



An Analysis of *Paid Family and Medical Leave* in the South

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Contents

1	CREL and Project Overview	4
1.1	Charles River Economics Labs	4
1.2	Project Background	4
2	Introduction and Motivations	4
2.1	Paid Family and Medical Leave	4
2.2	Motivation for the South	5
3	Literature Review	6
3.1	Past Studies	6
3.2	Previous Frameworks	7
3.2.1	Institute for Women’s Policy Research (IWPR) PFML Simulator	7
3.2.2	Department of Labor’s (DOL) Worker Paid Leave Usage Simulation (PLUS)	8
3.2.3	Program Rules and Simulation Parameters	11
4	Data	14
4.1	American Community Survey (ACS)	15
4.2	Family and Medical Leave Act (FMLA) Employee Survey	15
4.3	Current Population Survey (CPS)	15
4.4	Other Data	15
4.5	Key Outcome Variables	16
5	Methodology	16
5.1	Incorporating Wage Replacement into WorkerPLUS	17
5.1.1	Treatment of wage replacement in the original model	17
5.1.2	Modifications	17
5.1.3	Remaining limitations.	18
5.2	Job Security	18
5.2.1	Unemployment Risk Estimation via Gradient Boosting	19
5.2.2	Integration into the Worker PLUS Simulation	20
5.2.3	Code Modifications	21
5.2.4	Modification Visualizations: Texas Case Study	24
5.2.5	Limitations of the Job Security Extension	26
5.3	Awareness	27
5.3.1	Data Compilation	27
5.3.2	Linear Regression to Predict Awareness	28
5.3.3	Limitations of predicting leave take-up using CPS-MORG 2024 data	29
5.3.4	Regression Evidence	30
5.3.5	State-level Analysis	31

6	Results	33
6.1	Eligibility Expansion	33
6.2	Take-up Patterns	35
6.3	Distributional Benefits	37
6.4	Policy Mechanics: Graduated Wage Replacement	39
6.5	Sector and Gender Breakdowns	40
6.6	Fiscal Outcomes	42
7	Conclusion	44
7.1	Conclusion	44
7.2	Next Steps	44
8	Appendix	45

1 CREL and Project Overview

1.1 Charles River Economics Labs

Charles River Economics Labs is a group of undergraduate researchers at the University of Chicago, Harvard, and Stanford that completes pro bono economics research for governments and other social enterprises. The organization is advised by graduate researchers and faculty members at Harvard and the University of Chicago. Its past and current research partners include the United Nations Development Programme, the Department of Transportation, the World Bank, the US Department of State, and the Census Bureau, among others.

1.2 Project Background

The primary objective of this research project is to estimate the potential impact of a universal Paid Family and Medical Leave (PFML) policy proposal on workers and families across 14 Southern states. Currently, the Bureau of Labor Statistics (BLS) provides data regarding worker access to paid leave coverage only by Census region, rather than by individual state. Moreover, there is a significant lack of simulations that provide state-level results given implementation of paid leave. This project aims to fill the research gap by utilizing and integrating data from various alternative sources to develop robust estimates for take-up rate, program cost, and worker benefits derived from PFML in the Southern states.

2 Introduction and Motivations

2.1 Paid Family and Medical Leave

Paid Family and Medical Leave is a policy mechanism designed to provide workers with compensated time off to attend to critical life events. The policy proposal analyzed in this paper, based on recommendations from the Economic Policy Institute (EPI), includes a universal benefit of 12 weeks of paid leave. This coverage extends to several categories, including parental leave for birth, adoption, or fostering of a child, maternity leave, and medical leave for a worker’s own sickness or a relative’s sickness. The goal of such policies is to provide economic security and labor market stability during periods that might otherwise force workers to resign or face financial hardship.

Currently, the United States is the only member of the Organisation for Economic Co-operation and Development (OECD) that does not mandate paid leave for new parents. The federal standard is set by the Family and Medical Leave Act of 1993 (FMLA). While the FMLA provides job protection for up to 12 weeks, the leave is unpaid. Additionally, strict eligibility requirements limit its reach: employees must work for a firm with at least 50 employees and must have worked 1,250 hours in the previous year. These criteria exclude a large portion of the workforce, with estimates suggesting that only 56% of American workers are eligible for FMLA protections [1]. Among those who are eligible, many cannot afford to take unpaid time off, limiting the practical utility of the federal policy.

