# The Effects of Transparency Laws on Foundations in Higher Education

by

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# THESIS ABSTRACT

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In this study we examine how state-level foundation transparency regulations affect the endowments of institutions of higher education. Using a panel of over 6,000 US higher education institutions from 2004-2023, we employ an event-study framework to estimate the causal effect of laws subjecting university foundations to public records requirements on an institution's aggregate endowment value. We employ a group-time difference-in-differences estimator adapted from Callaway and Sant'Anna (2021), as well as a two-way fixed effect model with state-level economic controls. We find no evidence of a causal link between transparency and endowment value among private non-profit institutions. Among public institutions, our results vary by model specification. From our difference-in-differences analysis, we find no effect among public institutions, however our two-way fixed effects model suggests a positive and significant treatment effect on endowment value of approximately 10-12%. These results persist when excluding always-treated units. We thus find no evidence to suggest that increased transparency harms endowment growth and offer suggestive evidence that such regulation may instead improve endowment growth among public institutions. These novel findings contribute to the growing literature surrounding transparency and accountability in higher education.

# Contents

**1 Introduction** . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . **6**

**2 Methods** . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . **9**

2.1 Data . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 9

2.2 Difference-in-Differences . . . . . . . . . . . . . . . . . . . . . . . 11

2.3 Two-Way Fixed Effects . . . . . . . . . . . . . . . . . . . . . . . . 12

2.4 Robustness . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 13

**3 Results** . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . **14**

**4 Conclusion** . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . **16**

**References** . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . **17**

**Appendix: Figures and Tables** . . . . . . . . . . . . . . . . . . . . . . **19**

# List of Figures

1 US States by Treatment Status . . . 19
2 Pre-Treatment Trends in Public and Private Non-Profit Institutions . . . 20
3 DiD in Logs for Private Institutions . . . 21
4 DiD in Logs for Public Non-Profit Institutions . . . 22
5 DiD in Logs for Private Institutions Excluding Always-Treated . . . 23
6 DiD in Logs for Public Non-Profit Institutions Excluding Always-Treated . . . 24

# List of Tables

1 Summary Statistics . . . 20
2 Two-Way Fixed Effects Estimates . . . 25
3 Restricted Two-Way Fixed Effects Estimates . . . 25

# 1 Introduction

Endowment funds play a pivotal role in the operations of U.S. colleges and universities in recent years. These funds help to cover operational expenses and cushion against potential financial shocks. While typical enterprises are often financed by debt, the presence of a large capital reserve in the form of an endowment allows educational institutions to own their assets outright, avoiding debt and helping to ensure healthy and consistent finances into the future (Hansmann, 1990). A large endowment fund can help support innovative efforts and allow an institution more autonomy by reducing dependence on public funding (Meyer & Zhou, 2017). In general, university endowments play a role in maintaining academic quality, as well as potentially broadening access to elite education by providing funding opportunities (Lerner et al., 2008). One major function of the endowment is as an instrument through which funds may be donated to an institution. For many institutions, funds from private donors meaningfully contribute to funding capabilities.

In recent years, there has been a growing debate surrounding transparency in the oversight and management of university endowments. These endowments are often managed by a foundation established and controlled by their associated university or institution. Though a separate legal entity, the purpose and oversight of these foundations closely align with those of their associated institution, and can thus be treated as effectively the same body (Dimmock, 2012). While institutions thus maintain control of the endowed funds, many donations are given with restrictions – either explicit or implicit – on how the principal may be spent (Dimmock, 2012). For example, a donor may only give money on the condition that it be used exclusively for athletic rather than academic programs. Currently, the U.S. does not have any federal laws in place to regulate or require transparency in non-profit foundations (Jung, 2024). This leaves much of the regulatory decision-making to state legislators and foundation boards. This ultimately creates variation in transparency practices across states and institutions, leading to disagreement on what best-practices may actually be.

We may obtain some insight into the potential effects of transparency in higher education by first looking at its effect in other sectors. Some studies indicate that regulations which aim to increase transparency can improve social outcomes such as equity. For example, there is evidence that disclosing salaries for public sector employees may reduce the gender pay gap by as much as 40% (Baker et al., 2019). In the context of government spending, increased transparency is correlated with more equal political competition and power sharing, while decreased transparency is correlated with more political polarization (Alt et al., 2006). However, in the private sector the effects may not be so desirable. Some scholars argue that increased transparency in corporate governance, for instance, can harm a firms profitability while leading to higher executive compensation, and may even incentivize firms to distort information (Hermalin & Weisback, 2007). Still, even in the private sector there is evidence that foundations which rely on donations may benefit from transparency, as donors demand to know how their money is actually being spent (Rey-Garcia et al., 2012). These findings paint a somewhat conflicting picture of how transparency regulation should fit into higher education. Thus, some argue that the best route forward for higher education involves more radical reform so that the incentives of private institutions may more closely align with public welfare (Libby, 2025).

