Effect of TCJA On Firm Investment Behaviors: Lessons from the Hospital Industry

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Abstract:

This paper examines the effects of the Tax Cuts and Jobs Act of 2017 (TCJA) on employment and investment within the hospital industry. The analysis focuses on this sector due to its distinct mix of for-profit and non-profit firms. TCJA policies exogenously increase the available cash flow for for-profit hospitals compared to non-profit hospitals, which are almost unaffected by it, creating a natural control group that can be exploited and allowing for a difference-in-differences approach. This study hypothesizes that a corporate tax cut will not significantly affect investment and employment rates in for-profit hospitals relative to non-profit hospitals. The main variables of interest will be employment rate, capital investment, and readmission rate. These measures enable an assessment of how tax cuts impact labor outcomes, investment behavior, and the quality of care within the hospital industry. This paper collected data from the Centers for Medicare & Medicaid Services (CMS) and the Bureau of Labor Statistics (BLS) for the period 2015 to 2019.

(Conclusion placeholder)

1. Introduction

The hospital industry is economically vital due to its massive scale and essential societal responsibilities. Hospitals are among the largest employers in the U.S., providing over 6.6 million jobs and directly and indirectly supporting one in six jobs nationwide in 2023. This sector alone generates approximately 4.8 trillion dollars in total economic output. (American Hospital Association, 2025) According to Martin, Hartman, Washington, Catlin, & National Health Expenditure Accounts Team (2024), overall health care spending accounted for 17.6% of U.S. GDP, with hospital industry expenditure accounting for nearly a third of that. Together, these statistics illustrate the central role the hospital industry plays in the U.S. economy and society. That significance underscores the need to closely examine the effects of a significant tax policy, such as TCJA, on this industry and the potential economic risks or benefits it can generate.

The hospital industry offers a unique setting to examine the effects of TCJA that are seldom seen in other sectors of the economy. Most notably, the hospital industry comprises firms with various ownership structures, including private for-profit, private non-profit, and government hospitals. These hospitals participate and compete within the same market. This mix creates a natural environment for empirical analysis. To be more specific, because this study focuses on policies associated with tax cuts, a sector that comprises taxable and tax-exempt entities is ideal, as all tax-exempt entities are naturally unaffected. Non-profit and for-profit hospitals differ in the services they provide; for instance, non-profit hospitals are generally larger and more likely to provide less profitable services, such as psychiatric emergency care. In contrast, for-profit hospitals are much more responsive to profitability and more selective (Horwitz & Nichols, 2022). It is reasonable to assume that both types of hospitals share similar social and economic roles, as they provide essential care, employ large labor forces, and respond to local health needs. Under this assumption, this study treats non-profit and for-profit hospitals as functional comparables, satisfying the treatment and control group condition for a difference-in-differences framework.

The TCJA's most influential corporate side provisions include a flat tax rate cut for top corporate to 21%, allowing full expensing of equipment and machinery, and removal of the Alternative Minimum Tax. First, the TCJA replaced the graduated corporate tax rate structure with a flat 21% rate for corporations across all income levels, thereby lowering the effective tax rate for top-earning firms from 35% to 21% (IRS, October 2018). This policy significantly increased the cash flow for for-profit hospitals relative to non-profit hospitals. Second, full expensing allows firms to immediately deduct the cost of investment in qualified property, such as medical equipment or machinery, enabling more aggressive investing and hiring. Third, the elimination of the Alternative Minimum Tax permits firms to fully utilize deductions without being constrained by AMT's limitations. Together, all three changes directly benefited for-profit hospitals, while non-profit hospitals remained unaffected due to their tax-exempt status.

This paper hypothesizes that TCJA provisions affecting for-profit hospitals did not result in a significant change in labor investment and employment relative to non-profit hospitals. This proposal is supported and developed from a microeconomics theoretical model in which a firm maximizes profit subject to productivity constraint, implying limited flexibility and other priorities.

2. Literature Review

2.1 Tax cuts, inequality, and their economic impacts

Tax cuts are a highly debated fiscal policy. Economists and politicians who support such a policy argue that on the firms' side, tax cuts reduce the burden on corporations, enabling them to expand and invest more aggressively, thereby generating more employment opportunities and potentially increasing wages. On the consumer side, economists argue that individual tax cuts increase disposable income, stimulate consumption, promote broader economic activity, and foster growth. Conversely, critics argue that tax cuts provide only short-term benefits while potentially causing long-term economic problems. Among the most prominent concerns are the magnification of wealth inequality and the expansion of the federal deficit, which contribute to the already substantial U.S. national debt.

Numerous past studies and papers have thoroughly examined the economics and societal impacts of tax cuts. For example, Ljungqvist & Smolyansky (2018) collected state-level tax data from 1969 to 2010 and studied the effects of tax cuts by comparing contiguous counties across state borders, which served as a control group. Finding that a 1% corporate tax cut leads to employment in the affected county rising by approximately 0.2% and total wage income rising by approximately 0.3%, measured relative to the neighboring county across the state. Ultimately, they report that tax increases are generally harmful, while tax cuts appear to be effective only during recessions. Another research paper studied the effect of tax cuts on inequality. Nallareddy, Rouen, & Suárez Serrato (2018) analyzed individual-level income data, the share of income going to the top 1%, and state-level changes in corporate tax rates from 1917 to 2012. They concluded that state-level corporate tax cuts disproportionately benefit the wealthy through primarily capital gains. Moreover, a 1% cut in the corporate tax rate is associated with a 0.93% increase in the income share of the top 1% over the following three years. Another paper covered a similar topic: who benefits most from a tax cut? The answer is that, with the benefits of corporate tax cuts, firms in the service sector typically use the extra cash windfall to pay dividends and do not alter their investment or employment behavior (Cloyne, Kurt, & Surico, 2023).

