Research Design: Estimating the Effect of State Minimum Wage Increases on Poverty Among Full-Time Low-Wage Workers (2018-2023)

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Introduction

Public debates about economic fairness often center on minimum wage laws. While scholars often focus on employment effects, less attention is paid to whether higher wages lift full-time low-wage workers from poverty. This study addresses that gap by focusing explicitly on poverty outcomes among full-time workers who earn near or below the poverty threshold. Building on recent methodological advances and the literature synthesized in the Domain Review, this research will use modern difference-in-differences estimation, fixed-effects regressions, and exploratory clustering to assess whether state minimum wage increases between 2018 and 2023 measurably reduced poverty among full-time low-wage workers. The period 2018–2023 captures the policy environment before, during, and after the COVID-19 pandemic, while aligning with the availability of ACS microdata. Since the adoption of state policies is frequently politically endogenous, reflecting underlying partisan or economic conditions, the design incorporates controls for co-occurring labor policies, fixed effects, and state-specific temporal trends to explicitly account for possible bias. Guided by studies such as Arranz (2025), Winkler et. al (2025), Sabia and Burkhauser (2010), and Wang, Phillips, and Su (2019), this project emphasizes both the potential and limits of minimum wage laws as anti-poverty tools.

Data and Measures

State minimum wage data was obtained from the U.S. Department of Labor's *Changes in Basic Minimum Wages in Non-Farm Employment Under State Law – Historical Table.* For states without a binding state minimum wage or with a wage below the federal floor, the federal minimum wage of $7.25 per hour is assigned. In states with multi-tier systems (such as Minnesota's large versus small employer rates or Nevada's health-benefit tiers), the analysis uses the highest binding wage floor and records lower-tier exemptions separately. This ensures consistency and aligns with best practices. Microdata on poverty comes from the ACS 1-year Public Use Micro Sample via IPUMS USA (Ruggles, 2023). To capture working-age adults, the data will be filtered for individuals aged 18 to 64 who are working full-time (35 hours or more per week for more than 50 weeks). Low-wage individuals are defined as those in occupations near or below the poverty line ($15,650). The following variables will be utilized: YEAR, STATEFIP, EMPSTAT, UHRSWORK, WKSWORK1, INCWAGE, POVERTY, PERWT, and selected demographic variables for sensitivity checks. For 2020, IPUMS experimental weights are applied to account for disruptions caused by the COVID-19 pandemic, though some measurement error may persist.

Additionally, person weights are applied and aggregated to state-year averages to compute the outcome variable which is the proportion of full-time low-wage workers who are living in poverty. The BLS Local Area Unemployment Statistics (LAUS) provide monthly, seasonally adjusted unemployment data that is averaged to annual rates. The BEA State Annual Summary Statistics are used to derive macroeconomic indicators such as real GDP, regional pricing parities, and per capital personal income. The Consumer Price Index for All Urban Consumers (CPI-U) from FRED is used to convert all nominal numbers, including wages, to real terms. While annual ACS data provides robust coverage, they may smooth short-term shocks. Accordingly, the analysis emphasizes sustained and multi-year changes and lagged effects rather than single-year fluctuations.

Identification and Empirical Strategy

Building on the framework laid out in the proposal and Domain Review, this study proceeds in three stages. First, descriptive statistics and visualizations will chart state-level poverty trends in relation to minimum wage changes. Second, fixed-effects panel regressions will estimate the association between state minimum wages and poverty rates among full-time low-wage workers while adjusting for state economic and demographic controls. Third, difference-in-differences (DiD) models with event-study specifications will compare states that increased their minimum wage to those that did not during the same period (Feng et. al, 2024).

To address endogeneity, the model includes state and year fixed effects to capture unobserved structural differences, along with state-specific time trends to control for varying growth trajectories. Where possible, additional restrictions are included for co-occurring labor and anti-poverty programs, such as state earned income tax credits (EITC) or unemployment insurance generosity. These adjustments limit omitted-variable bias and improve casual interpretation. Formally, the intended model is expressed as:

$$Y_{st} = \sum_{k \neq -1} \beta_k D_{s,t+k} + \gamma_s + \delta_t + X_{st}\theta + \varepsilon_{st} ,$$

where Y_{st} is the poverty rate among full-time low-wage workers in state s, year t; $D_{s,\, t+k}$ are event-time indicators for leads and lags around the first wage increase; and $\delta_t$represent state and year fixed effects; and $X_{st}$is a vector of state-level controls. Standard errors will be clustered at the state level, with diagnostics from MacKinnon, Nielsen, and Webb (2023) used to verify the appropriate clustering level. To formally test the parallel-trends assumption, the design will employ Bilinski and Hatfield's (2018) non-inferiority equivalence approach. This method quantifies whether observed pre-treatment differences are substantively negligible, rather than assuming them away. When pre-trends appear non-parallel, the model will be re-estimated with state-specific time trends as a robustness check. Because minimum wage effects may not materialize immediately, models will incorporate lagged treatment variables (one – and two-year lags) to capture delayed adjustments in wages and poverty outcomes. Event-study estimates will also help visualize dynamic impacts across time relative to policy implementation.

