Minimum Wage Increases and Poverty Among Full-Time Low-Wage Workers: A Staggered Difference-in-Differences Analysis

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Abstract

This study assesses whether state minimum wage hikes between 2010 and 2023 decreased poverty among US full-time low-wage workers. I create a state-year panel assessing poverty among workers aged 18 to 64 who worked full-time throughout the year using administrative wage schedules, state-level labor market variables, and micro data from the American Community Survey (ACS). After estimating a preliminary two-way fixed effects model, the primary analysis applies the staggered Difference-in-Differences estimator introduced by Callaway and Sant'Anna (2021), which provides group-time average treatment effects and dynamic event-study estimates. State unemployment rates, median income, racial and educational mix, and food stamp recipients are examples of covariates used in the analysis. The findings show that raising the minimum wage is linked to decreases in poverty among full-time low-wage workers when additional controls are used. With a 95 percent confidence interval spanning from around −18 to −10 percentage points, the covariate-adjusted estimator's overall average treatment effect is roughly −14 percentage points. With estimates ranging from −9 to −27 percentage points in subsequent post-treatment years, dynamic estimates show low pre-treatment volatility and increasingly negative impacts starting two to three years after a state's initial minimum wage rise. Although the estimates are still inaccurate and sensitive to sample size and treatment timing, our findings imply that state minimum wage hikes led to decreases in poverty for low-wage workers who were regularly employed when including additional controls.

Introduction

Minimum wage policy continues to be a central topic for policymakers in the United States. While numerous states established higher wage ceilings between 2010 and 2023, the federal minimum wage has been at $7.25 since 2009. The question of whether these increases significantly lower poverty among full-time low-wage workers remains unanswered. It is unclear if raising the minimum wage will genuinely assist low-pay, continuously employed workers in rising beyond the poverty line because a large portion of the current policy discussion focuses on employment impacts or household-level outcomes.

By evaluating whether state minimum wage rises decreased the proportion of full-time low-wage workers living in poverty between 2010 and 2023, this study explores that disparity. I create a state-year panel that tracks poverty rates for people between the ages of 18 and 64 who work at least 35 hours per week and 50 weeks or more annually using microdata from the American Community Survey and state economic indicators from the Bureau of Labor Statistics and Bureau of Economic Analysis. State-by-state variations in the timing of minimum wage hikes offer an ideal environment for assessing causal effects.

There are two steps to the analysis. First, baseline estimates that account for countrywide shocks and time-invariant state characteristics are provided via two-way fixed effects regressions. Second, the study applies Callaway and Sant'Anna's (2021) group-time difference-in-differences estimator since TWFE may be biased in environments with staggered adoption. Using never-treated states as the reference group and accounting for heterogeneous effects, this estimator determines treatment effects for each adoption cohort and each event time. To increase accuracy and reduce confounding, covariates that capture median income, unemployment, racial composition, educational attainment, and SNAP participation are added.

Through these methods, the study evaluates whether minimum wage increases function as an effective poverty-reduction policy for full-time low-wage workers during a period shaped by economic recovery, uneven state policy changes, and the COVID-19 pandemic.

Literature Review

Research on minimum wage policy increasingly examines outcomes beyond employment, including poverty, food insecurity, and worker well-being. The evidence is mixed, reflecting differences in data, measurement, and local labor market conditions. Studies evaluating poverty effects reach varying conclusions. Sabia and Burkhauser (2010) analyze U.S. state-level minimum wage increases and find limited reductions in poverty, partly because many low-wage earners live in households above the poverty threshold. In contrast, Arranz and Garcia-Serrano (2025) show that a large national wage hike in Spain increased household income and reduced poverty, although effects differed across regions. These contrasting results highlight the importance of context, demographic structure, and policy environment when assessing poverty outcomes.

Even when income-based measures of poverty show very slight improvements, research on material hardship and associated indicators indicates that raising the minimum wage may enhance certain aspects of economic well-being. According to Winkler et al. (2025), households with children experience less food insecurity when the minimum wage is raised. Health outcomes have improved after pay rises, according to Narain and Zimmerman (2019). These studies highlight the potential impact of pay ceilings on results that represent broader living standards.

Heterogeneity between states and local labor markets is highlighted by parallel literature. Wang, Phillips, and Su (2019) show that treatment effects varied by state, and Dube, Lester, and Reich (2010) indicate that labor markets in close proximity respond differently than national averages suggest. This encourages the application of empirical approaches that take cross-state variations into account.