These past studies reached similar conclusions regarding the cost of corporate tax cuts; most agreed that corporate tax cuts disproportionately benefited wealthier individuals who can invest and profit from capital gains, while having less effective impacts on boosting overall employment and economic growth.

2.2 Hospital industry framework and TCJA

Most past studies in this section have focused on state-level changes in corporate tax rates and their effects on broader economic activity and development. Understanding the specific impact of one nationwide tax rate legislation required a different method. (Add why)

King (2019) analyzed the impact of the TCJA on the healthcare industry by examining CMS cost report data and secondary sources, such as IRS filing data, to ensure completeness. The main findings of this paper are that TCJA makes capital investment more profitable and potentially leads non-profit hospitals to cut less profitable but essential services. It also emphasizes that policymakers failed to consider the unique competition-market dynamics in the hospital industry, which could result in unintended side effects. Fox & Pyle (2022) studied TCJA directly by examining the unique dynamics between banks and credit unions. Even though their study was not conducted in the hospital industry, they found a very similar setting: credit unions, which enjoy tax-exempt status, serve as close substitutes for small- to medium-sized banks. Thus, creating a treatment group and control group environment, and allowing for a DID framework. Fox and Pyle analyzed data on labor compensation, loan interest payments, and loan income from 2013 to 2019. Their study concluded that banks enjoyed about 40% of total tax savings, and there was no evidence that tax cuts benefited employees and customers. Liew & Murphy (2024) examined readmission rates and financial records from California hospitals and analyzed investments to evaluate the effect of TCJA on the competitive dynamics of the hospital industry. Liew and Murphy concluded that the increase in cash flow for for-profit hospitals led to the rise in capital investment relative to non-profit hospitals. They also measured quality of care through readmission rates and found that, after TCJA, for-profit hospitals had lower readmission rates, suggesting an increase in medical care quality.

All three prior studies analyzed the economic impacts of TCJA, focusing on settings where non-profit and for-profit organizations compete in the same market. This paper will build on the framework implemented by Liew & Murphy (2024). While their studies primarily focused on the effects of investment and quality of care in for-profit hospitals relative to their counterparts, this paper will extend their framework to focus more on employment and labor compensation data, examine labor investment and employment behavior of private for-profit hospitals, and how their profit-maximizing approach responds to a tax cut.

3. Economics Theory and Model

3.1 Theory overview and background

This paper will build on the microeconomic theory that a firm will maximize profits subject to production constraints. This theory was formalized and developed by scholars such as Paul Samuelson (1947), Hicks (1932), and Shepard (1953). Paul Samuelson formalized optimization in economics using the Lagrange multiplier and the theory of constrained optimization. The core idea of this theory is how profit-seeking firms choose the most efficient combination of resources, typically labor and capital, to produce a given output at the

lowest possible cost. This optimization process also revealed that cost minimization under this framework is equivalent to profit maximization. This framework operates under some key assumptions. First, firms operate in a competitive input market, meaning they have no power over labor or capital prices. Second, firms' decisions are rational and based on economic efficiency. Third, firms' production only affects itself, leaving no room for externalities. Obviously, the real world is more complex, and sometimes these assumptions may not hold; however, economic models and theories provide a starting point for empirical research. This paper will use profit maximization theory as a foundation for understanding and analyzing the profit-maximizing behaviors of for-profit hospitals. Notably, the effects of said behaviors on employment and labor compensation in response to TCJA's lowered effective tax rates for for-profit hospitals compared to non-profit hospitals.

3.2 Model variables and optimization

This model of optimization involved several variables and assumptions, in addition to those covered in the previous subsection. First, this model assumes that firms will use only specific amounts of capital (K) and labor (L) as input resources and produce (Q) units of output using the production function (F):

$$Q = F(K, L)$$

Second, this paper assumes that firms can not affect the market price for capital (r) and labor (w), and the functional form for the estimation of cost (C) is:

$$wL + rK = C$$

To calculate the profit of a firm under this model, simply subtract the cost from total revenue, which is just the price of the product/service (P) times the quantity produced (Q):

$$\pi = P*Q - wL - rK$$

From the previous equation, Q can also be written as: $Q = F(K, L)$. Plug this back into the profit function:

$$\pi = P*F(K, L) - wL - rK$$

This model will utilize the profit function above and optimize it using the Lagrange method, subject to the productivity constraint.

