Effect of Vermont 2017 sick leave law on Job satisfaction

Final Report

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1 Introduction

Entgeltfortzahlung is the word in German that refers to the continued payment of wages by an employer to an employee who is unable to work due to illness. The statistics associated with 'Entgeltfortzahlung' in Germany is one of the most impressive in the world; in 2013 employees reported being sick for 15.1 days.(Statistisches Bundesamt (2025)) Compare to 4.9 days in the US(Barnato (2013)). This stark difference can somewhat be explained by the different policies in place in those countries. While German people can enjoy up to 6 weeks of paid sick leave (Payroll Germany (2025)) in the US only some portion of the population have access to paid sick leave usually not exceeding one week (GovDocs (2025)). The United States is the only industrialized country without universal access to paid sick leave. (Heymann et al. (2010); Schliwen et al. (2011)). On the eve of 2026, only 22 states across the USA will require employers to provide eligible employees with paid time (idem). But this actually constitutes a good improvement in the situation. At the start of last decade more than fifty five states had any(Law and the Workplace (2016)).

Given the context of a raise interest of this policy in the US, we will in this paper answer this question what is the effect of sicl leave law on job satisfaction ?

We focus on evaluating the effects of Vermont's paid sick leave law, which took effect on January 1, 2017 and required most employers in the state to allow employees to accrue and use paid sick time. Under this law, employees earn sick leave at a rate of at least one hour for every 52 hours worked, with minimum required sick leave amounts phased in over time(Law and the Workplace (2016)). We examine the impact of Vermont's 2017 paid sick leave law on employees' job satisfaction. By analyzing how the Vermont law has affected employees' perceptions and attitudes toward their jobs, our study highlights the broader significance of paid sick leave for workplace satisfaction.

2 Research Design

This study adopts a systematic approach to examine the determinants of job satisfaction in the United States through a three-stage analytical design:

1. **Exploratory Spatial and Temporal Analysis:** We begin with visualizations and trend analysis to identify regional clusters of high/low satisfaction and track temporal shifts alongside macroeconomic indicators.
2. **Correlational Analysis:** Next, we employ Ordinary Least Squares (OLS) regression to systematically evaluate the association between job satisfaction and key socioeconomic factors, including unemployment rates, income levels, and rural-urban divides.
3. **Causal Inference:** Finally, to move beyond correlation, we implement a **Difference-in-Differences (DiD)** design. This stage specifically isolates the causal impact of state-level labor mandates, notably **Paid Sick Leave**, by utilizing policy variation across states and time.

2.1 Identification Strategy

To estimate the causal effect of labor policies, my main identification strategy is based on a **Difference-in-Differences (DiD)** framework. The core assumption of this design is that, in the absence of the policy intervention, the average outcomes for the treated and control groups would have followed parallel trends.

We define the treatment group as states that implemented specific mandates (e.g., **Vermont** for Paid Sick Leave), while demographically similar states without such policies (e.g., **Texas**) serve as the control group. We estimate the Average Treatment Effect on the Treated (ATT) using the following Two-Way Fixed Effects (TWFE) specification:

$$JobSat_{it} = \alpha + \beta_1(Treat_s) + \beta_2(Post_t) + \beta_{did}(Treat_s \times Post_t) + \gamma X_{it} + \epsilon_{it}$$

Where the subscripts i, s, and t denote the individual, state, and time (month/year), and β_{did} captures the causal impact of the policy.

2.2 Treatment and Outcome Variables

Treatment Variables: The treatment assignment is defined at the state level based on the policy effective year:

- **Treated ($Treat_s$):** A binary indicator equal to 1 if the state adopts the policy (e.g., Paid Sick Leave), and 0 otherwise.
- **Post ($Post_t$):** A binary indicator equal to 1 for periods after the policy implementation date, and 0 otherwise.

Outcome Variable: The primary outcome is the **Job Satisfaction Index (jobsat)**. This is a continuous variable ranging from -1 to 1, computed as the mean of sentiment scores derived from geo-tagged employment-related tweets within a county-month. Higher values indicate more positive subjective well-being.

2.3 Covariates and Moderators

To isolate the policy effect from economic fluctuations, we control for both labor market and regional characteristics (X_{it}):

- **Unemployment Rate (unemployment_rate):** Controls for local labor market tightness and economic security.
- **Median Household Income (acs5):** We did log transformation to control for regional wealth effects and purchasing power.