Such discourse is closely related to broader social and cultural concerns regarding university endowments. One major concern is the growing concentration of wealth to a small number of elite institutions. In 2013, among the 120 U.S. universities with the largest endowments, the top 10% of institutions collectively held approximately the same value in endowments as the bottom 90% combined (Meyer & Zhou, 2017). Some of the top schools, such as Harvard University, now hold wealth in the tens of billions. Given the current political environment, in which wealth inequality and social mobility are in the forefront of social discourse, it is trivial to imagine how such disparity within our educational institutions could prompt calls for increased oversight. Meyer and Zhou (2017) argue that while large endowments have historically improved public welfare by fueling academic freedom and innovation, a shift towards a "winner-takes-all" market has led to endowments being used more as a means to cushion top universities from the need to compete. Thus, top institutions may no longer be incentivized to innovate and improve. The authors also note that such vast wealth should theoretically allow such institutions to lower tuition requirements and broaden access to a more diverse student population, but in reality this is not observed. In fact, there is evidence that larger endowments are associated with higher selectivity as universities are able to increase spending on instruction and student services, resulting in fewer low-income students and persons of color enrolling (Bulman, 2022).

While much of the discourse discussed so far relates to how transparency should or should not fit into higher education, few authors analyze how transparency affects observed outcomes for university foundations. This is important, as endowment growth can broaden access to elite institutions, while poor endowment performance can lead to cuts in instructional staff and educational programs (Lerner et al., 2008). In this paper, we seek to inform the debate surrounding foundation transparency by investigating its effects on university financial growth. In particular, we test to see if state-level foundation transparency regulations affect the aggregate endowment value of institutions subject to such regulations relative to institutions that are not. We collect data from the Integrated Postsecondary Education Data System (IPEDS) on endowment value from over 6,000 institutions of higher education in the US. Using both a difference-in-differences model, as well as a two-way fixed effects model, we determine whether a causal link exists between transparency regulation and changes in endowment growth. This allows us to understand more concretely whether these regulations actually affect the financial health of institutions of higher education, and in which direction. We find that among private non-profit institutions, transparency has no statistically significant effect on endowment assets. Among public institutions, our results are less conclusive. With a two-way fixed effects model, we estimate that transparency regulation increases endowment assets by as much as 11.7%, while a difference-in-differences model fails to identify any significant effect. We find no evidence to suggest that increased transparency harms the financial health of any institution of higher education.

# 2 Methods

To analyze the effect of transparency regulation on endowment funds, we first collect data on public and private non-profit institutions of higher education in the United States. This data includes many institutional characteristics including aggregate endowment fund value for each institution in a given year. We then assign a treatment status to each university in a given year based on state legislation. We additionally collect state-level economic data for control variables as needed.

With this data, we first employ a dynamic difference-in-differences model. This allows us to compare endowment outcomes for treated institutions to an estimated counterfactual trend which would have been realized had treatment never been effected. We also estimate a two-way fixed effects model to isolate any idiosyncratic effects attributable to individual institutions or time periods. Finally, we repeat both of these processes on a subset of the data intended to reduce any bias which may arise from insufficient pre-treatment data.

## 2.1 Data

We collect institutional characteristics including endowment fund value from the Integrated Postsecondary Education Data System (IPEDS). Included in this data set is every college, university, and technical and vocational institution that receives federal student financial aid. The data obtained covers 2004 through 2023, which is the time frame to be used in this analysis. Myriad characteristics are documented in this data set for each institution in each year, including but not limited to student body demographics, average tuition and financial aid, academic program offerings, and countless others. The primary institutional variable of interest is endowment size, calculated as the total value of endowment assets, which we have converted to be measured in millions of nominal U.S. dollars. This will be used as the outcome variable in our statistical analyses.

We obtain state-year level transparency regulation data compiled by Ducharme (2025). Ducharme categorizes each state by its level of foundation transparency regulation. In particular, we are concerned with the states in which a state statute or court ruling explicitly provides for a public university to be subject to the Freedom of Information Act (FOIA). We then obtain the years in which each regulation was enacted for these states. We can thus define the treated group in our data set to include any institution in a state that provides explicit FOIA access in a given year.

It should be noted that some states received treatment through legislation or court ruling at an earlier date than 2004, and will thus be considered "always treated" within the time frame of this analysis. This presents some challenges to the assumptions of our difference-in-differences model. These challenges are explored in more detail and addressed in the Robustness section of this paper.

We obtain state economic variables from the Bureau of Economic Analysis on an annual basis for each year of our analysis. These include state GDP, personal income statistics, and others which we use as control variables in some parts of our analysis.

Summary statistics for select variables of interest are shown in Table 1, with dollar values reported in millions of nominal US dollars in the year they were reported. There is a striking disparity between the average endowment value of around 181 million USD and the maximum endowment value of over 53 billion USD. This maximum value is from Harvard University in 2022, which is the most recent year included in the data. This disparity is also reflected in the difference between the average total value of assets (271 million USD) and maximum value of assets (92 billion USD). This highlights the previously discussed social concerns surrounding equity. Table 1 also shows that about 65% of institutions observed reside in a state which receives treatment, with the average treated institution receiving treatment in 1996. While this is earlier than the scope of our data, many states are treated later. Washington is the most recently treated state, its regulation taking effect in 2020.