The Lagrange Function form is denoted below as Z, and λ represents the Lagrange multiplier:

$$Z(K, L, \lambda) = P*F(K, L) - wL - rK + \lambda(Q - F(K, L))$$

To solve the model, take the partial derivative of each variable: K, L, λ, and set each to zero to get the first-order condition. The first order conditions are listed below:

(The partial derivative of F(K, L) with respect to K and L is written as F_K and F_L.)

$$\frac{\partial Z}{\partial K} = P{*}F_K - r - \lambda F_K = 0$$

$$\frac{\partial Z}{\partial L} = p{*}F_L - w - \lambda F_L = 0$$

$$\frac{\partial Z}{\partial \lambda} = Q - F(K, L) = 0$$

Solving these three first-order conditions gives the following equation:
(The left-hand side of this equation is MRTS because F_L is the marginal product of labor, MPL, and F_K is the marginal product of capital, MPK.)

$$\frac{F_L}{F_K} = \frac{w}{r}$$

This is the optimal bundle of labor and capital that a firm should use to maximize profit under the production constraint. However, this model assumes the firm produces under no tax. To examine the effect of a change in corporate income tax policy, such as the TCJA, a more specific model needs to be established and compared with this one to identify the theoretical differences.

3.3 Corporate income tax in optimization

This new model will build on the one covered in the previous subsection, operating under the same parameters, variables, and assumptions, with the addition of one new variable: τ, which represents the corporate tax rate. Corporate income tax is calculated by subtracting all the deductions from the gross income and applying the flat corporate income tax rate on the remaining taxable income. In this model, τ is applied directly to the profit function and represents a flat-rate tax on the firm's profit, resembling real-world tax policy. The profit function with a corporate income tax is defined below:

$$\pi = (1-\tau) * [P * F(K, L) - wL - rK]$$

Similarly, the optimization process with the Lagrange multiplier and first-order conditions:
Lagrange Formula:

$$Z(K, L, \lambda) = (1-\tau) * [P{*}F(K, L) - wL - rK] + \lambda (Q - F(K, L))$$

First order conditions:

$$\frac{\partial Z}{\partial K} = (1-\tau) *[P{*}F_K - r] - \lambda F_K = 0$$

$$\frac{\partial Z}{\partial L} = (1-\tau) * [\ p * F_L - w\ ] - \lambda F_L = 0$$

$$\frac{\partial Z}{\partial \lambda} = Q - F\ (K, L) = 0$$

Solving for the optimal bundle:

$$\frac{F_L}{F_K} = \frac{w}{r}$$

Mathematically, the introduction of corporate income tax (τ) under this model cancels out when solving the first-order conditions. The result is that the firm's optimal bundle of labor employed and capital used remains unaffected by the corporate income tax. Similarly, changing the corporate income tax rate will not have an effect, this can be proven by the fact that the profit-maximizing labor and capital bundle does not contain a tax variable. The conclusion from the optimization model with corporate income tax is that, with only a flat tax on profit, the firm's maximizing profit approach will result in unchanged labor and capital usage amounts. Thus, the employment rate under this model remains unchanged by the introduction of any policy that alters the corporate income tax rate, such as the TCJA. This economic theoretical model serves as the foundation for the paper's hypothesis that the TCJA provision didn't have a significant impact on the employment rate and labor compensation of for-profit hospitals. To examine whether the theoretical model accurately reflects the real world and test the hypothesis, a regression model and a DID framework are needed. The following section focuses on data and model estimation.

4. Data

This paper used Hospital Provider Cost Report Data from the Centers for Medicare & Medicaid Services (CMS). This dataset includes the years 2015-2022 and is publicly available online. Since CMS and BLS are federal agencies with standardized reporting procedures, these datasets are generally considered reliable and suitable for causal inference analysis.

4.1 Data cleaning and variable selection

This paper collects and cleans the primary dependent variables: log(FTE employees on payroll) and log(total salaries from worksheet A) from CMS data sets. The dataset comprises 30923 observations of hospitals spanning 8 years. For the cleaning process, this study excludes all hospitals that either switched their status from for-profit to non-profit or vice versa, as well as hospitals that lack a complete record for the entire 8-year duration. This study also considers government hospitals as non-profit for the DID framework for several

reasons. First, government hospitals are often exempt from federal and state corporate income tax, similar to the private non-profit hospitals. Second, government hospitals are publicly owned, and any surplus would be reinvested into the hospitals' operations. Under these conditions, government hospitals closely resemble non-profit private hospitals, given their employment behavior under the influence of tax cut policies; therefore, all the government hospitals in the dataset are reorganized under the private non-profit hospital category. Consequently, the primary focus of this paper is to explore the impact of tax cut policy on employment behavior between for-profit and non-profit hospitals. The DID framework relies on a clear distinction between the treatment and control groups, and hospitals that switched statutes during the five-year duration could potentially violate this setting and the parallel trend assumptions; removing these observations is necessary for unbiased and accurate regression estimation. Moreover, hospitals with incomplete data during the eight-year duration may also pose problems for model estimation, as DID requires consistent data to measure changes within hospitals; incomplete data could bias this estimation. This paper then creates a binary variable from the type of control, which equals one if the hospital is for-profit. This process drastically decreases the number of observations to 21775 but ensures the completeness of the data. Table 1 provides a summary of the distribution of hospital types. This result is expected, according to statistics from the Department of Health and Human Services, which indicate that about 36.1% of hospitals are for-profit, while the rest are either non-profit private hospitals (49.2%) or government hospitals (14.7%). The distribution in this dataset, in Table 1, after cleaning, is slightly deviated from real-world data, but still exhibits sufficient variation and robustness to support statistical inference.