To evaluate robustness, the study will conduct sensitivity analyses by (1) redefining "low wage" thresholds, (2) excluding states with unusual exemption structures, and (3) controlling for co-occurring policy changes. Clustered standard errors and fixed effects ensure results are not driven by serial correlation or omitted heterogeneity. Potential threats to validity include migration between states, which may reallocate low-wage workers following policy changes; smoothing effects from ACS annual data that could obscure short-term shocks; and measurement inconsistencies in 2020 due to pandemic-era survey adjustments. These are addressed by emphasizing multi-year differences, lagged specifications, and sensitivity checks. If the parallel-trends assumption remains weak, alternative quasi-experimental approaches such are synthetic control or propensity-score weighting may be considered as robustness checks. All data preparation and analysis will be conducted in R (R Core Team, 2023) using tidyverse and other packages for data management and the *did* package (Callaway & Sant'Anna, 2021) for estimation.

Expected Findings and Limitations

Overall, I expect that states increasing their minimum wage between 2018 and 2023 will show modest but significant reductions in poverty rates among full-time low-wage workers, though effects may vary by state cluster and over time. Since treatment isn't randomized, causal claims rely on parallel-trends credibility and model robustness. Limitations include measurement error in ACS wage variables, the inability to model coverage exemptions precisely, and potential spillovers across state lines. Nonetheless, by combining modern DiD estimators, formal pre-trend testing, and clustering, this study aims to provide more policy-relevant estimates of when and where minimum wage increases achieve their intended poverty-reduction goals.

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Appendix

Table 1: Data Documentation Table

Variable Name	Data Type	Missingness (%)	Category	Variable Description
POVERTY_RATE_FULLTIME_LOW_WAGE	Numeric (%)	0% (after aggregation)	Response	Main outcome variable: percentage of full-time low-wage workers living below/near/at poverty threshold
MINWAGE	Numeric	0%	Predictor	Binding state minimum wage
UNEMPLOYMENTRATE	Numeric (%)	0%	Covariate	Annual average, seasonally adjusted unemployment rate
REAL_GDP	Numeric	< 1%	Covariate	Real GDP
PER_CAPITA_INCOME	Numeric	< 1%	Covariate	State per capita personal income
REGIONAL_PRICE_PARITIES	Numeric	< 1%	Covariate	Cost-of-living index across states
CPI_U	Numeric	< 1%	Covariate	Consumer price index for all urban consumers.
UI_BENEFIT_INDEX	Numeric	< 1%	Covariate (policy control)	Proxy for unemployment insurance generosity (average weekly benefit ÷ average weekly wage)

STATEFIP	Categorical	0%	Fixed Effect	State identifier for state-level fixed effects.
YEAR	Numeric	0%	Fixed Effect	Year identifier capturing national-level shocks through time fixed effects
AGE	Numeric	< 1%	Sensitivity/ Demographic Control	Respondent age in years
SEX	Categorical	< 1%	Sensitivity/ Demographic Control	Respondent gender (Male/Female)
RACE	Categorical	< 1%	Sensitivity/ Demographic Control	Broad racial categories
EDUC	Categorical	< 1%	Sensitivity/ Demographic Control	Highest educational attainment
CITIZEN	Categorical	< 1%	Sensitivity/ Demographic Control	Citizenship status
EMPSTAT	Categorical	< 1%	Sensitivity/ Demographic Control	Employment status (employed, unemployed, not in labor force
UHRSWORK	Numeric	< 1%	Sensitivity/ Demographic Control	Usual hours worked per week. Helps verify "full-time" status
WKSWORK2	Categorical	< 1%	Sensitivity/ Demographic Control	Weeks worked
OCC	Categorical	< 1%	Sensitivity/ Demographic Control	Broad occupation categories
INCWAGE	Numeric	< 1%	Sensitivity/ Demographic Control	Annual wage and salary income (nominal)

The table above lists all variables used in the study, showing their data types, estimated missing values, and roles. Variables come from IPUMS USA microdata combined with state-level data from the U.S. Department of Labor, Bureau of Labor Statistics, Bureau of Economic Analysis, and Federal Reserve Economic Data. Person-level records were filtered for working-age adults employed full time and then aggregated to state-year averages to create the main poverty outcome measure. This documentation increases transparency and replicability by clearly defining each variable's characteristics and role in the analysis.

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