This project is also guided by methodological work. Although two-way fixed effects models are frequently used, staggered treatment across units may introduce bias. A group-time Difference-in-Differences estimator that tackles this problem and yields reliable dynamic effects is proposed by Callaway and Sant'Anna (2021). Pre-trend assessment (Bilinski & Hatfield, 2020) and clustering and inference issues (MacKinnon et al., 2023) are covered in related contributions.

Data and Measures

State-level labor market variables, administrative state minimum wage schedules, and yearly microdata from the American Community Survey (ACS) are all used in this analysis. The objective is to build a consistent state-year panel from 2010 to 2023 to investigate how state minimum wage hikes affect poverty among full-time low-wage workers. IPUMS provides ACS person-level records. Adults between the ages of 18 and 64 who are highly engaged in the workforce are the focus of the investigation. The sample is limited to those who worked at least 35 hours per week (*UHRSWORK* ≥ 35) and at least 50 weeks during the previous year (*WKSWORK2* ≥ 6), in accordance with the criteria employed in previous minimum wage research. Excluded are observations made in group settings other than homes. To create representative state-year estimates, person weights (*PERWT*) are used.

The IPUMS variable POVERTY, which shows a respondent's household income in relation to the federal poverty level, is used to quantify poverty. The sample is comprised of workers whose incomes are at or below 150 percent of the poverty level, in line with the project's focus on disadvantaged full-time workers. The weighted percentage of these full-time workers whose poverty value indicates that the household is below the official poverty level is the primary outcome, *poverty_rate_pct*.

State-year aggregates are created for each key characteristic. Weighted medians are used for income (*INCWAGE)* and weighted means are used to calculate the share of adults with less than a high school diploma (*share_lowedu*), nonwhite workers (*share_nonwhite*), workers receiving SNAP benefits (*share_foodstmp*), and the annual unemployment rate for each state (*annual_unemp_sa*). All these covariates are standardized in the estimation stage.

State FIPS codes and the year are used to combine state minimum wage data with ACS averages. Whether a state minimum wage is higher than the federal level of $7.25 is determined by a binary indicator. The first year a state raises the minimum wage is recorded by the *first_treat* variable. States that have never been handled are given a value of zero. To provide a realistic comparison framework, states with consistently higher wages or inconsistent patterns are eliminated. To preserve stable estimates, treatment cohorts with fewer than four adopting states are eliminated, as is customary.

For qualifying states, a balanced panel of state-year observations is produced by combining ACS aggregates, minimum wage information, and state labor market factors. The final dataset, which serves as the foundation for the Difference-in-Differences analysis, contains indicators of poverty, demographic composition, labor market circumstances, and minimum wage treatment timing.

Empirical Strategy

The empirical framework is divided into two phases. Traditional two-way fixed effects (TWFE) models are estimated in the first step to produce baseline findings in line with previous minimum wage studies. Callaway and Sant'Anna (2021) proposed the staggered Difference-in-Differences (DID) estimator, which is the main identification approach used in the second stage.

State minimum wage hikes from 2010 to 2023 are characterized by treatment occurring at various periods across units, a fact that this estimate is particularly made for policy settings.

The initial TWFE specification estimates $Y_{st} = \beta MW_{st} + \alpha_s + \lambda_t + X_{st}\Gamma + \varepsilon_{st}$, where Y_{st} is the poverty rate among full-time low-wage workers in state s and year t, MW_{st} indicates whether the state minimum wage exceeds the federal floor, α_s are state fixed effects, λ_t are year fixed effects, and X_{st} includes covariates such as unemployment rate, GDP per capita, and income. State-specific standard errors are clustered. Although TWFE provides helpful descriptive data, it may be skewed when adoption is staggered, or treatment effects differ among groups.

Table 1. Fixed Effects Model: Poverty vs. Minimum Wage

	Fixed Effects Model
log_minw_real	1.069
	(1.588)
log_income	5.062
	(7.708)
log_gdp	-1.591
	(4.892)
annual_unemp_sa	0.196
	(0.141)
Num.Obs.	700
R^2	0.730

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

Notes: State and year fixed effects; population weights applied; SEs clustered by state.