One point of interest from Table 1 is the relationship between annual endowment growth, tuition, and total revenues. For the average institution, tuition accounts for more than twice as much revenue as endowment growth, indicating that most schools rely on students to cover a significant portion of expenses. However, the story changes when we look at institutions at the maximum. Here, annual endowment growth is nearly five times greater than tuition revenue, and represents more than half of total revenue. This suggests that for the richest and most elite universities, endowments play a much more significant role in funding than the average institution.

## 2.2 Difference-in-Differences

To obtain an estimate for the treatment effect on endowment size, we use a difference-in-differences model adapted from Callaway and Sant'Anna (2021). This generalized model allows for variation in treatment time across groups, reflecting the variation in legislation timing among treated states. Thus rather than estimating a tradition average treatment effect among treated individuals (ATT), we instead estimate the group-time average treatment effect, defined as

$$ATT(g,t) = E[Y_t(g) - Y_t(0)|G = g]$$

where $ATT(g,t)$ is the group-time average treatment effect for group $g$ in period $t$, and $Y_t(g)$ denotes the outcome variable at time $t$ for group $g$. In this case, our time scale is in years, so each $t$ represents a single year. Because treatment is assigned (and thus timed) at the state level, each group contains every institution in each given treated state. We can thus think of this group-time ATT as the difference between the observed average endowment fund value of institutions in a given treated state and the unobservable average value that would have been realized had the institutions (and their associated state) never been treated.

The condition that must be met in order for our ATT estimate to be considered causal is the parallel trends assumption. This is the assumption that the pre-treatment trends in the outcome variable among the treated group should reflect similar contemporaneous trends in the untreated group. To check this assumption, we plot the outcome variable for the untreated and pre-treatment groups to compare their trends. Additionally, we separate public universities from private non-profit universities, assigning each to their own plot. This is because we define our treatment group in the Data section of this paper as any institution in a state which explicitly provides FOIA access to any *public* university foundation. Thus the effect on public and private universities is not necessarily the same.

Figure 2 shows pre-treatment trends for public and private non-profit institutions. While pre-treatment trends for treated versus untreated units are not perfectly aligned, in the case of public institutions they do appear to follow roughly the same path, with peaks and troughs occurring mostly contemporaneously. In the case of private non-profit institutions, similarities in pre-treatment trends begin to break down after 2016. It should be noted that in the later observed years, the number of treated units for which treatment is yet to occur decreases as most states are already treated. For this reason, we might expect pre-treatment trends to diverge similarly to what is observed in Figure 2. In fact, statistical evidence that the identification assumption is met for both public and private institutions is discussed in the Results section of this paper.

## 2.3 Two-Way Fixed Effects

To supplement the group-time ATT estimator from our difference-in-differences model, we employ a more classical two-way fixed effects (TWFE) model using ordinary least squares (OLS) according to the following equation:

$$Y_{it} = \beta D_{it} + \alpha_i + \gamma_t + X_{it} + \epsilon_{it}$$

where $Y_{it}$ denotes the natural logarithm of the aggregate endowment value for institution $i$ in year $t$, $D_{it}$ is a binary indicator equaling 1 if institution $i$ is treated in year $t$ and 0 otherwise, $X$ is a vector of control variables, and $\alpha$ and $\gamma$ denote institution and year fixed effects respectively. The controls used in this case are state-level economic variables including real GDP, PCE, and average personal income. Reported standard errors are clustered at the state level, which is the level at which treatment is assigned.

This model, as with the previously discussed difference-in-differences model, relies on the assumption that trends in the outcome variable are similar among treated and untreated units. As we have established, this assumption appears to be met more consistently among public institutions than private ones, as seen in Figure 2. However, as will be discussed in the Results section of this paper, we do find statistical evidence that this assumption is met for both private and public institutions. Under this assumption, we expect the coefficient $\beta$ to identify the average treatment effect among treated units (ATT). While this model no longer accounts for treatment heterogeneity resulting from differences in treatment timing, it brings the added benefit of introducing fixed effects. Thus any change in the outcome variable attributable to idiosyncratic differences between units and years should not effect our estimator.

## 2.4 Robustness

One shortcoming of the models described thus far is the lack of pre-treatment data for some treated units. Recall that the relevant data are observed in the period of 2004-2023. While some treated units receive treatment during this time frame, others were treated far earlier. For example, institutions in Colorado are regulated by the Colorado Open Records Act (CORA), which was passed in 1969 (Ducharme, 2025). Thus all institutions within Colorado received treatment at a date prior to the range observed. In the context of a difference-in-differences model, in which we expect treated units to be observed before and after treatment in order to calculate the difference in pre- and post-treatment trends, this discrepancy presents a challenge. Additionally, our estimates rely on the assumption that pre-treatment trends among treated units match trends among control units. Because no data is available for the pre-treatment period of institutions treated prior to the start of our observed data range, this assumption cannot be completely confirmed.