3 Data

This study utilizes a comprehensive panel dataset at the county-month level (2013–2023), primarily sourced from the Harvard Dataverse repository associated with the study “Job Satisfaction, Labor Market Conditions, and Rural–Urban Inequality” (Iacus (2025)).

Table 1: Summary Statistics

Variable	Mean	SD	P25	Median	P75
jobsat	0.39	0.4	0.064	0.39	0.75
labor_force	67613	192959	8259	18550	49826
employed	64114	181993	7798	17556	47419
unemployed	3499	12374	406	909	2415
unemployment_rate	5.3	2.6	3.6	4.7	6.4
acs5	53733	15916	42981	51031	60962
population	139394	387762	18666	40324	105941

3.1 Data Sources

While the dataset is provided as a unified file, it integrates high-frequency social media metrics with administrative records from multiple federal agencies: The job satisfaction index(jobsat) : Extracted from Human Flourishing Geographic Index (HFGI) dataset, classified using a fine-tuned large language model (LLM) . Unemployment rates and labor force data: Extracted from the Bureau of Labor Statistics (BLS) Local Area Unemployment Statistics (LAUS). Household income: Sourced from the American Community Survey (ACS) 5-year estimates.

3.2 Key Variables

- Outcome: jobsat : Tweet-based job-satisfaction index in [-1, 1], higher values indicate more positive sentiment.

3.2.1 Economic covariates:

- employed / unemployed / labor_force: Detailed labor market size and description.
- unemployment_rate: Local labor market pressure.
- acs5: Median household income.

3.2.2 Demographic covariates:

- population : County population.

3.2.3 Identification & Time:

- StateCounty: Five-digit county FIPS code.
- State: Two-digit state FIPS code.
- year / month: Time dimensions.
- date: First day of the corresponding month.

Summary Statistics

4 Methodology

4.1 Pre-trend assessment

Using only observations before January 1, 2017, we compute state-level average job satisfaction over time. Vermont is used as the reference state. States that enacted paid sick leave laws during the sample period are excluded to avoid contamination of the control group. We then construct all possible combinations of the remaining potential control states and compare their average trends to Vermont's trend. The standard deviation of the difference between the two trends is used as a measure of similarity, with smaller values indicating more parallel pre-policy trends. After testing different group sizes, we find that combinations of four states minimize this standard deviation most effectively and therefore provide the closest pre-policy trend match to Vermont.

4.2 DiD model and TWFE

Second, we estimate the policy effect using a baseline Difference-in-Differences (DiD) model and a Two-Way Fixed Effects (TWFE) specification. The baseline DiD compares changes in job satisfaction before and after the policy in Vermont relative to the matched states, while the TWFE model controls for state-specific fixed effects and common time shocks to provide more robust estimates of the impact of the 2017 paid sick leave law.

4.3 Maching

Thirdly we implement a post-matching analysis to refine the causal comparison. First, we conduct a post-matching Difference-in-Differences visualization, plotting average job satisfaction for Vermont and the matched control group before and after the 2017 policy. This visualization allows us to visually assess whether trends remain parallel prior to treatment and whether a divergence emerges following the implementation of the paid sick leave law.