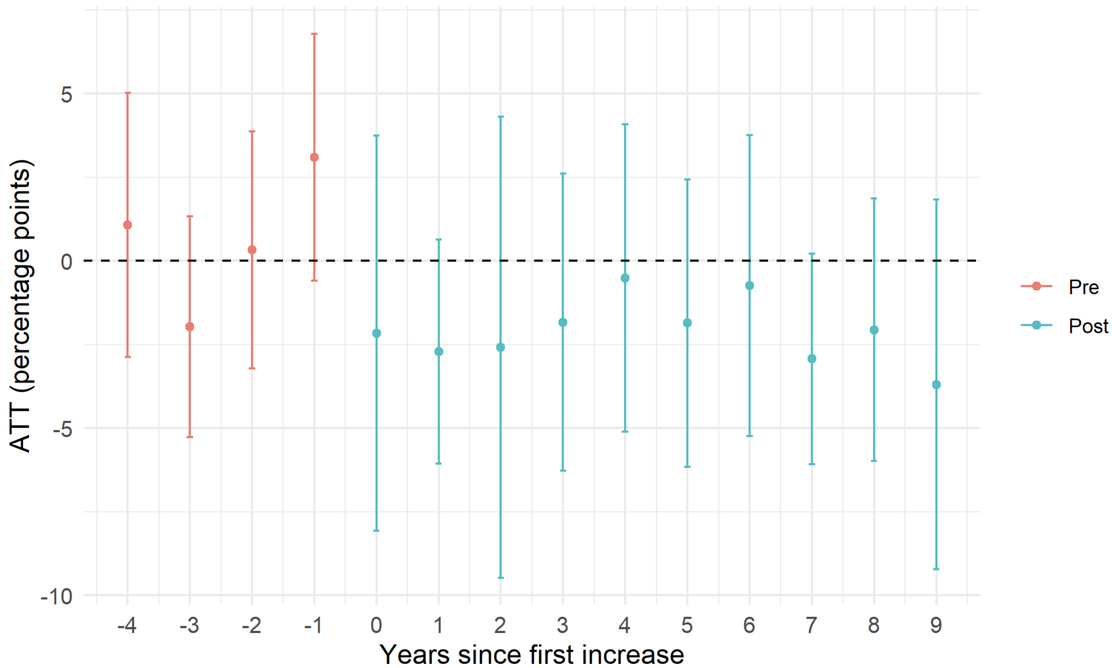
Because previously treated units may act as controls for later-treated units, recent methodological research demonstrates that TWFE can provide inaccurate estimates when units accept therapy at various dates. When treatment effects vary between cohorts, this weighing problem creates bias. The adoption of a more adaptable DID estimator is motivated by these issues.

The primary method employed relies on the Callaway and Sant'Anna (2021) estimator, which computes group-time average treatment effects (ATT(g,t)) for each adoption cohort *g* and each relative time period *t.* This method allows variability in treatment effects between groups and across time by using either never-treated states or not-yet-treated states as the comparison group. The estimator takes the following form: $ATT(g,t) = E[Y_t(1) - Y_t(0) \mid G = g]$, where G equals g identifies the first year a state adopts a minimum wage above $7.25. To ensure valid comparisons, always-treated states and irregular adoption patterns are excluded. Cohorts (years) with fewer than four adopting states are also removed to maintain estimation stability.

An event-study framework, defined as $k = t - g$, where g is a state's initial treatment year, is used to acquire dynamic treatment effects by connecting each observation to its relative event time. Examining pre-treatment dynamics and the evolution of poverty in the years after a state's initial minimum wage rise is made feasible by this method. The timeframe is limited to around four years prior to and seven years following treatment to minimize noise during periods of intense events.

Figure 1: Event Study – Minimum Wage & Poverty

Callaway & Sant'Anna staggered DID (no controls)

