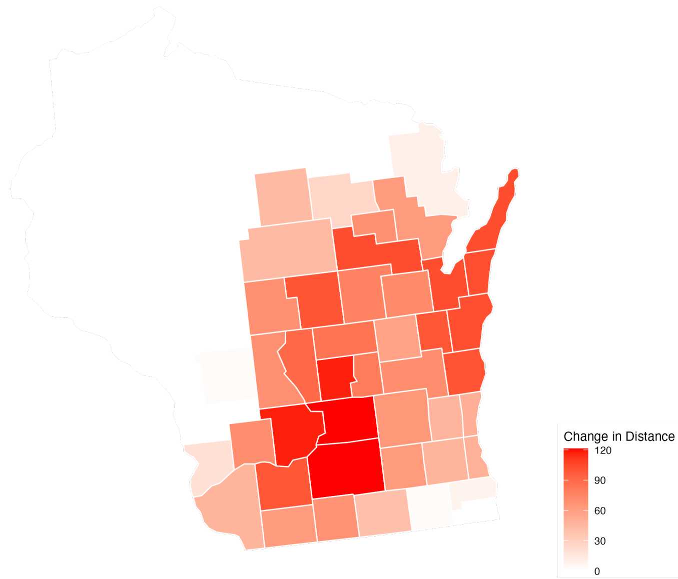

Figure 3: Map of D_i in Wisconsin

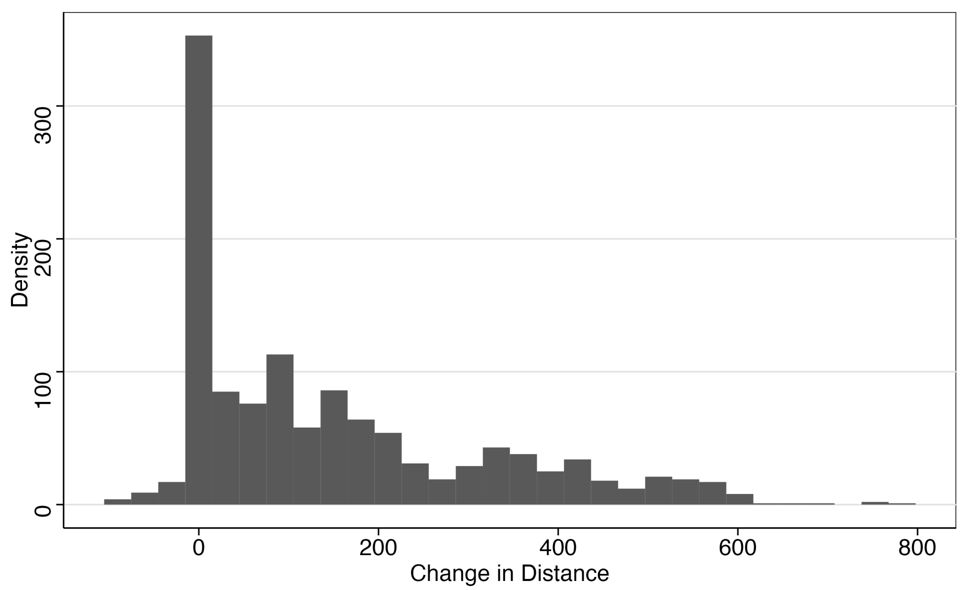

Figure 4: Histogram of D_i