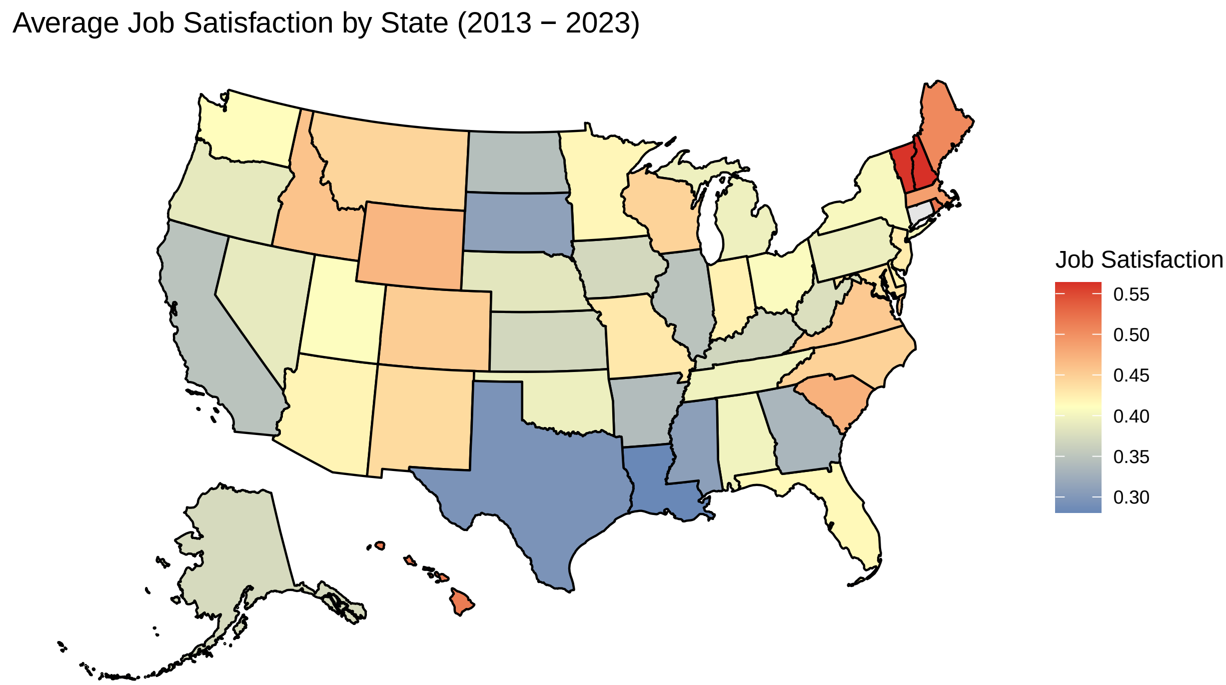
Lastly we estimate a post-matching Two-Way Fixed Effects (TWFE) model using the matched sample. By limiting the analysis to Vermont and the selected control states, this specification controls for unobserved, time-invariant differences across states as well as common shocks over time within a more comparable setting.

5 Results

5.1 Exploratory Data Analysis

We begin by examining the average job satisfaction across each state over the past decade. As shown in **Figure 1**, satisfaction scores range from approximately 0.30 (blue) to 0.55 (red). It should be noted that Connecticut (09) is shaded in gray due to missing data.

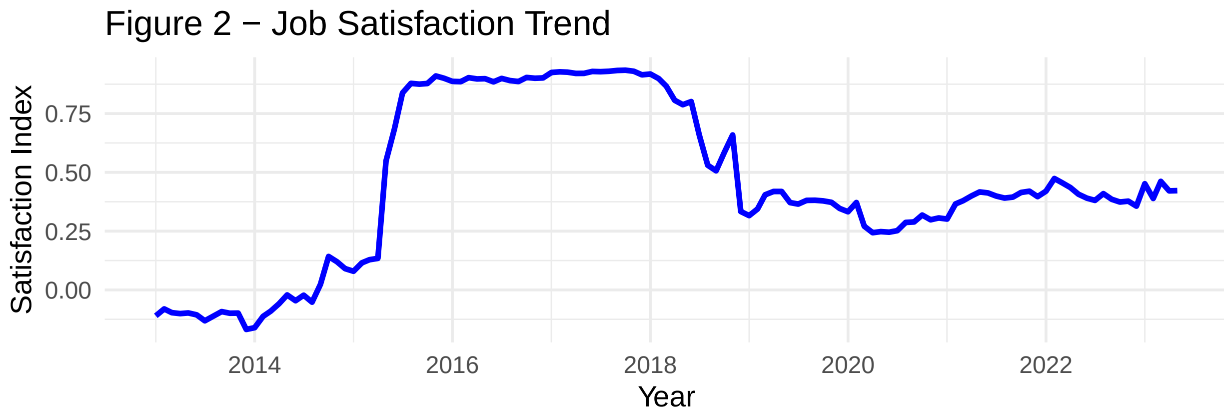
Figure 1. Average Job Satisfaction of Each State



Next, we examine the temporal trends of job satisfaction alongside the unemployment rate (**Figure 2**). We observe a sharp peak in unemployment around 2020, which coincides with the COVID-19 outbreak. However, job satisfaction does not exhibit a perfect inverse relationship; it began declining earlier, in 2018. This divergence suggests that beyond macroeconomic conditions, other latent factors or specific policy interventions may be driving the decline in worker well-being.

While these visual trends suggest a potential link between economic conditions and well-being, graphical inspection alone cannot account for confounding factors such as income levels or unobserved regional differences. To rigorously quantify these associations, we proceed to a formal regression analysis.