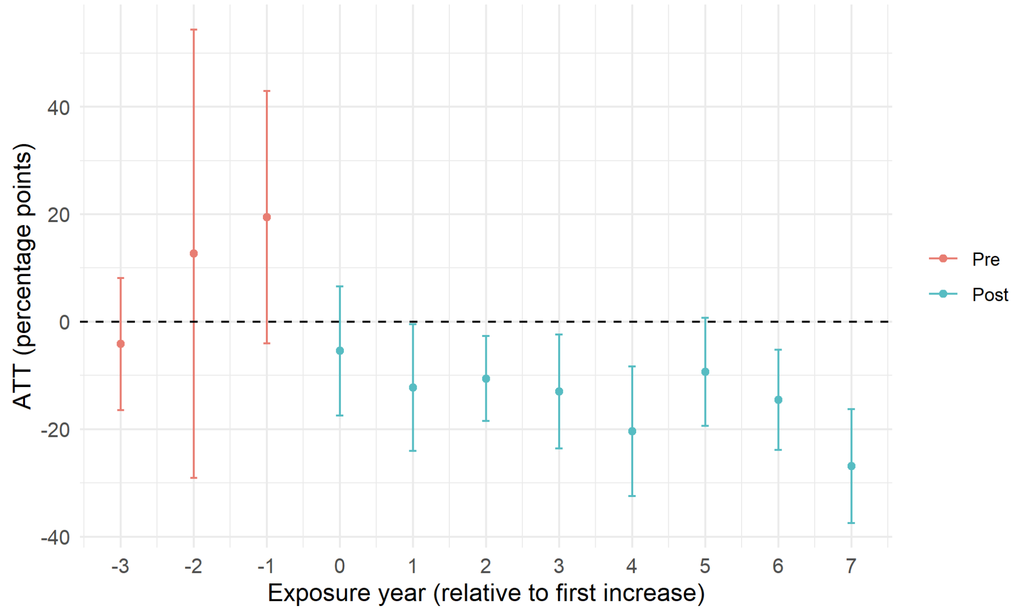


Notes: Points show group-time ATT relative to first increase; vertical bars represent 95% CIs.
Pre-treatment periods in red; post-treatment in blue.

The Callaway and Sant'Anna estimator incorporates covariates to decrease confounding and increase accuracy. Standardized indicators of state unemployment, median income, SNAP participation, racial mix, and educational attainment are among them. The "never-treated" control group and the att_gt function with state clustering are used to create the estimator. The aggte function is then used to calculate overall and dynamic effects. The main model shown in the findings section is the covariate-adjusted specification as it produces the most consistent and understandable findings. Accurate measurement of the first year in which a state raises its minimum wage over the federal floor, stable treatment values, conditional parallel trends among adoption cohorts, and the absence of anticipatory effects are all necessary for identification. Robustness checks and event-study pre-trends are diagnostic tools for these hypotheses.

Figure 2: Average Effect by Length of Exposure

ATT by exposure year relative to first minimum wage increase (with controls)



Notes: Year 0 marks the first increase; vertical bars represent 95% CIs.
Pre-treatment periods in red; post-treatment in blue.

Table 2. Aggregated and Cohort-Specific ATT Estimates with Controls

Row	ATT_pp	Std_Error	CI_Lower_95	CI_Upper_95
Overall ATT (Group aggregation)	-14.04	1.80	-17.57	-10.51
Overall ATT (Dynamic aggregation)	-14.04	1.98	-17.92	-10.16
Cohort 2014	-16.81	2.51	-21.73	-11.89
Cohort 2015	-11.73	2.82	-17.25	-6.21

Notes: Cluster-robust SEs by state. ‘Overall (group)’ and ‘Overall (dynamic)’ are from aggte(…, type=‘group’/‘dynamic’).