Some states have more favorable legislation for non-profit hospitals, for example, New York State's restriction on publicly traded for-profit companies owning hospitals (New York Health Foundation). Due to these policies, some of the states have a minimal number of for-profit hospitals. These policies are partly reflected in the data set, where the number of

Distribution of Hospital Types (Table 1)		
For-profit	920	25.27%
Non-profit	2720	74.73%

states has a small percentage of for-profit hospitals. This disproportionate distribution of for-profit and non-profit hospitals can result in a biased estimation of DID regression because of the absence of a treatment group in the state. The full percentage distribution of hospital ownership is presented in Appendix 1. To counter this potential bias in the estimation, this paper excludes states with fewer than 5% for-profit hospitals. A 5% threshold is a reasonable choice because it ensures a meaningful control and treatment group, while also preserving the number of observations and variance in the data. Table 2 provides a list of states excluded from the dataframe. After this, the CMS provider cost dataframe has 17,815 observations. This means the final cleaned dataframe has 3563 hospitals across five years from 43 different states. This is a substantially large

dataset, which could provide sufficient variance and statistical robustness to identify the impacts of TCJA on the hospital industry.

States Excluded from DID Analysis (Table 2)	
CT	0.0
HI	0.0
MD	0.0
ME	0.0
VI	0.0
VT	0.0
MN	0.9
NY	3.3
IA	3.5
MT	4.4
OR	4.5
WA	4.5

The primary interest is to measure the impacts of TCJA on employment and labor compensation. To measure these metrics, this paper chooses FTE Employees on Payroll and Total Salaries from the CMS dataset as the primary dependent variables to quantify and measure the specific effect. The CMS collected data for FTE Employees on Payroll by adding up all the hours worked by full-time employees in the first week of each quarter, then dividing by 160 for the full quarter and by 80 for the semi-quarter. This variable represents both the headcount and the hours worked for the labor force. It is a precise and quantifiable measurement of the total labor force available to hospitals, making it helpful for this study to explore the main question. The other primary dependent variable is Total Salaries. CMS collected data on this variable from the total salary expense recorded in the hospital's accounting books or balance. While FTE Employees measured the quantity and size of the labor force, total salaries measured the overall labor compensation. These two variables complement each other, providing a quantified measurement of the overall labor force and labor compensation in the hospital industry. The primary explanatory variables for this study are binary variables for for-profit status and the post-TCJA period. Both variables are easily accessible from the dataset itself and straightforward to use. Some other minor variables are included as control variables or fixed effects, such as the number of beds, state code, total discharge, total cost, and a binary variable indicating whether the location is urban or rural. These minor variables either control for the size of the hospitals or serve to control for the state-level fixed effects.

4.2 Summary Statistics

This section will focus on the characteristic statistics of the cleaned data set—particularly, the distribution and key statistics of variables from non-profit hospitals and for-profit hospitals. Although the last section discussed the parallel trend between these two groups, detailed statistics can provide a deeper understanding of them.

Characteristic statistics tables of the variables of interest, grouped by treatment group (for-profit hospitals) and control group (non-profit hospitals), are calculated. (how calculated)

Descriptive Statistics of Numeric Non-profit Hospitals Variables (Table 3)					
Variable	Mean	SD	Min	Max	Median
Log(FTE Employees)	6.06	1.39	-2.66	13.37	5.96
Log(Total Salary)	17.26	1.44	11.12	21.86	17.17
Number of beds	150.89	201.95	1.00	3,716.00	59.00
log(Total Discharge)	6.29	1.78	0.00	10.01	6.22
log(Toral Cost)	18.04	1.47	13.80	22.23	17.91

Descriptive Statistics of Numeric For-profit Hospitals Variables (Table 4)					
Variable	Mean	SD	Min	Max	Median
Log(FTE Employees)	5.44	0.97	2.13	9.14	5.30
Log(Total Salary)	16.52	1.05	13.03	20.21	16.36
Number of beds	105.11	107.08	7.00	1498.00	72.00
log(Total Discharge)	6.22	1.23	0.00	9.55	6.11
log(Toral Cost)	17.37	1.12	14.14	20.72	17.21

(how is this important)Tables 3 and 4 present the summary statistics for all numeric variables, including two variables of primary interest: Log(FTE Employees) and Log(Total Salaries) for all the non-profit hospitals in the data. For most variables, non-profit hospitals have a larger mean and maximum, which is expected because non-profit hospitals are typically larger and therefore have a larger labor force, higher salaries, and greater costs.