Figure 2 & 3. Temporal Trends of Job Satisfaction and the Unemployment Rate



Our exploratory data analysis provides the empirical justification for the variable selection in our regression models:

Geographic Variation: The spatial disparity observed in the Map (Figure 1) highlights intrinsic differences between states. This necessitates the inclusion of State Fixed Effects to control for time-invariant regional characteristics (e.g., culture, climate).

Temporal Shocks: The fluctuations shown in the Trend Plot (Figure 2), particularly during the COVID-19 pandemic, underscore the need for Year Fixed Effects to absorb common national shocks.

Economic Drivers: Finally, To quantify the relationship of economic well-being (income) and labor market tightness (unemployment) , we include Household Income and Unemployment Rate as key controls in our hierarchical regression analysis.

5.1.1 Correlation Analysis - Baseline Regression

Table 2 presents the hierarchical regression results for the selected sub-sample of states (Vermont, New Hampshire, Georgia, Hawaii, and Wisconsin).

1. Baseline Controls (Model 1):We begin with a baseline model that includes only State and Year Fixed Effects. This specification captures the variation in job satisfaction driven solely by time-invariant regional characteristics and national temporal trends, serving as a benchmark for subsequent models.
2. The Role of Income (Model 2):Upon introducing household income, we observe a positive and statistically significant relationship between financial stability and job satisfaction ($\beta = 0.133, p < 0.01$). This confirms that within these selected states, higher income levels are a fundamental driver of worker well-being.

3. The Impact of Labor Market Conditions (Model 3):Model 3 introduces the unemployment rate. As hypothesized, the coefficient is negative and significant ($\beta = -0.010, p < 0.01$). This implies that a 1 percentage point increase in the unemployment rate is associated with a 0.010 decrease in job satisfaction scores, holding income and state characteristics constant. This validates that macroeconomic distress negatively affects individual sentiment.

4. Mitigation of Omitted Variable Bias:A crucial observation arises when comparing Model 2 and Model 3. The coefficient for income decreases from 0.133 to 0.105 after controlling for unemployment. This attenuation suggests that omitting labor market conditions leads to an overestimation of the income effect. In other words, part of the "happiness" previously attributed to income was actually due to low unemployment. Thus, Model 3 provides the most unbiased estimates.Model Fit:Across all specifications, the Adjusted R-squared remains high (~0.636), indicating that our full model effectively explains a substantial portion of the variation in job satisfaction for this specific group of states.

Table 2: Regression Results: Hierarchical Analysis

	Dependent variable:		
		jobsat	
	Controls Only	Add Income	Full Model
	(1)	(2)	(3)
Unemployment Rate			-0.010^{***}
			(0.001)
Log Income		0.133^{***}	0.105^{***}
		(0.007)	(0.008)
Constant	-0.128^{***}	-1.540^{***}	-1.153^{***}
	(0.005)	(0.076)	(0.084)
Observations	23,932	23,932	23,932
R^2	0.629	0.635	0.636
Adjusted R^2	0.629	0.635	0.636
F Statistic	$2{,}901.260^{***}$ (df = 14; 23917)	$2{,}770.610^{***}$ (df = 15; 23916)	$2{,}615.716^{***}$ (df = 16; 23915)
Note:			*p<0.1; **p<0.05; ***p<0.01

5.2 Best Fited group and Visualization

5.2.1 Group simulation

Table 3: Top 5 Most Parallel State Groups to Vermont (Pre-2017)

states	sd_diff
13, 15, 33, 55	0.0321
12, 33, 46, 55	0.0321
2, 12, 33, 55	0.0322
15, 17, 33, 55	0.0322
15, 21, 33, 55	0.0324

Based on the pre-policy trend simulation, the control group consisting of Iowa, Georgia, New Hampshire, and Wisconsin (13, 15, 33, 55) exhibits the closest alignment with Vermont's pre-2017 job satisfaction trend.

This group produces one of the lowest standard deviations in the difference between average job satisfaction and Vermont's trend, indicating a high degree of parallel movement prior to the policy implementation. As a result, this group is selected as the primary comparison group for subsequent visualization and Difference-in-Differences analyses.