In the absence of a federal mandate, thirteen states and the District of Columbia have enacted their own paid family leave programs as of 2026. These states are primarily located in the Northeast and the West Coast. Most of these programs were enacted in the last decade, with only New Jersey, Rhode Island and California having paid leave programs before the last comprehensive FMLA survey conducted in 2018. Despite their relatively recent implementation, research on these existing programs indicates positive outcomes for both workers and firms. In terms of labor market effects, access to paid leave increases the likelihood that workers, particularly women, return to their pre-leave employers. This reduces turnover costs for businesses and helps workers maintain their tenure and wage progression. Regarding public health, studies show that paid leave is associated with higher vaccination rates, longer durations of breastfeeding, and better maternal health outcomes. Finally, paid leave addresses equity gaps; without a universal mandate, access to paid time off is highly correlated with income, leaving low-wage workers with the fewest options during family or medical emergencies.

2.2 Motivation for the South

This report focuses on 14 Southern states because the region presents a distinct socioeconomic environment compared to the rest of the country. While paid leave mandates are becoming more common in the Northeast and West, the South generally relies solely on the unpaid provisions of the federal FMLA. Consequently, workers in the South have fewer statutory protections than their counterparts in other regions, making an analysis of the potential benefits of PFML particularly relevant for this region.

Additionally, the demographic and economic profile of the South also differs from the national profile. The region faces significant public health challenges, including higher rates of chronic illness and maternal mortality compared to national averages. This suggests that the medical and care components of a paid leave policy could have a substantial impact on the region’s economic and health outcomes. Thus, it is important to study the impacts of PFML on Southern states specifically. This project aims to fill this research gap by simulating PFML implementation using data that reflect the demographic and economic conditions in the Southern states.

3 Literature Review

3.1 Past Studies

A variety of studies from several research institutions have been conducted on PFML. While many overlap in content and reasoning, their purposes differ and findings are often mixed.

In relation to the topic of gender, the Stanford Institute for Economic Policy Research published a study which found that PFML significantly increases leave-taking rates, especially among mothers after birth [2]. The research demonstrated that higher wage replacement rates drive higher use of the program, but also revealed consistent equity gaps in usage patterns. Without concrete job protection guarantees and outreach efforts regarding PFML policies, low-wage workers consistently under-use PFML benefits despite having the greatest need for wage support during leave. This underutilization was especially present among workers at small firms and those in lower-wage positions, highlighting how policy design and implementation can either mitigate or exacerbate existing economic inequalities.

In contrast, evidence on long-term labor market effects is more limited. An American Economic Association study assessed the long-term effects on earnings potential and women’s employment using administrative tax data and a regression-discontinuity design [3]. The study found no evidence that California’s paid family leave increased employment, boosted earnings, or encouraged childbearing over a 12-year period. Workers taking up paid leave were no more likely to work for pay after childbirth relative to the comparison group, and the policy showed statistically insignificant effects on long-term employment and wage outcomes. These findings suggest that while paid family leave does not harm long-term career paths, it may not generate the employment or wage

gains that some supporters expect.

Another important dimension of PFML concerns economic security and distributional impacts. A Department of Labor study focused on the effects of PFML on vulnerable populations and found that PFML programs reduce poverty and financial stress for families in the short term [4]. The study further found that Black and Hispanic workers experience greater economic gains from access to PFML compared to other demographic groups, suggesting that the program may help narrow racial economic disparities. These findings highlight the role of paid leave policies as an income stabilization mechanism and equity tool, particularly for workers facing financial or institutional constraints.

Altogether, existing research suggests that PFML affects leave-taking behavior and short-term economic outcomes, but evidence on long-term labor market effects remains mixed. These findings also highlight the importance of job security, policy design, and access constraints in determining program participation, which motivates the extensions to the Worker PLUS framework introduced in this study.

3.2 Previous Frameworks

3.2.1 Institute for Women’s Policy Research (IWPR) PFML Simulator

One previous framework to modern PFML impact microsimulations worth mentioning is the IWPR’s model developed by Albelda and Clayton-Matthews. At a high level, it takes a representative state workforce sample and runs each worker through a staged leave-taking process, using a sequence of logit behavioral equations, and uses explicit assumptions when the data are unable to identify behavior directly.