4.3 Paralle Trend

        Two models are employed for causal inference analysis: the difference-in-differences estimation and the first-differenced estimator. Both of these two estimations require data that satisfy the parallel trend assumption. Under this condition, it is crucial to examine the parallel trend of the primary dependent variables carefully so that causal inference analyses can be performed and the results are unbiased. For a few reasons, the natural log of both variables is used. First, hospitals vary in size, with some having substantially larger labor forces than others. For example, Cleveland Clinic Hospital has over 26000 FTE employees, while ST. Francis Hospital Wilmington has only about 886 FTE employees. These drastically different numbers could make the effect uneven and difficult to compare. Using the natural log in this case eliminates the significant difference, making the results more even and comparable, as the result can be interpreted in percentage terms. Second, the natural log can smooth the distribution of the data, especially counteracting any potential bias caused by outliers. By using the mean value of the logged primary dependent variable and grouping by years from 2015 to 2022, this study plots the following parallel trend graphs.
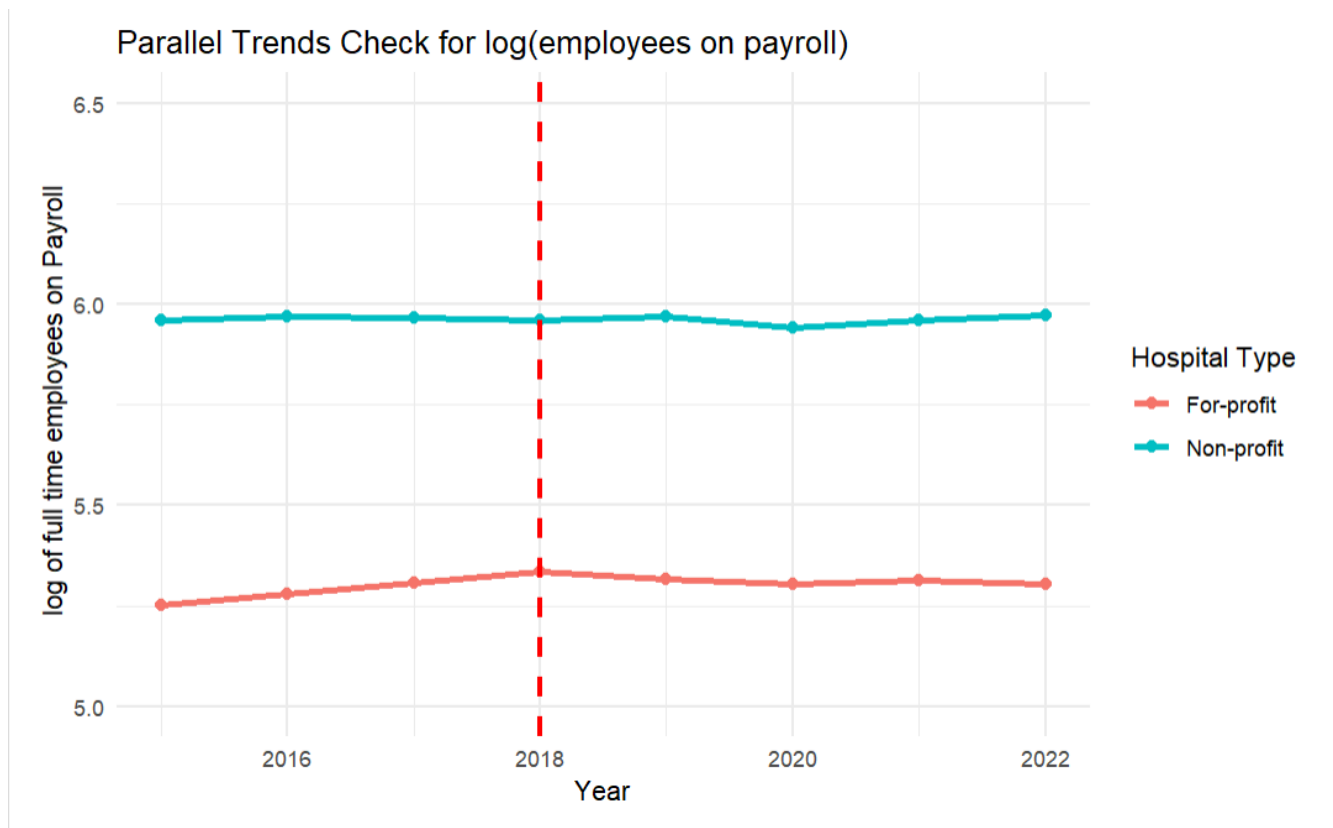
(Figure 1)

Figure 1 represents the average value of log(FTE Employees) for for-profit hospitals and non-profit hospitals from 2015 to 2022. The red vertical line in 2018 represents the treatment year, as TCJA took effect on January 1, 2018. The primary focus of the parallel trend check is before the treatment, in this case, before TCJA. This plot presents a close parallel relationship between for-profit and non-profit groups before the treatment year, making it appropriate to assume the parallel trend assumption holds for the log(FTE employees) variable. Furthermore, the plot shows an interesting trend for for-profit hospitals, as their FTE employees decreased slightly after the TCJA act took effect, compared to non-profit hospitals, which remained approximately unchanged. This finding corresponds with the microeconomic theory covered in the last section.