To address these issues, we restrict our data to exclude “always treated” units. That is, any institution in a state which is assigned treatment prior to 2005 is excluded from the data used for the following regression models. We then use this restricted set of data to repeat the difference-in-differences and TWFE approaches outlined in the previous sections of this paper. This ensures that for any treated unit we may observe a pre-treatment period, allowing us to test our pre-trends assumption more robustly. The drawback to this approach is the reduced sample size, which results in decreased statistical power.

# 3 Results

Group-time ATT estimates from our difference-in-differences model are displayed graphically in Figures 3 and 4. Each post-treatment point estimate (shown in blue) represents the ATT for a given group $t$ years after treatment, where $t$ is enumerated by the horizontal axes. The associated vertical bars show 95% confidence intervals using the calculated standard errors. Thus, a given point estimate is significant at the 5% level if the associated error bar does not intersect 0 on the vertical axis. That is, any point estimate for which the error bar intersects with the horizontal line at 0 is statistically indistinguishable from 0, indicating that no statistically significant treatment effect is observed.

For both private and public non-profit institutions, we observe no statistically significant treatment effect. In other words, our difference-in-differences analysis does not identify any effect of foundation transparency regulation on endowment assets.

Figures 3 and 4 also give some statistical backing to our identification assumption. Rather than comparing pre-treatment trends visually as we did with the pre-trends plots in Figure 2, the group-time ATT estimates provide an explicit metric for determining if the parallel trends assumption is met. Pre-treatment estimates (shown in red in Figures 3 and 4) denote the average difference in log outcomes between treated and untreated units in the pre-treatment period. Thus, when the error bar around a given point estimate intersects 0 on the vertical axis, we may conclude that there is no statistically significant difference in trends between treated and untreated units $t$ years before treatment, where $t$ is the value of the horizontal axis at the given point. Across both public and private non-profit institutions, there exists no observed period in which pre-treatment outcome values differed significantly. This finding, supplemented with our prior visual assessment of trends, allows us to conclude that our identification assumption is met.

ATT estimates from our TWFE models are shown in Table 2, both with and without included economic control variables. When not controlling for state economic data, we find a treatment effect of 11.7% among public institutions, and 10.1% when including controls. These estimates are significant at the 0.1% level. As with the difference-in-differences models, we do not observe any significant effect among private non-profit institutions. We may interpret these estimates to indicate that public institutions to which foundation transparency regulations apply see on average an increase to their aggregate endowment value of around 10.1% attributable to the enactment of those regulations.

For robustness, we repeat the process of our difference-in-differences and TWFE models for a subset of our data excluding always-treated units as previously outlined. We may henceforth refer to these models which use a restricted subset of data as our "restricted" models. Estimates from the restricted difference-in-differences models are shown for public and private non-profit institutions respectively in Figures 5 and 6. As with the unrestricted model, we again find no statistically significant treatment effect. For every given group-time ATT point estimate, our error ranges overlap with 0, preventing us from identifying any non-zero effect. This gives further confidence to the previous null findings of our difference-in-difference models.

Estimates from our restricted TWFE model are shown in Table 3. We again find no statistically significant treatment effect on private institutions. We identify a treatment effect on public institutions of 8.1% significant at the 1% level, which rises to an effect of 11.4% significant at the 0.1% level when including state economic variables as controls. This aligns with the results of our unrestricted model to indicate an ATT of around 10% among public institutions.

# 4 Conclusion

The question of how transparency regulations affect the financial health and growth of institutions of higher education is central to the debate surrounding the role that these regulations should play in society. While proponents of transparency regulation argue that transparency breeds greater accountability, skeptics may be quick to point out the potential for such regulations to scare off potential donors and thus reduce access to high quality educational resources. This critical view is prefaced on the assumption that transparency leads to a decrease in endowment growth, which we test herein. We estimate a difference-in-differences model as well as a two-way fixed effects model to determine what effect, if any, transparency regulations have on endowment assets for institutions of higher education.

We do not find any correlation to suggest that transparency hurts endowment asset growth in public or private non-profit universities. To the contrary, we find inconsistent evidence that suggest there may be a positive causal link between transparency and endowment growth. This finding supports the implementation of transparency regulation, as it identifies a previously not discussed potential benefit of transparency while providing evidence to dispute a primary opposing argument.

While these findings contribute to a growing literature and may help inform the debate of transparency and its role in higher education, they are far from conclusive. More inquiry is required to better understand why our results for public institutions are so sensitive to model specification. One potential opportunity to expand on these findings may come from identifying a larger data source. Obtaining data for earlier years would help increase statistical power by allowing observation of pre-treatment variables for all treated units. Additionally, we use a single binary indicator as our treatment variable, but treatment may be heterogeneous. One state's regulation may differ significantly from that of a neighboring state. Further inquiry into the nature of transparency regulations and treatment heterogeneity may help us understand which regulations are most effective. Overall, while more study is needed to conclusively determine the effects of transparency in higher education, this analysis is the first to analyze such effects explicitly.

