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

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9/28/2025

Introduction

Public debates about economic fairness often center on minimum wage laws. While much of the scholarly focus has been on employment impacts, far less attention has been devoted to whether higher wages actually lift full-time low-wage workers out of 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. Focusing on these years allows for analysis of both short-term shocks and longer-term policy trends. Guided by studies such as Arranz (2025), Winkler et al. (2025), Sabia and Burkhauser (2010), and Wang, Phillips, and Su (2019), the 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, I assign the federal minimum wage of $7.25 per hour. In states with multi-tier systems, such as Minnesota's large versus small employer rates or Nevada's health-benefit tiers, I adopt the binding wage floor (highest rate) and record lower-tier or exemption details in separate notes. This approach follows the best practices highlighted within the domain review and ensures consistency across states.

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 (i.e. more than 35 hours per week for more than 50 weeks). In addition, low-wage individuals will be defined as working in occupations near or below the poverty line. The variables extracted from the data source are YEAR, STATEFIP, EMPSTAT, UHRSWORK, WKSWORK1, INCWAGE, POVERTY, PERWT, and other various demographic variables retained for sensitivity checks. To get the outcome variable, which is the percentage of full-time low-wage workers living in poverty, I will use person weights and aggregate to state-year averages.

Monthly seasonally adjusted data averaged to yearly state rates will be used to calculate unemployment rates from the BLS Local Area Unemployment Statistics (LAUS). The BEA State Annual Summary Statistics (SASUMMARY) will be utilized to produce macroeconomic indicators, such as regional pricing parities, real GDP, and per capita personal income. The Consumer Price Index for All Urban Consumers: All Items in U.S. City Average (CPI-U) from the Federal Reserve Economic Data (FRED, series CPIAUCSL) is used to convert all nominal dollar values, including wages, to real terms.

This will yield a dataset that contains each state's minimum wage, poverty rate among full-time low-wage workers, unemployment rate, per capita income, real GDP, and cost-of-living measures for 2018–2023, creating a comprehensive panel to analyze policy effects. A detailed data table will be placed in an appendix for clarity (the version I currently have).

Analytical 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). In order to evaluate dynamic effects and check for parallel trends, the DiD framework contains leads and lags of treatment indicators in addition to state and year fixed effects. To estimate treatment effects under staggered adoption, I will use the "did" R package (Callaway & Sant'Anna, 2021) and the heterogeneity-robust estimators described by Feng et al. (2024) (the package is generally employed for difference-in-differences). The intended model is the following: $$Y_{st} = \sum_{k \neq 1} \beta_k 1\{t - T_s = k\} + \gamma_s + \delta_t + X_{st}\theta + \varepsilon_{st}$$

Where Y_{st} is the poverty rate among full-time low-wage workers in state *s*, year *t; T_s* is the first treatment year (state's initial wage increase); γ_s and δ_t are state and year fixed effects; and X_{st} is a vector of state-level controls. Standard errors will be clustered at the state level, and diagnostics from MacKinnon, Nielsen, and Webb (2023) will be applied to test whether state-level clustering is appropriate or whether an alternative level of clustering is needed. To explicitly verify the parallel-trends assumption, I will employ Bilinski and Hatfield's (2018) non-inferiority equivalency-testing approach. This method makes sure that observed impacts aren't caused by pre-existing state-to-state disparities by offering boundaries and adaptable pre-trend models. Furthermore, I will change the definition of "low-wage" workers, use different cost-of-living adjustments, and exclude states with odd exemptions in order to do sensitivity tests.

To uncover heterogeneity in policy effectiveness, I intend to use clustering methods to group states by economic and demographic characteristics prior to estimating DiD effects. This draws on the clustering literature surveyed by Jain (2010) and on the state-heterogeneity framework employed by Wang, Phillips, and Su (2019). This exploratory step may reveal clusters of states where minimum wage policies have stronger or weaker poverty impacts. If key assumptions of the difference-in-differences design are violated, alternative quasi-experimental strategies such as synthetic control or propensity-score weighting could be applied as robustness checks

All data preparation and analysis will be conducted in R (R Core Team 2023). I will utilize dplyr (Wickham et al. 2023) for data manipulation, tidyr (Wickham & Girlich 2023) for reshaping data between wide and long formats and did (Callaway & Sant'Anna 2021) for difference-in-differences estimation. Other various packages will be utilized and added along the way. It is important to keep in mind throughout the process that my analysis and code is reproducible, so comments will be provided throughout the file.