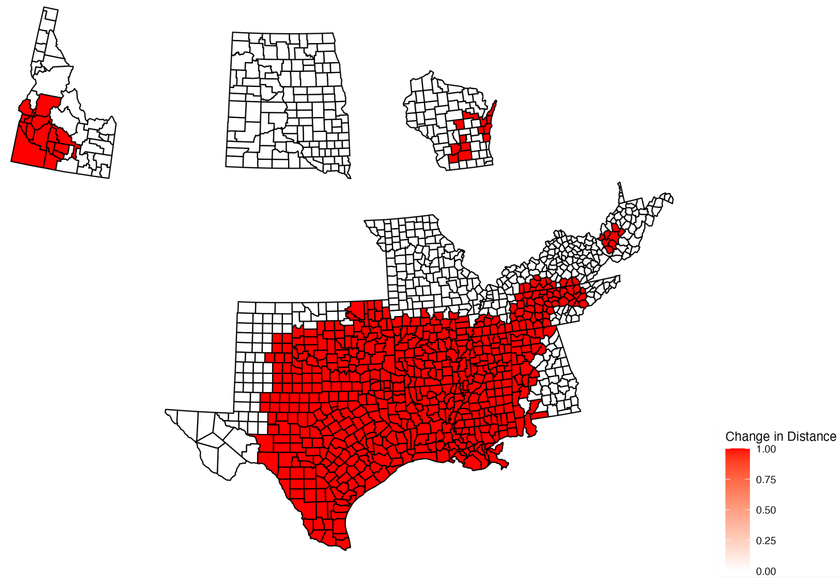

Figure 5: Map of W_i

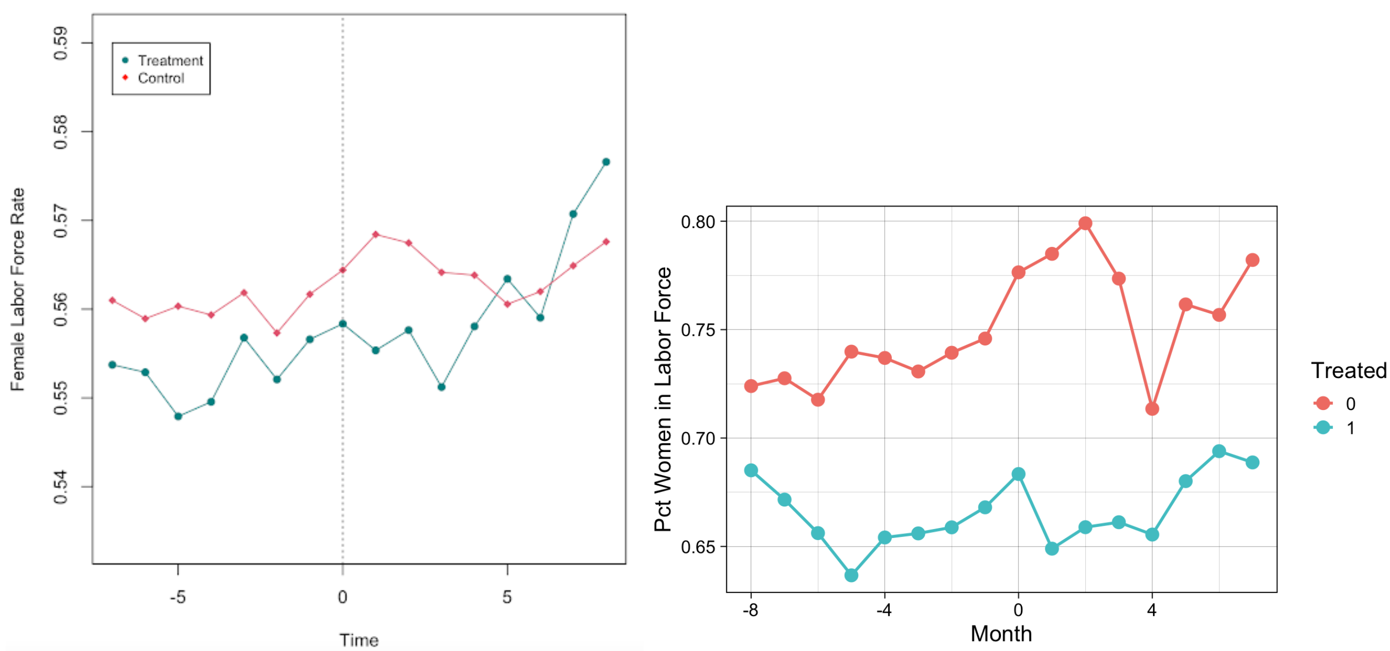