(Introduction)
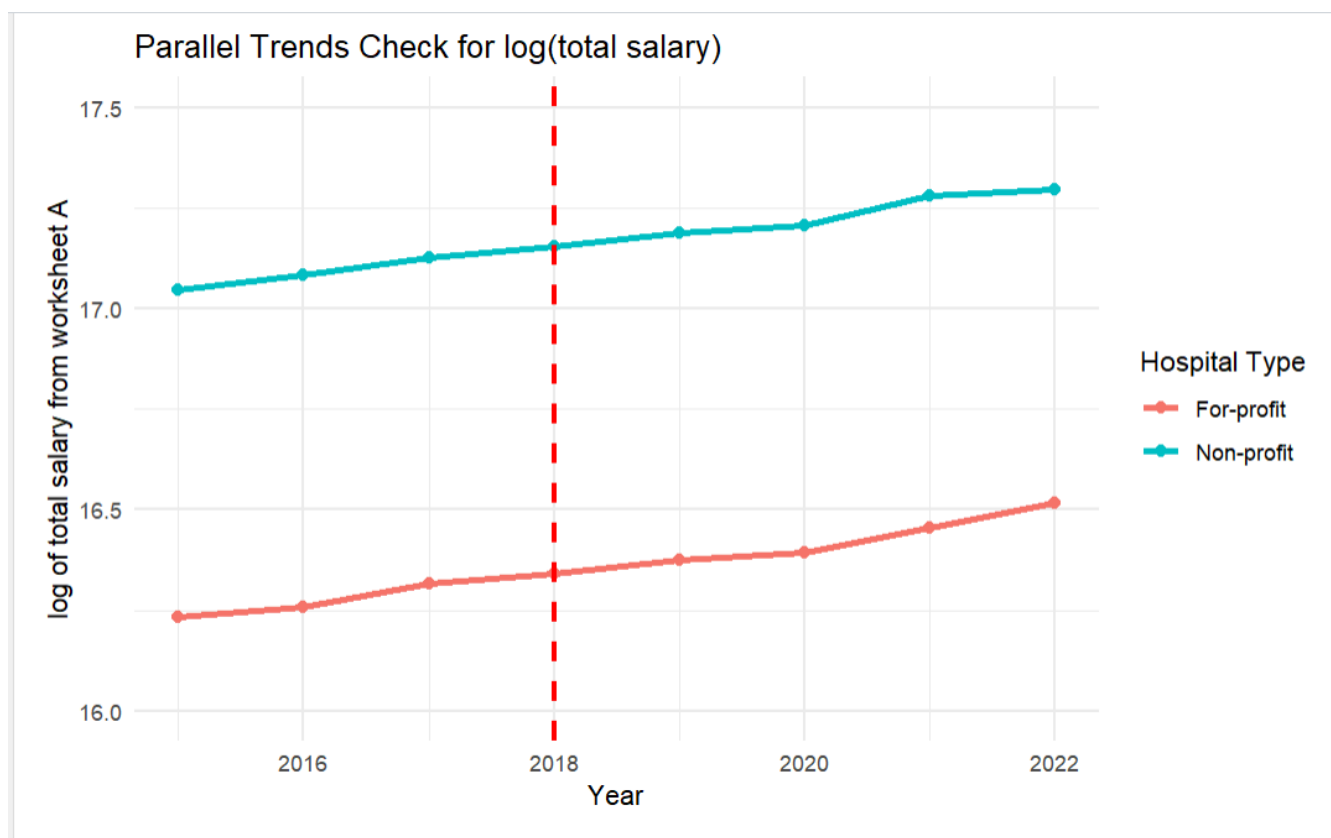
(Figure 2)

Figure 2 illustrates the parallel trend plot for log (total salaries) for non-profit and for-profit hospitals, presented in the same setting as Figure 1. There is a close parallel relationship between non-profit and for-profit before the treatment, TCJA, in 2018. However, unlike FTE employees, total salaries remain roughly unchanged by TCJA in for-profit hospitals compared to non-profit hospitals, as the parallel relationship persists after 2018. Parallel trends hold for both primary interest variables, which enable the use of DID and first-differencing

methods. The following section will cover the causal inference analysis model specification and interpret the estimation results to provide a comprehensive understanding of the actual impacts.

5. Econometrics

5.1 DID model estimation

First, estimating the simple DID model on log(FTE employees) using only the post and for_profit binary variables. The model specification is listed below:

$$log(FTE\ Employees)_{it} = \beta_0 + \beta_1 ForProfit_i + \beta_2 Post_t + \beta_3(ForProfit_i * Post_t) + \varepsilon_{it}$$

In this specification, $log(FTE\ Employees)_{it}$ represents the log of full-time employees of hospital i in time period t. β_0 is the intercept, which means the average FTE employees for a non-profit hospital before the TCJA treatment. β_1 is the baseline difference between for-profit and non-profit hospitals. β_2 represents the time effect that impacts all hospitals. β_3 is the primary interest variable that represents the treatment effect, specifically the impact of TCJA on FTE Employees. This coefficient can be interpreted as the percentage change in the number of FTE employees at for-profit hospitals after the TCJA compared to non-profit hospitals. Table 5 below presents the estimated results of four different models from 2019 to 2022, based on the dataset.

(Table 5)

Table 5: Difference-in-Differences Regression log(FTE Employees) results

	DID 2017 vs 2019	DID 2017 vs 2020	DID 2017 vs 2021	DID 2017 vs 2022
(Intercept)	6.061***	6.061***	6.061***	6.061***
	(0.028)	(0.028)	(0.028)	(0.028)
post	0.011	-0.006	0.000	0.010
	(0.039)	(0.039)	(0.039)	(0.039)
for_profit	-0.610***	-0.610***	-0.610***	-0.610***
	(0.051)	(0.051)	(0.051)	(0.051)
post × for_profit	-0.004	-0.004	-0.028	-0.051
	(0.072)	(0.072)	(0.072)	(0.072)
Num.Obs.	6114	6113	6115	6105
R2	0.046	0.046	0.047	0.049
RMSE	1.28	1.28	1.28	1.28
Std.Errors	IID	IID	IID	IID

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

The primary interest coefficients in these models are close to zero and are relatively consistent across the years. This is expected based on the micro theory. However, none of the coefficients are statistically significant, which could be due to omitted variable bias or state-level economic activities that may bias the dependent variables. Interestingly, the coefficients for the post and for-profit binary variables are significant. This could be because TCJA affected all hospitals similarly. This corresponds with the parallel trend graph, where the trend persists after the treatment is administered. However, this can also be caused by the high correlation between the binary variable and the interaction term, which could lead to a larger standard error for the interaction term, thus making it statistically insignificant.