5.2.2 Visualization

Figure 4 − Job Satisfaction Trend (Pre−2017)

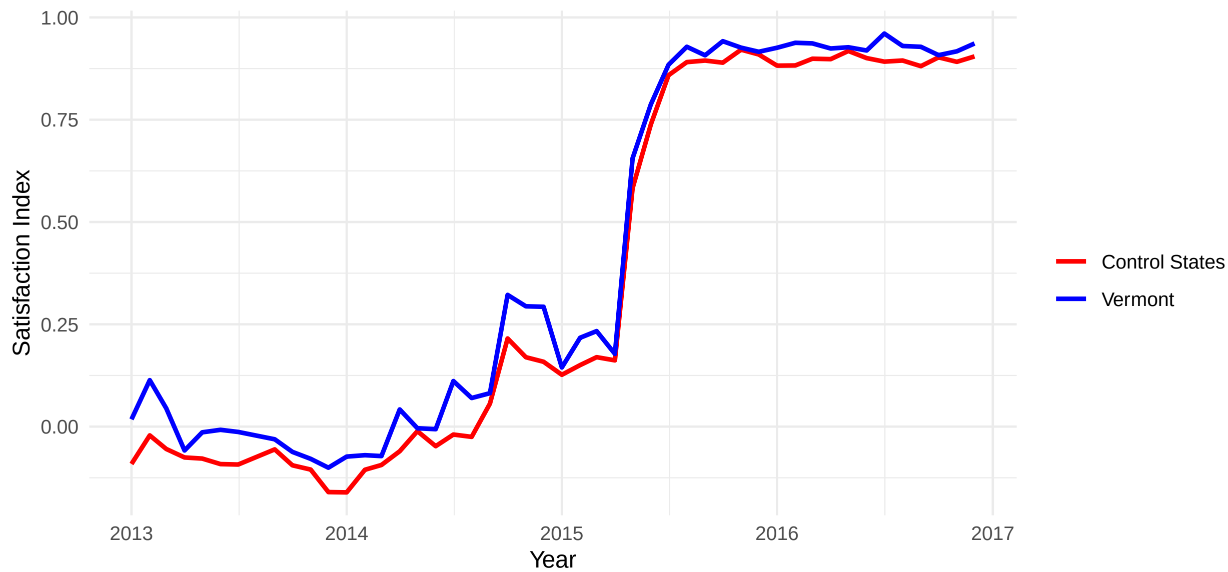
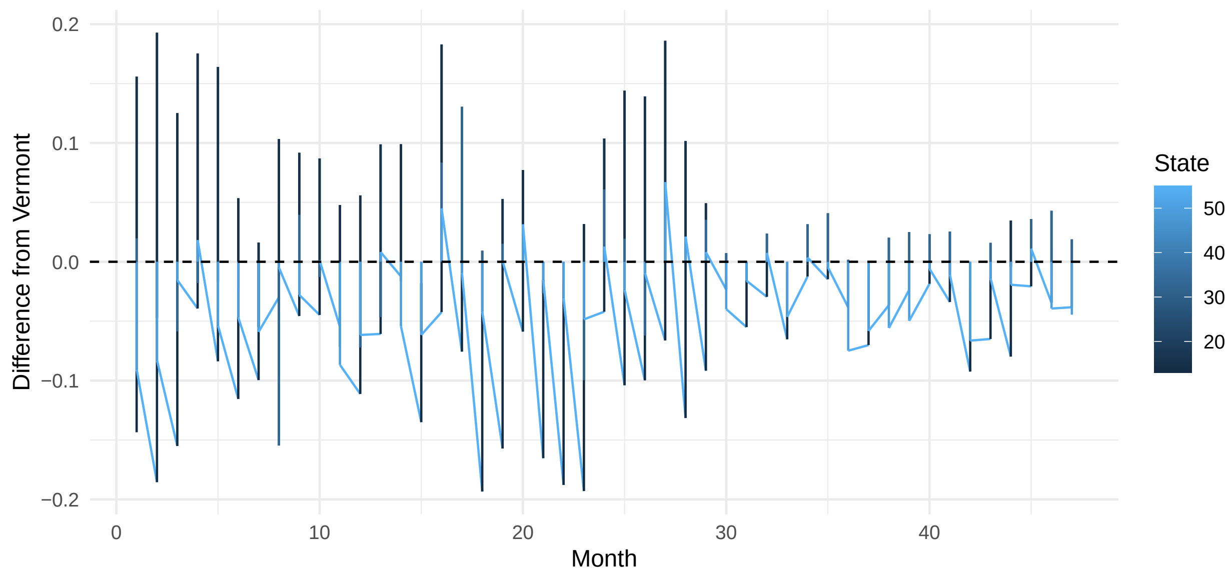


Figure 5



While these states do not form a perfectly matched control group, the visualization shows that their pre-policy job satisfaction trends closely align with Vermont's overall trend. Although minor deviations remain, the general movement over time is comparable.