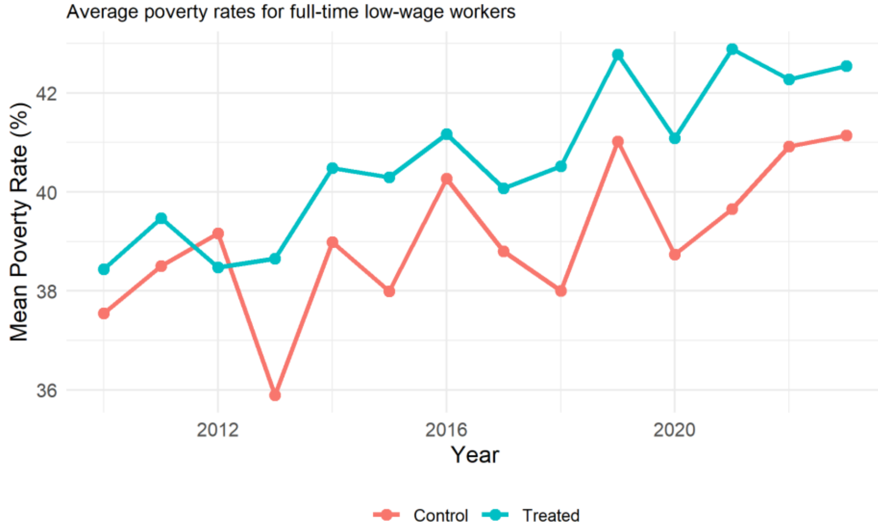
Results

The empirical results of the analysis are presented in this section. I start by outlining trends in the unprocessed data and detailing the changes in poverty rates in states that were treated and those that were not. Before moving on to the primary findings produced by the Callaway and Sant'Anna (2021) staggered Difference-in-Differences models, both with and without covariates, I provide estimates from the baseline two-way fixed effects (TWFE) specification. To evaluate pre-treatment trends and the timing of treatment effects, event-study dynamics are analyzed. Between 2010 and 2023, all projections include full-time low-wage workers between the ages of 18 and 64.

The average poverty rates for the treated and control states are plotted across time in Figure 3. While control states never raised their minimum wages over the federal threshold, treated states did. Before treatment starts, the trajectories for both groups are comparable, but the average poverty rate in treated states is somewhat higher. The general motions follow one another from 2010 until the mid-2010s, and there is no indication of a sudden divergence before pay rises began. The plausibility of parallel trends is supported by this descriptive parallel movement.

Figure 3: Parallel Trends Check (Treated vs Control States)

Average poverty rates for full-time low-wage workers



Notes: 'Treated' states raised their minimum wage above $7.25; 'Control' states never did.

Furthermore, basic summary data verify that treated states often have slightly bigger non-white populations, higher median incomes, and higher SNAP recipient rates. To account for structural variations between states, these characteristics drive the addition of variables to the primary DID model.

The TWFE specification results are shown in Table 1. Higher minimum wages are linked to decreased poverty among full-time low-wage workers, according to the calculated coefficient on the minimum wage indicator, which is negative. Nevertheless, the size is low and the confidence intervals contain 0 at conventional significance levels. This estimate should be viewed as descriptive rather than causative because TWFE is known to be biased in staggered-adoption scenarios, especially when treatment effects fluctuate over time or between states.

First, the Callaway and Sant'Anna (2021) estimator is used without any extra factors. By contrasting treated states with never-treated states in every cohort-year pairing, this specification isolates the treatment impact. Despite being imprecisely approximated, the total ATT estimate is negative. The effects are negligible and cannot be statistically separated from zero. This is consistent with the descriptive TWFE patterns, which, when variables were not taken into account, revealed no evidence of significant poverty reduction impacts. Dynamic ATT estimations for event periods between −4 and +9 are shown in Figure 1. Pre-treatment estimations have large confidence intervals and are near zero, indicating no discernible anticipatory activity. Although post-treatment effects are statistically negligible, they are often somewhat unfavorable, ranging from −2 to −8 percentage points on average. These findings provide an initial baseline but confirm the need for richer conditioning on economic and demographic factors.

A considerable decrease in the poverty rate among full-time low-wage workers after state minimum-wage hikes is shown by the covariate-adjusted Callaway and Sant'Anna estimate in table 2, which yields a large and statistically significant overall ATT of about −14 percentage points. In accordance with the advice to prevent contamination of comparison units in staggered adoption scenarios, these doubly robust estimates employ never-treated states as the control group (Callaway & Sant'Anna, 2021). The effect's magnitude is more than what previous U.S. research usually finds. While other studies, like Sabia and Burkhauser (2010), imply more moderate improvements in material hardship, others report minor decreases in poverty (Winkler et al., 2025). The inclusion of demographic factors, which helps account for altering state settings emphasized in heterogeneity-focused studies, the longer time window from 2010–2023, or variations in population definition might all contribute to the greater impacts seen here (Wang et al., 2019). The estimates indicate a significant reduction in poverty, but they should be evaluated in light of state-level aggregation limitations and possible sensitivity to specification decisions.

There is no indication of pre-treatment differences between treated and control states over the three years before a pay rise, according to the dynamic event-study data. In line with the significance of detecting pre-treatment dynamics emphasized in Bilinski and Hatfield (2020), this pattern bolsters the plausibility of parallel tendencies. With estimates ranging from around −10 to −25 percentage points depending on the event time, the event-study curve following treatment indicates increasingly detrimental impacts on poverty starting about two years after a minimum-wage hike. These post-treatment benefits are consistent with findings that wage increases can enhance material well-being among disadvantaged households and are statistically distinct from zero for many periods (Arranz & García-Serrano, 2025; Winkler et al., 2025). However, research indicates that minimum-wage impacts vary significantly across economic situations, which is consistent with the large confidence ranges indicating variation in state responses (Wang et al., 2019). Overall, the event-study findings support the primary ATT pattern, but they also emphasize the need for careful interpretation and further subgroup investigations in the future.