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# Appendix: Figures and Tables

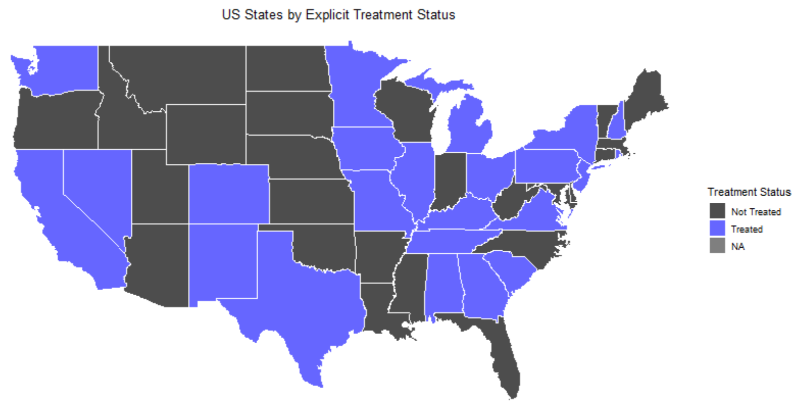


Figure 1: US States by Treatment Status


Figure 2: Pre-Treatment Trends in Public and Private Non-Profit Institutions

Table 1: Summary Statistics

| | Mean | SD | Min | Max |
|---|---|---|---|---|
| Aggregate Endowment | 180.89 | 1258.76 | 0.00 | 53 165.75 |
| Annual Change in Endowment | 14.77 | 194.80 | −10 788.45 | 11 271.37 |
| Total Assets | 271.37 | 1793.21 | −65.94 | 92 857.39 |
| Total Revenue | 151.05 | 590.07 | −10 117.23 | 18 439.12 |
| Tuition and Fees | 33.46 | 90.22 | −0.01 | 2452.22 |
| Undergraduate Student Headcount | 3543.55 | 8219.63 | 1.00 | 411 663.00 |
| Graduate Student Headcount | 1813.69 | 3839.55 | 1.00 | 91 356.00 |
| Annual Undergraduate Admissions | 2287.47 | 4140.68 | 0.00 | 89 207.00 |
| Percent Admitted to Undergrad | 69 | 22 | 0 | 100 |
| Treated Ever (1 if true) | 0.65 | 0.48 | 0.00 | 1.00 |
| Treatment Year | 1996.86 | 15.79 | 1963.00 | 2020.00 |

*Financial variables such as endowments and revenues are reported in millions of nominal US dollars.*