Figure 6: Female Labor Force Rate Plots

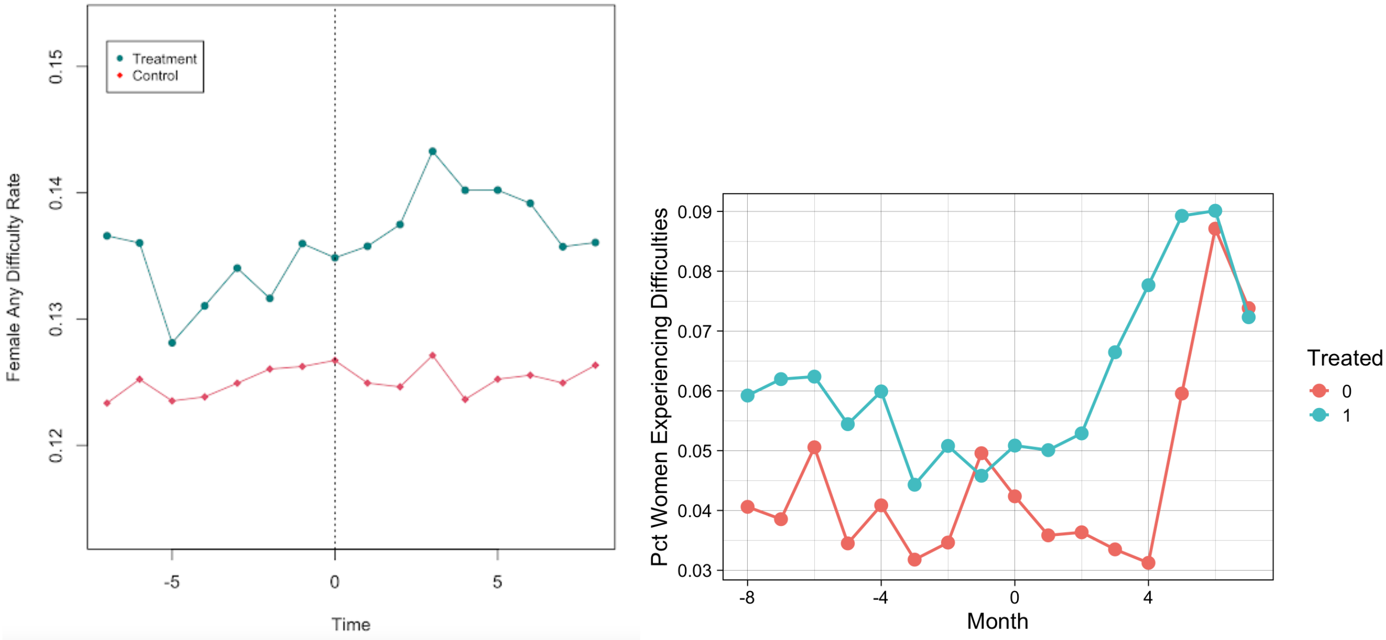

Figure 7: Female Any Difficulty Plots

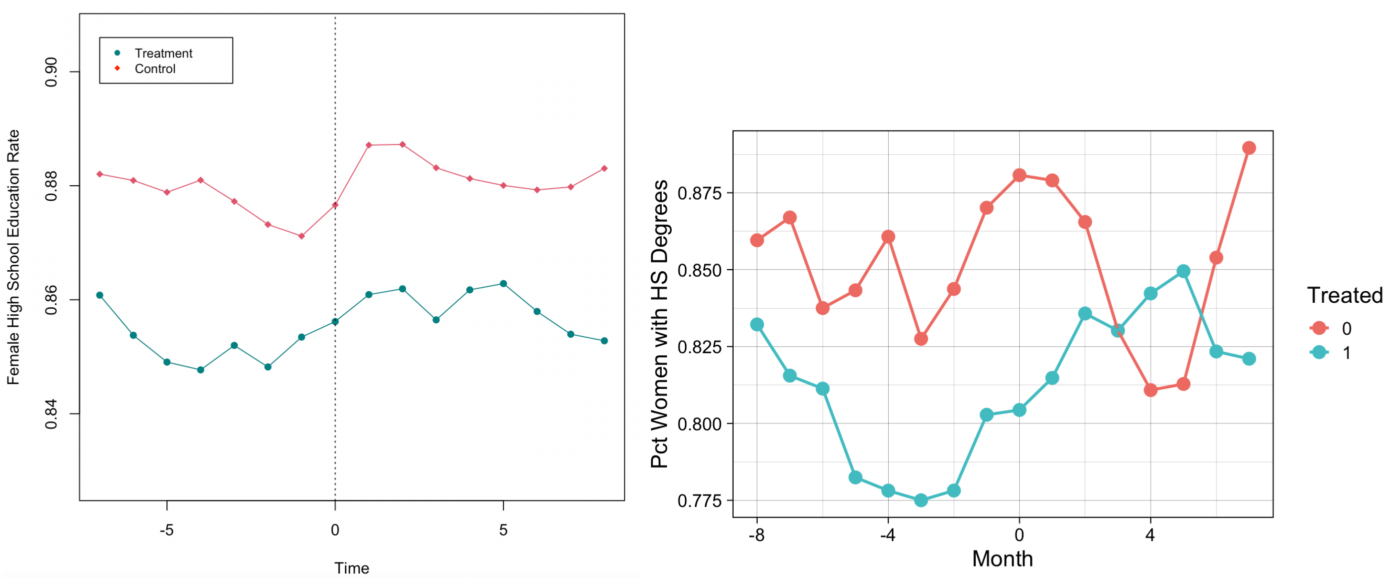