5.3 Baseline DiD

We first estimate the impact of Vermont's 2017 paid sick leave law on job satisfaction using a baseline Difference-in-Differences (DiD) model, comparing changes in satisfaction before and after the policy in Vermont relative to a control group of states without paid sick leave.

Table 4: DiD Analysis: Effect of Paid Sick Leave in Vermont

	Dependent variable:
	Average Job Satisfaction
Treated x Post (DiD Estimator)	0.013 (0.053)
time	0.146^{***} (0.030)
treated:time	0.130^{*} (0.067)
Constant	0.406^{***} (0.024)
Observations	620
R^2	0.080
Adjusted R^2	0.075
Residual Std. Error	0.324 (df = 616)
F Statistic	17.739^{***} (df = 3; 616)
Note:	*p<0.1; **p<0.05; ***p<0.01

The difference-in-differences regression shows that Vermont's paid sick leave policy is associated with a significant increase in job satisfaction, with an estimated effect of 0.13 (SE = 0.067, p = 0.053). Despite a low adjusted R-squared, indicating the model explains little of the overall variation, the policy effect itself is robust and statistically meaningful at 10%.

5.4 Two-Way Fixed Effects

To account for potential confounding factors and heterogeneity across states and time, we also implement a Two-Way Fixed Effects (TWFE) model.

Table 5: TWFE DiD Analysis: Vermont Paid Sick Leave

	Dependent variable:
	Average Job Satisfaction
Treated x Post (DiD Estimator)	0.130^{***} (0.014)
Observations	620
R^2	0.151
Adjusted R^2	−0.071
F Statistic	86.995^{***} (df = 1; 491)
Note:	*p<0.1; **p<0.05; ***p<0.01

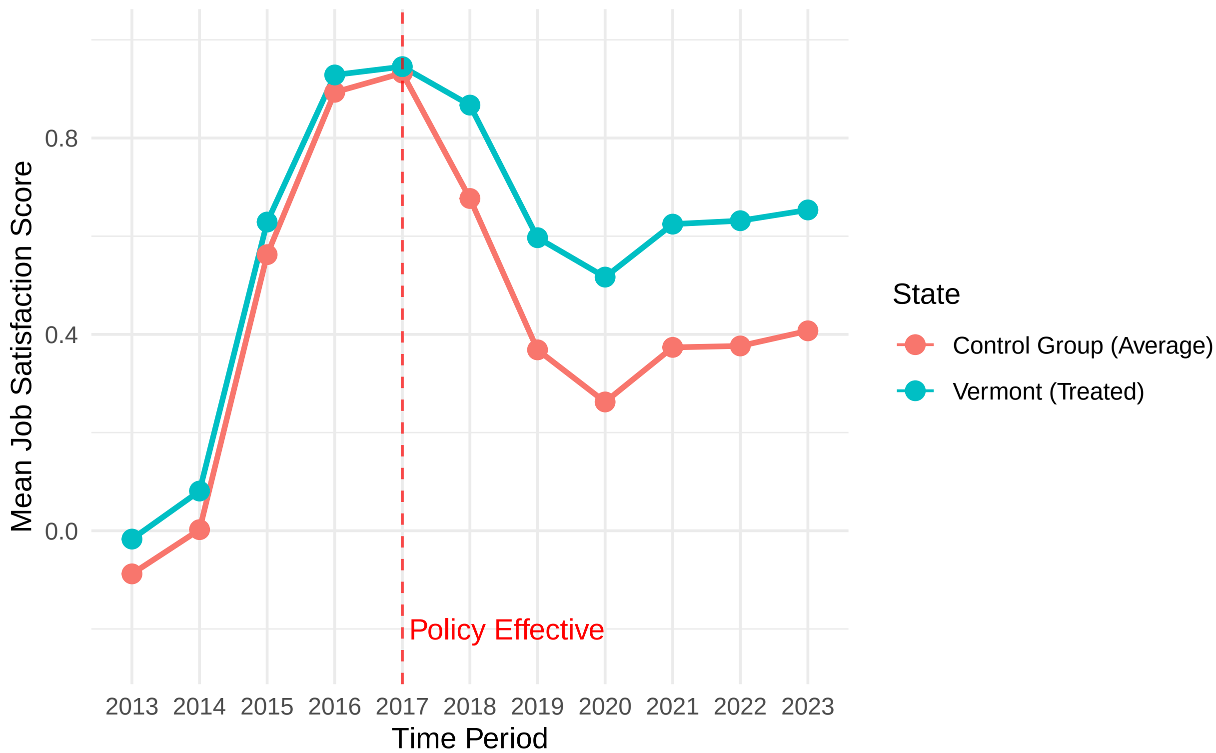
The two-way fixed effects regression indicates that Vermont's paid sick leave policy had a positive and statistically significant effect on job satisfaction, with an estimated DiD coefficient of 0.13 (SE = 0.014, p = <0.001). This suggests that, after the policy implementation, job satisfaction in Vermont increased relative to the control states.