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. Because treatment is not randomized, causal claims rest on the credibility of the parallel-trends assumption and the robustness of our modeling. 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	Role (predictor/covariate/response)
YEAR	Numeric (integer)	0%	Panel Key (state-year)
STATEFIP	Categorical (factor)	0%	Panel Key (state identifier)
PERWT	Numeric (weight)	0%	Covariate / Sensitivity Check
SEX	Categorical (binary)	<1%	Covariate / Sensitivity Check
AGE	Numeric (continuous)	<1%	Covariate / Sensitivity Check
RACE	Categorical (factor)	<1%	Covariate / Sensitivity Check
RACED	Categorical (factor, detailed)	<1%	Covariate / Sensitivity Check
CITIZEN	Categorical (binary)	<1%	Covariate / Sensitivity Check
EDUC	Categorical (ordinal)	<1%	Covariate / Sensitivity Check
EDUCD	Categorical (factor, detailed)	<1%	Covariate / Sensitivity Check

EMPSTAT	Categorical (factor)	<1%	Covariate / Sensitivity Check
EMPSTATD	Categorical (factor, detailed)	<1%	Covariate / Sensitivity Check
OCC	Categorical (factor)	<1%	Covariate / Sensitivity Check
WKSWORK1	Numeric (continuous)	<1%	Covariate / Sensitivity Check
WKSWORK2	Numeric (continuous)	~1% (2018 only)	Covariate / Sensitivity Check
UHRSWORK	Numeric (continuous)	<1%	Covariate / Sensitivity Check
INCTOT	Numeric (continuous)	~5–10%	Covariate / Sensitivity Check
INCWAGE	Numeric (continuous)	~5–10%	Covariate / Sensitivity Check
POVERTY	Numeric (index)	<1%	Covariate / Sensitivity Check
OFFPOV	Categorical (binary)	Varies by year (2018 missing)	Covariate / Sensitivity Check
MINWAGE	Numeric (continuous)	0%	Predictor (policy variable)
UNEMPLOYMENT_RATE	Numeric (continuous)	0%	Covariate / Sensitivity Check
REAL_GDP	Numeric (continuous)	0%	Covariate / Sensitivity Check
PER_CAPITA_INCOME	Numeric (continuous)	0%	Covariate / Sensitivity Check
REGIONAL_PRICE_PARITIES	Numeric (continuous)	0%	Covariate / Sensitivity Check
CPI_U	Numeric (continuous)	0%	Covariate / Sensitivity Check
POVERTY_RATE_FULLTIME_LOW_WAGE	Numeric (percent)	0% after aggregation	Response Variable (main outcome)
PCE_CHN	Numeric (continuous)	0%	Covariate / Sensitivity Check
Disposable_Personal_Income	Numeric (continuous)	0%	Covariate / Sensitivity Check
Population	Numeric (continuous)	0%	Covariate / Sensitivity Check
Employment_Total	Numeric (continuous)	0%	Covariate / Sensitivity Check
Price_Index_Deflator	Numeric (continuous)	0%	Covariate / Sensitivity Check

Transfer_Receipts	Numeric (continuous)	0%	Covariate / Sensitivity Check
Taxes_Production_Imports	Numeric (continuous)	0%	Covariate / Sensitivity Check
Regional_Price_Parities_Housing	Numeric (continuous)	0%	Covariate / Sensitivity Check
Regional_Price_Parities_Goods	Numeric (continuous)	0%	Covariate / Sensitivity Check
Regional_Price_Parities_Services	Numeric (continuous)	0%	Covariate / Sensitivity Check
Nominal_GDP	Numeric (continuous)	0%	Covariate / Sensitivity Check
Real_GDP_Chained	Numeric (continuous)	0%	Covariate / Sensitivity Check
Per_Capita_GDP	Numeric (continuous)	0%	Covariate / Sensitivity Check
Total_Personal_Income	Numeric (continuous)	0%	Covariate / Sensitivity Check
Per_Capita_Disposable_Income	Numeric (continuous)	0%	Covariate / Sensitivity Check
Compensation_of_Employees	Numeric (continuous)	0%	Covariate / Sensitivity Check
Wages_and_Salaries	Numeric (continuous)	0%	Covariate / Sensitivity Check
Proprietors_Income	Numeric (continuous)	<5%	Covariate / Sensitivity Check
Civilian_Labor_Force	Numeric (continuous)	<5%	Covariate / Sensitivity Check
Employment_Count	Numeric (continuous)	<5%	Covariate / Sensitivity Check
Unemployment_Count	Numeric (continuous)	<5%	Covariate / Sensitivity Check
Tipped_Minimum_Wage	Numeric (continuous)	<5%	Covariate / Sensitivity Check
Youth_Minimum_Wage	Numeric (continuous)	<5%	Covariate / Sensitivity Check

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.

For additional information on APA Style formatting, please consult the [APA Style Manual, 7th Edition].