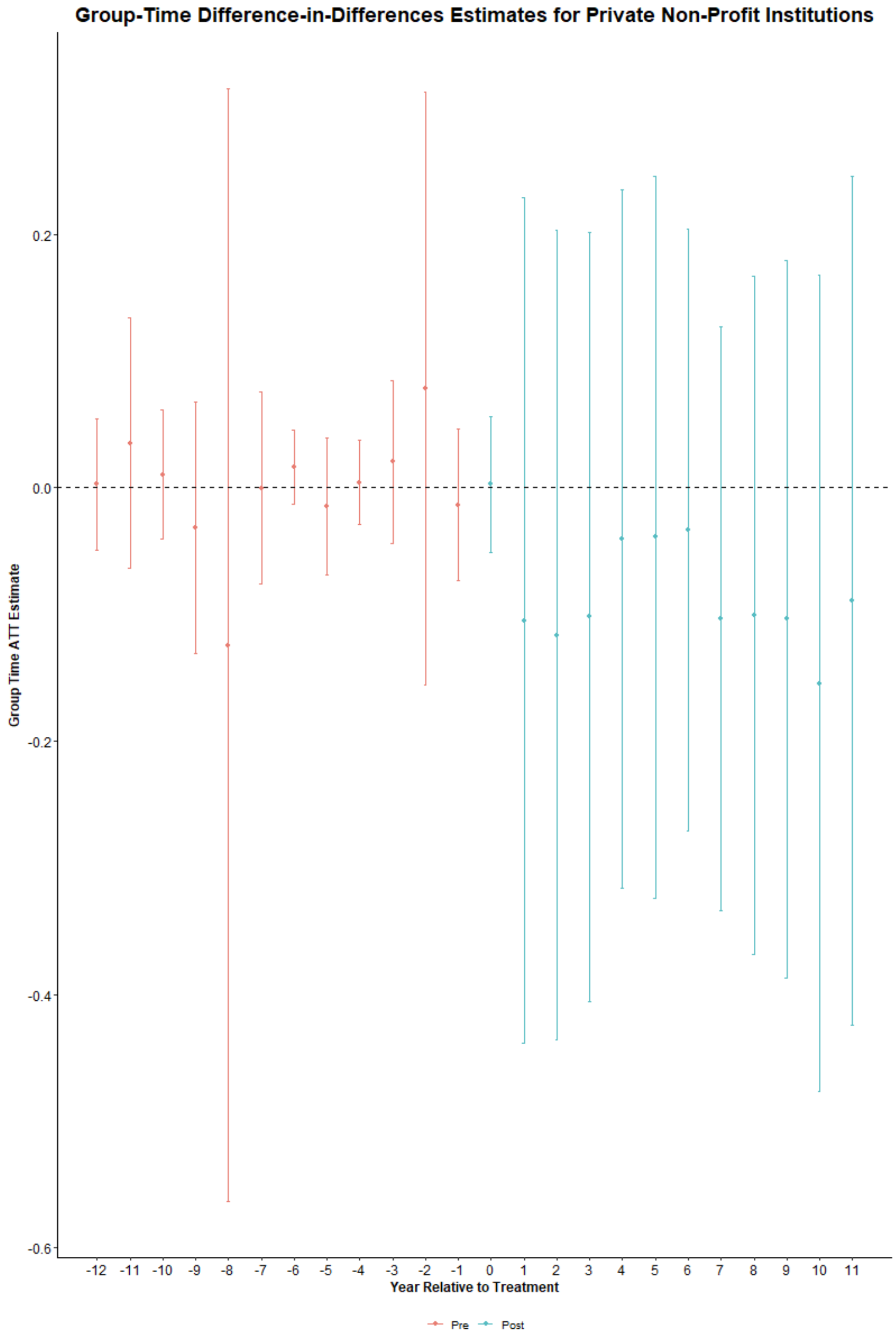


Figure 3: DiD in Logs for Private Institutions

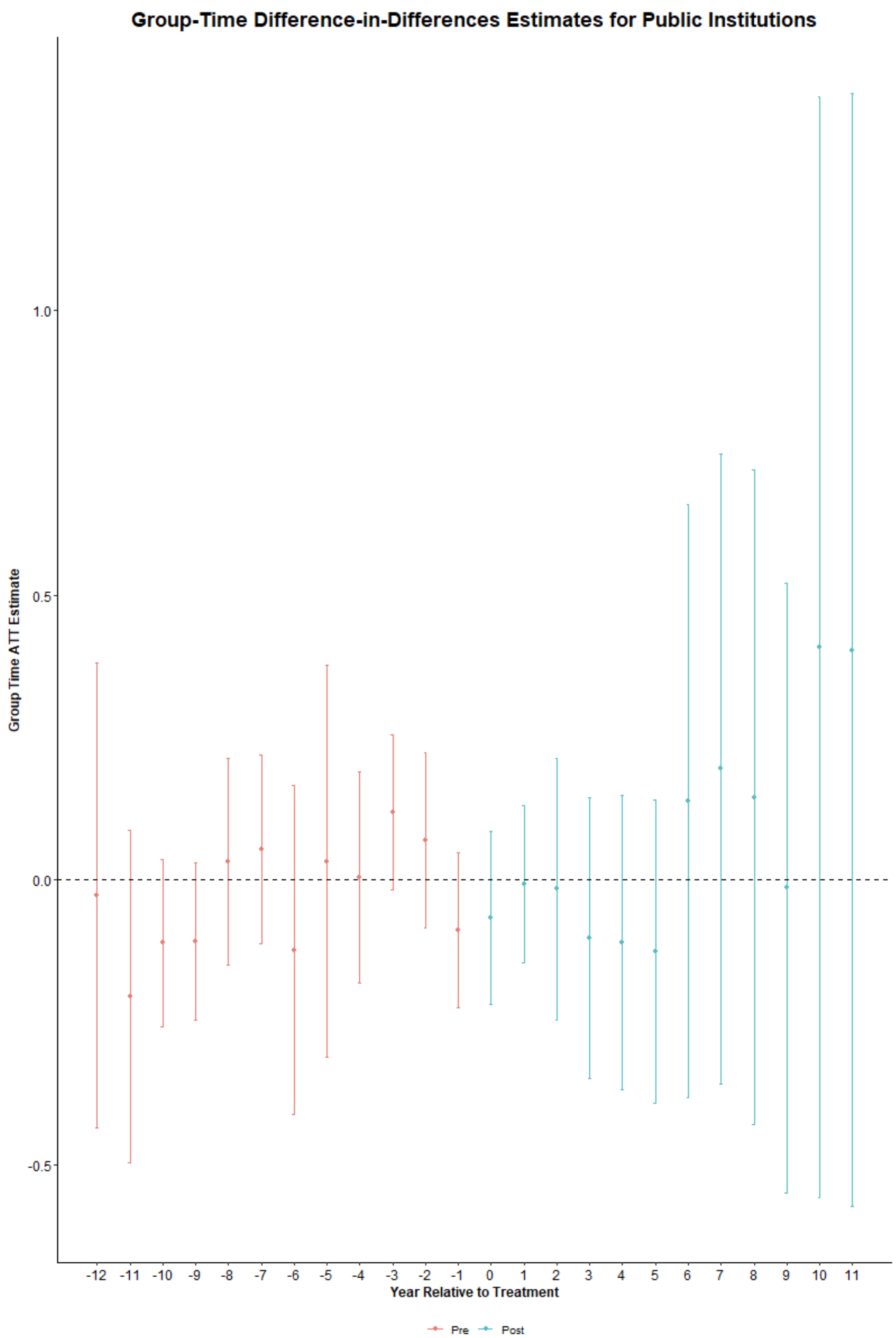


Figure 4: DiD in Logs for Public Non-Profit Institutions

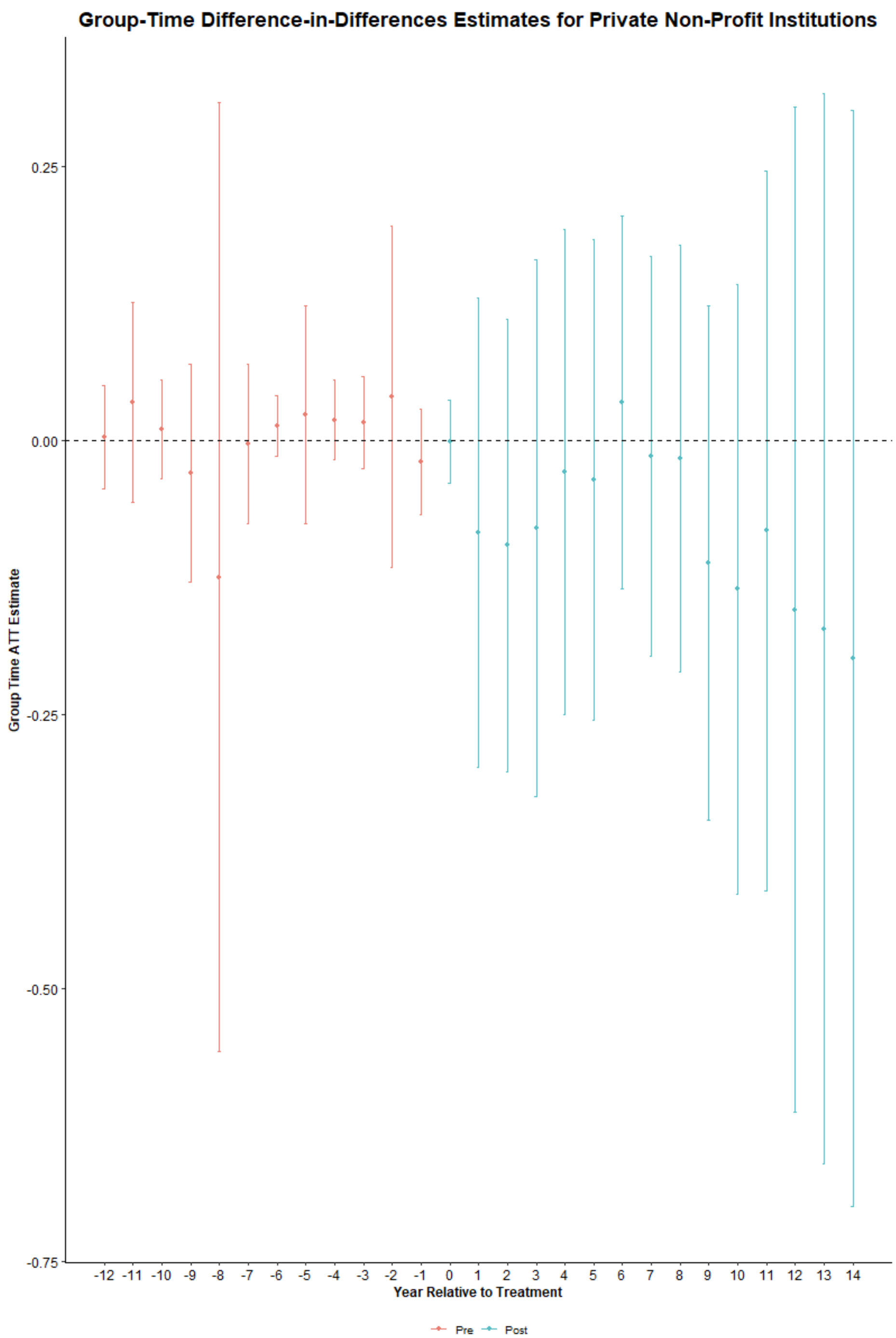


Figure 5: DiD in Logs for Private Institutions Excluding Always-Treated

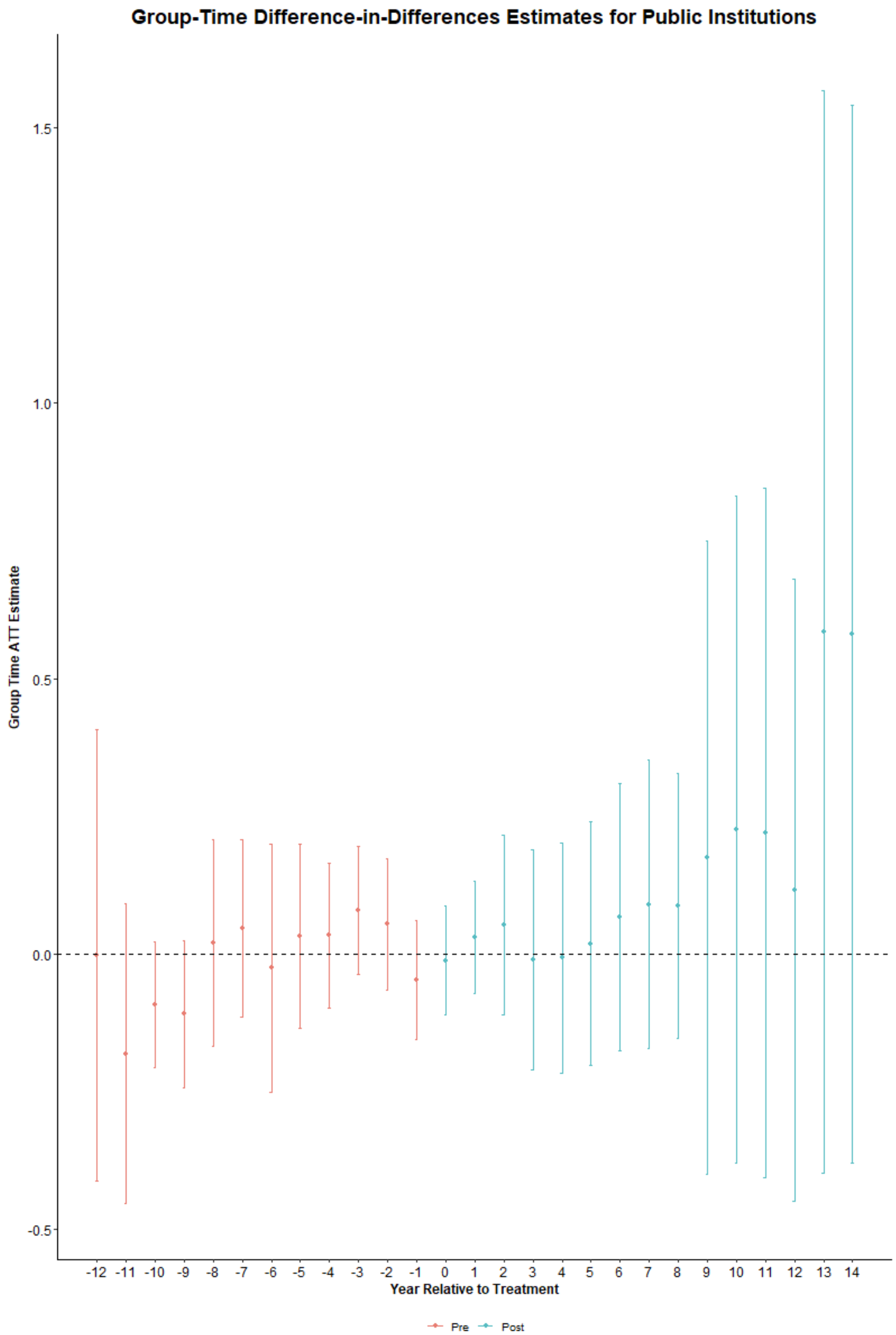


Figure 6: DiD in Logs for Public Non-Profit Institutions Excluding Always-Treated

Table 2: Two-Way Fixed Effects Estimates

| | Public | Private Non-Profit | Public | Private Non-Profit |
|---|---|---|---|---|
| Log Treatment Effect | 0.117*** | −0.005 | 0.101*** | −0.008 |