To combat those potential effects that cause estimations to be biased. This paper presents a model that controls for hospital size through bed numbers and total costs, hospital operation amounts through total discharges, and location-related characteristics through an urban binary variable. In addition, it also includes the state fixed effect to control for states' economies that can influence the hospitals' employment. Below is the model specification:

$$log(FTE\ Employees)_{it} = \beta_0 + \beta_1 ForProfit_i + \beta_2 Post_t + \beta_3(ForProfit_i * Post_t) + \chi'_{it}\gamma + \lambda_s + \varepsilon_{it}$$

In this estimation specification, there are two additional elements: control variables are included in $\chi'_{it}\gamma$ while the state fixed effect is λ_s. Table 6 shows the results of this regression model. A similar pattern is observed in this table: the coefficients for the interaction term are not significant, whereas the coefficients for the binary variables are substantial. This suggests the same problems are present in this estimation.

Next, this paper employs the same method and specification to examine the impact of TCJA on the other primary interest variable: log(Total Salaries), with the following two equations:

1. Base DID Estimation :

$$log(Total\ Salaries)_{it} = \beta_0 + \beta_1 ForProfit_i + \beta_2 Post_t + \beta_3 (ForProfit_i * Post_t) + \varepsilon_{it}$$

2. DID Estimation with Control and Fixed Effect :

$$log(Total\ Salaries)_{it} = \beta_0 + \beta_1 ForProfit_i + \beta_2 Post_t + \beta_3 (ForProfit_i * Post_t) + \chi'_{it}\gamma + \lambda_s + \varepsilon_{it}$$

Table 7 presents the results for Base DID, and Table 8 presents the results for DID with control and fixed effects.

One interesting finding among the results is that the coefficient for post * for-profit interaction term on the 2017 vs 2022 regression model is significant at the 10 percent level. This coefficient implies that, holding all other variables constant, for-profit hospitals have an average 3% higher total salaries after the TCJA compared to non-profit hospitals from 2017 to 2022. This implies that the TCJA's effects could take years to be fully realized. However, this finding needs to be treated with caution because it is the only significant interaction term. To rule out problems with the DID model specification, this paper implements the first-differencing model in the following subsection to examine the same time period and variables.

5.2 First differencing model estimation

First Differencing (FD) involves running a regression based on the difference in the dependent variable between two time periods. FD has a more robust estimate of the causal effect due to the structure of its error term, which removes the time-varying effects. The specification of the FD model for log(FTE Employees) is listed below, and Table 9 presents all the results of this estimation:

$$\Delta log(FTE\ Employees)_i = \beta_0 + \beta_1 \Delta ForProfit + \Delta\chi'_i + \Delta\varepsilon_i$$

From table 9, the coefficient for for-profit is statistically significant at the 10% level in 2021 and at 1% level in 2022. Both coefficients are negative. The regression model estimation for 2021 estimates a 2.3% lower in average FTE employees for for-profit hospitals from 2017 to 2021, while the one for 2022 estimates that for-profit hospitals have 4.9% fewer FTE employees. This finding further confirms the trend from the previous DID study and economic theory.

Next, this paper implements the same FD specification for log(Total Salary). Below is the model specification:

$$\Delta \, log(Total \, Salary)_i = \beta_0 + \beta_1 \Delta \text{ForProfit} + \Delta \chi'_i + \Delta \varepsilon_i$$

The First Differencing regression estimations for log(total salary) present a similar pattern to the estimations for log(FTE employees). To be more specific, the coefficient terms for the for-profit binary variable are statistically significant at 1% level for the three regression models for the years from 2020 to 2022. Moreover, the coefficients are all negative and present a decreasing trend. This implies that as the year progresses, for-profit hospitals have a lower total salary compared to non-profit hospitals, from 2.6% less in 2020 to 4% less in 2021 and eventually 5.3% less in 2022.

6. Conclusion

This study examines the impacts of TCJA on employment, focusing on for-profit hospitals compared to non-profit hospitals using DID and DF methods, with total FTE employees and total salaries as measures of employment and labor compensation. This study finds that, despite the initial stability of employment and labor compensation for for-profit hospitals, these hospitals generally have a lower labor force count and total salary compared to non-profit hospitals after two or three years of the tax cut policy. This implies that hospital ownership type influences how hospitals respond to major tax policies and how firms' profit maximization strategies respond to a tax cut, as well as the impact of such a strategy on employment behaviors. However, most of the statistical significance is found in the first differencing method, rather than the difference-in-differences method. The data also face limitations, including a short time period and the potential for omitted variables that vary over time across hospitals. Future studies could extend this work by incorporating additional years of data and other measures of employment to capture the timing of for-profit hospitals' responses.