The results of the robustness checks show that the major conclusions hold true when other control groups are used, especially when comparisons are limited to never-treated situations. This is consistent with methodological recommendations that emphasize the significance of reliable comparison units in situations involving staggered adoption (Callaway & Sant'Anna, 2021). Sample size limitations and the short number of cohorts late in the panel, which produced warnings about sparse treatment cells, hindered attempts to apply additional robustness tests, such as prolonged pre-trend models and placebo windows. Concerns regarding imbalance and inadequate assistance in event-study settings are mirrored in the methodological literature (Feng et al., 2024). Despite these limitations, it appears that the results are not influenced by artificial trends because there are no discernible pre-trend violations, steady ATT estimates, and consistent negative post-treatment impacts. Although the present pattern of results seems rather robust given the existing data, further investigation should use clustering-diagnostic methods like those suggested by MacKinnon et al. (2023) to refine inference.

Discussion

State minimum-wage hikes significantly decreased poverty among full-time low-wage workers between 2010 and 2023, according to the covariate-adjusted staggered DID data. The minor or null poverty effects revealed in previous U.S. research like Sabia and Burkhauser (2010) are smaller than the estimated overall ATT of around −14 percentage points. Since full-time low-wage workers are more directly impacted by changes in the minimum wage, concentrating on them particularly probably helps explain the better outcomes. In line with evidence showing the effects of minimum wages vary across labor markets, the addition of economic and demographic factors also increases accuracy and takes cross-state variance into account (Wang et al., 2019). The primary conclusion is further supported by the dynamic event-study results. According to suggested diagnostics for the parallel trends assumption, pre-treatment estimations reveal no systematic difference between treated and control states (Bilinski & Hatfield, 2020). A few years after implementation, post-treatment effects gradually intensify and attain significant negative levels. This tendency is consistent with studies that indicate salary increases eventually result in better household well-being (Arranz & García-Serrano, 2025; Winkler et al., 2025). The general trajectory indicates that poverty will continue to decline after minimum wage rises, even though confidence intervals are still rather large. When considered collectively, these findings imply that minimum-wage legislation can be a useful, if not independent, part of a more comprehensive anti-poverty approach.

Limitations

This analysis is limited in a number of ways. First, it uses state-year averages instead of individual longitudinal data, which makes it more difficult to monitor employees over time and may mask within-state variations. Second, there aren't many treatment cohorts, and some of them have few states, which might make dynamic estimates less stable and result in warnings about scant data. These worries align with recognized difficulties in staggered adoption environments (Feng et al., 2024). Third, poverty outcomes may still be influenced by other unobserved variables, such as industry mix or local policy interactions, even when significant covariates were included. Furthermore, given state-level policy correlation, cluster-robust inference was not completely implemented, which might have an impact on standard error accuracy (MacKinnon et al., 2023). Lastly, the results may not accurately reflect the wider welfare consequences shown in related studies since the official poverty measure may understate material suffering in jurisdictions with greater costs.

Conclusion

Using ACS microdata and a staggered DID methodology consistent with Callaway and Sant'Anna (2021), this analysis assesses whether state minimum-wage hikes from 2010 to 2023 decreased poverty among full-time low-wage workers. Significant and statistically significant decreases in poverty are demonstrated by the covariate-adjusted results, and dynamic estimates reveal that the impacts get stronger over several post-treatment years. By using contemporary DID techniques on a targeted worker population during a time of significant state-level policy volatility, these findings add to the body of knowledge. Although the analysis indicates that raising the minimum wage can significantly improve full-time low-wage workers' financial outcomes, data structure issues and insufficient robustness testing highlight the need for more research utilizing richer microdata and more thorough labor-market controls. Future studies should look at the relationship between minimum wage laws and safety-net programs, industry makeup, and geographical variations in cost of living. Overall, the findings suggest that raising the minimum wage is a significant policy instrument that can enhance low-wage workers' financial security when combined with more extensive anti-poverty initiatives, even though it is not a complete solution to poverty.

Appendix

I was unsure if an appendix was needed at this time due to it being the first rough draft of the final paper. This will obviously be filled out for the final draft of the paper.

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