| | (0.027) | (0.012) | (0.024) | (0.015) |
| Num.Obs. | 23 929 | 26 027 | 19 112 | 20 243 |
| R2 | 0.936 | 0.961 | 0.961 | 0.970 |
| R2 Adj. | 0.932 | 0.959 | 0.958 | 0.968 |
| R2 Within | 0.001 | 0.000 | 0.002 | 0.000 |
| R2 Within Adj. | 0.001 | 0.000 | 0.002 | 0.000 |
| AIC | 45 079.0 | 37 025.9 | 26 213.3 | 22 943.4 |
| BIC | 57 106.2 | 50 419.6 | 37 568.2 | 35 355.0 |
| RMSE | 0.58 | 0.46 | 0.45 | 0.39 |
| Controls Included | | | X | X |

+ p <0.1, * p <0.05, ** p <0.01, *** p <0.001

Table 3: Restricted Two-Way Fixed Effects Estimates

| | Public | Private Non-Profit | Public | Private Non-Profit |
|---|---|---|---|---|
| after_leg_year_explicit | 0.081** | −0.019 | 0.114*** | −0.015 |
| | (0.028) | (0.014) | (0.024) | (0.016) |
| Num.Obs. | 14 570 | 15 725 | 11 740 | 12 380 |
| R2 | 0.927 | 0.967 | 0.960 | 0.973 |
| R2 Adj. | 0.922 | 0.964 | 0.956 | 0.971 |
| R2 Within | 0.001 | 0.000 | 0.005 | 0.000 |
| R2 Within Adj. | 0.001 | 0.000 | 0.005 | 0.000 |
| AIC | 29 086.1 | 19 253.8 | 16 246.1 | 12 568.0 |
| BIC | 35 959.6 | 26 978.2 | 22 798.7 | 19 791.4 |
| RMSE | 0.62 | 0.42 | 0.45 | 0.37 |
| Controls Included | | | X | X |

+ p <0.1, * p <0.05, ** p <0.01, *** p <0.001