6 Matching

6.1 Post-Matching DiD

Figure 6 − DiD Analysis: Job Satisfaction Change

Vermont (50) vs. other states



The figure illustrates the results of a Difference-in-Differences (DiD) analysis, comparing the mean job satisfaction scores of Vermont (the treatment group) and a synthetic control group (composed of the average of matched states) from 2013 to 2023. The vertical dashed line indicates the implementation of the paid sick leave policy in 2017.

As shown in Figure 6, the pre-treatment trends for Vermont and the control group are virtually indistinguishable between 2013 and 2017, satisfying the fundamental parallel trends requirement for a valid DiD design. After the policy apply on 2017, we observe a distinct divergence: while both groups experienced a downward trend in job satisfaction, the decline in Vermont was markedly attenuated compared to the control states. This sustained gap between the treatment and control groups suggests that the implementation of the paid sick leave law in Vermont led to a relative increase in job satisfaction, estimated by the difference in the post-treatment slopes.

6.2 Post-Matching TWFE Estimation

The post-matching TWFE estimate shows a positive and statistically significant treatment effect. The coefficient on interaction_dummy is 0.1436 (SE = 0.0245, *$p < 0.001$), implying that after January 2017, Vermont's average job satisfaction increased by about 0.14 units per month relative to the matched control states, conditional on state (is_vermont) and month fixed effects.

The model fits the data well ($R^2 = 0.984$) using 248 monthly observations. Overall, this provides strong evidence of a positive treatment effect under the TWFE assumptions.

Dependent Variable:	avg_jobsat
Model:	(1)
Variables	
interaction_dummy	0.1436***
	(0.0245)
Fixed-effects	
is_vermont	Yes
month	Yes
Fit statistics	
R^2	0.98379
Observations	248

IID standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, +: 0.1*

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

7 Conclusion

The United States remains the only industrialized country without universal access to paid sick leave, making state-level policies such as Vermont's particularly important to study. By identifying a four-state control group, we are able to implement a Difference-in-Differences framework using newly constructed matched data, which proves especially useful for evaluating policy impacts. Our pre-trend assessment supports the validity of the design, and the baseline DiD estimates are significant at the 10 percent level. The Two-Way Fixed Effects (TWFE) results show stronger evidence, with significance at $p < 0.001$, and the post-matching TWFE estimates remain highly statistically significant, underscoring the robustness of our findings. These results are consistent with recent evidence showing that paid sick leave reduces worker stress (Asfaw (2024)), suggesting that improvements in mental well-being may be closely linked to higher job satisfaction. While we are reasonably confident in our results, further research using longer panels and alternative identification strategies is needed to fully understand the long-term effects of paid sick leave on workplace outcomes.

8 Discussion

8.1 Limitation of this paper

Despite providing useful insights, this study has several limitations. As a Difference-in-Differences (DiD) analysis, our estimates rely on the assumption that Vermont and the control states would have followed parallel trends in job satisfaction absent the policy, which may not hold perfectly. The control group, while chosen carefully, is not a perfect match, introducing some uncertainty into the estimates. Additionally, unobserved factors could influence job satisfaction and confound the results. Consequently, while the results suggest a positive impact of paid sick leave on job satisfaction, they should be interpreted with caution, acknowledging inherent uncertainties in causal inference using DiD methods.

As novices in the field of research, we recognize that our understanding and experience are still developing. This limited exposure means that our interpretations, analyses, and conclusions may lack the depth and nuance of more seasoned researchers.

8.2 Repository

A copy of this paper and all related resources associated is free to access at kesly & al. (2025). Please drop by to comm ent, your critics are highly welcomed.

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