Figure 8: Female HS Education Rate Plots

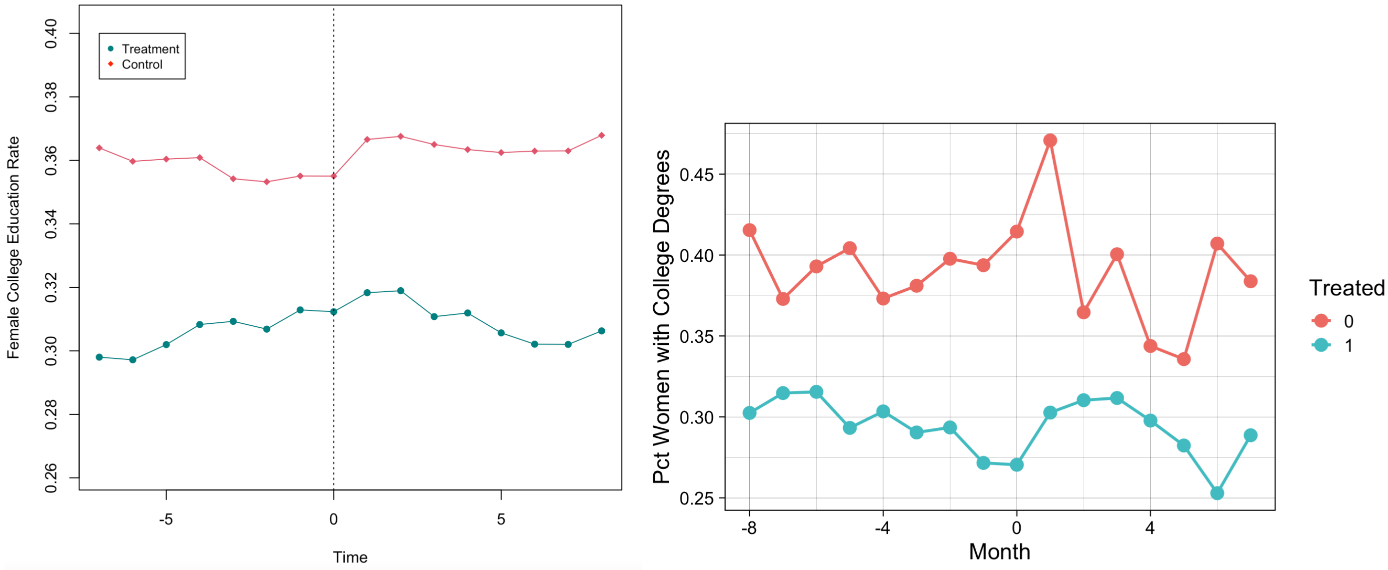

Figure 9: Female College Education Plots