Appendix

(Table 6)

Table 6: Difference-in-Differences Regression log(FTE Employees) with control and fixed effects results

	DID 2017 vs 2019	DID 2017 vs 2020	DID 2017 vs 2021	DID 2017 vs 2022
post	-0.051***	-0.083***	-0.135***	-0.183***
	(0.010)	(0.013)	(0.014)	(0.014)
for_profit	-0.101***	-0.094***	-0.108***	-0.103***
	(0.016)	(0.016)	(0.016)	(0.016)
Number.of.Beds	0.000	0.000	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
log(Total.Discharges.Title.XVIII)	0.032***	0.028***	0.026***	0.018*
	(0.006)	(0.008)	(0.007)	(0.007)
log(Total.Costs)	0.859***	0.856***	0.779***	0.792***
	(0.008)	(0.010)	(0.013)	(0.013)
urban	-0.043***	-0.047***	-0.051***	-0.049***
	(0.012)	(0.014)	(0.014)	(0.014)
post × for_profit	0.008	0.012	-0.001	0.002
	(0.017)	(0.020)	(0.019)	(0.019)
Num.Obs.	7281	7280	7281	7271
R2	0.933	0.895	0.901	0.901
R2 Within	0.920	0.876	0.883	0.883
RMSE	0.34	0.43	0.42	0.42
Std.Errors	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust

- $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

(Table 7)

Table 7: Difference-in-Differences Regression log(total salaries) results

	DID(Log salary) 2017 vs 2019	DID(Log salary) 2017 vs 2020	DID(Log salary) 2017 vs 2021	DID(Log salary) 2017 vs 2022
(Intercept)	17.207***	17.207***	17.207***	17.207***
	(0.029)	(0.029)	(0.029)	(0.029)
post	0.065	0.104**	0.170***	0.224***
	(0.040)	(0.040)	(0.040)	(0.041)
for_profit	-0.721***	-0.721***	-0.721***	-0.721***
	(0.053)	(0.053)	(0.053)	(0.053)
post × for_profit	-0.004	-0.031	-0.045	-0.053
	(0.074)	(0.074)	(0.074)	(0.075)
Num.Obs.	6114	6113	6115	6105
R2	0.059	0.062	0.065	0.067
RMSE	1.33	1.32	1.33	1.33
Std.Errors	IID	IID	IID	IID

- $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

(Table 8)

Table 8: Difference-in-Differences Regression log(total salaries) with control and state fixed effect results

	DID(Log salary) 2017 vs 2019	DID(Log salary) 2017 vs 2020	DID(Log salary) 2017 vs 2021	DID(Log salary) 2017 vs 2022
post	-0.008	-0.017*	-0.026**	-0.030**
	(0.008)	(0.008)	(0.009)	(0.010)
for_profit	-0.116***	-0.117***	-0.124***	-0.127***
	(0.014)	(0.014)	(0.014)	(0.014)
Number.of.Beds	0.000	-0.000	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
log(Total.Discharges.Title.XVIII)	-0.003	-0.004	-0.004	-0.006
	(0.005)	(0.005)	(0.005)	(0.005)
log(Total.Costs)	0.943***	0.944***	0.900***	0.903***
	(0.008)	(0.008)	(0.011)	(0.010)
urban	-0.011	-0.012	-0.012	-0.015
	(0.010)	(0.010)	(0.010)	(0.010)
post × for_profit	0.010	0.014	0.013	0.030*
	(0.015)	(0.015)	(0.014)	(0.014)
Num.Obs.	7281	7280	7281	7271
R2	0.959	0.959	0.960	0.959
R2 Within	0.950	0.949	0.951	0.950
RMSE	0.28	0.28	0.28	0.28
Std.Errors	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust

- $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

(Table 9)

Table 9: First Differencing Regression log(FTE Employees) results

	Log (FTE Employees) 2017 vs 2019	Log (FTE Employees) 2017 vs 2020	Log (FTE Employees) 2017 vs 2021	Log (FTE Employees) 2017 vs 2022
(Intercept)	0.013**	0.003	0.010	0.022**
	(0.005)	(0.007)	(0.007)	(0.008)
for_profit	0.003	0.005	-0.023*	-0.049***
	(0.008)	(0.011)	(0.011)	(0.012)
d_beds	0.001***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
d_income	-0.000*	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
d_discharges	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
d_urban	0.029	-0.010	0.009	0.004
	(0.021)	(0.022)	(0.019)	(0.020)
Num.Obs.	3057	3056	3058	3048
R2	0.016	0.031	0.040	0.052
RMSE	0.21	0.28	0.27	0.31

- $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

(Table 10)

Table 10: First Differencing Regression log(Total Salary) results

	Log (Total Salary) 2017 vs 2019	Log (Total Salary) 2017 vs 2020	Log (Total Salary) 2017 vs 2021	Log (Total Salary) 2017 vs 2022
(Intercept)	0.082***	0.123***	0.187***	0.242***
	(0.003)	(0.004)	(0.005)	(0.006)
for_profit	-0.003	-0.026***	-0.040***	-0.053***
	(0.006)	(0.007)	(0.008)	(0.010)
d_beds	0.000***	0.001***	0.001***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
d_income	-0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
d_discharges	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
d_urban	0.009	-0.000	0.009	0.011
	(0.015)	(0.014)	(0.014)	(0.017)
Num.Obs.	3057	3056	3058	3048
R2	0.132	0.071	0.068	0.073
RMSE	0.15	0.18	0.20	0.25

- $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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