The core idea of the IWPR’s model is to estimate leave-taking behavior using a national survey conducted by the Department of Labor (DOL) regarding the Family and Medical Leave Act of 1993 (FMLA), and then map those behavioral relationships onto a microdata sample from the Current Population Survey (CPS) which is ideally state-representative, so that outcomes by state and distributions across demographic groups can be simulated. This includes computing the probability of leave-taking/need, pay during leave, and other related outcomes that are conditional on demographics and leave type.

Arguably, the aspect of Albelda and Clayton-Matthews’ framework most relevant to our work is the simulator’s *sequential logit* equations. Each individual’s simulated path mimics “the sequence of decisions and events that a person makes and experiences,” and at each point, the model uses logit probabilities to resolve binary choices (e.g., take leave or do not, paid or unpaid).[5]

More specifically, each decision node works like this:

- A logit (logistic) equation produces a probability of “yes,”
- The simulator draws a uniform random number $u \sim U(0, 1)$,
- The decision is “yes” if the draw is $\leq$ the predicted probability.

They also document the standard logit probability mapping:

$$\Pr(Y = 1) = \frac{\exp(x\beta)}{1 + \exp(x\beta)} \quad (1)$$

This *sequential logit* framing presents a natural template to create extensions for PFML microsimulations (e.g., job security concerns, awareness/administrative frictions, stigma, employer constraints). Each can be represented as another decision node that affects take-up, timing, or duration, allowing us to insert it into the same staged flow—either as (i) an additional logistic transition or (ii) a modifier of probabilities at an existing node.

3.2.2 Department of Labor’s (DOL) Worker Paid Leave Usage Simulation (PLUS)

The DOL’s Worker PLUS is an open-source microsimulation developed to simulate PFML program usage and costs under a wide variety of policy rules and population definitions. It is designed as an evolution of the Albelda Clayton-Matthews simulator, with improvements in outputs/UX, runtime, and modeling options.

It allows users to (i) simulate alternative PFML policy designs, (ii) estimate program benefit costs, (iii) estimate payroll-tax revenue, (iv) analyze leave-taking patterns for participants, and (v) compare scenarios within a consistent modeling framework. After running, it delivers a post-simulation American Community Survey (ACS) Public Use Microdata Sample (PUMS) file at the worker level which includes the simulated leave outcomes, benefits, and subgroup distributions.

Core Data Sources

Similar to the IWPR’s simulation, Worker PLUS trains predictive models using the DOL’s FMLA Employee Survey microdata, and then simulates leave-taking outcomes for workers in a state by mapping outcomes to a population base created by CPS and ACS PUMS microdata. Improvements include a broader set of prediction methods the user can choose from (instead of solely logit equations) and a modularization of the pipeline into prediction and simulation components, which produce standardized microdata outputs for analysis.

Modeling Options

Worker PLUS allows the user to choose among many different classifiers for leave-taking prediction, including Logistic Regression (GLM), regularized logistic regression, Ridge classifier, KNN, Naive Bayes, SVM, Random Forest, and XGBoost. The Worker PLUS model relies on tabular data (rows and columns) from the FMLA and ACS surveys, and XGBoost is widely considered the “king” of tabular data, since it excels in finding complex, non-linear relationships (e.g., how a specific combination of wages, industry, and dependents may dramatically increase the need for leave). Moreover, many models can overfit, but XGBoost has built-in L1 and L2 regularization as a precaution, penalizing overly complex trees. Lastly, since XGBoost uses parallel processing (building parts of trees simultaneously) and cache optimization (organizing data in a computer’s memory to be accessed quickly), it is highly optimized for speed, allowing for efficient simulations. Thus, we concluded XGBoost would prove best for the purposes of this project.

Simulation Pipeline

The Worker PLUS model utilizes a pipeline that maps predicted leave behavior from DOL FMLA Employee Survey data onto a representative worker population built from American Community Survey (ACS) and Current Population Survey (CPS) micro-data samples and simulates program outcomes under user-specified policy parameters. More specifically, it executes the following sequential steps for each observation in the target population:

1. **Population Construction and Feature Harmonization:** Using ACS PUMS micro-data, the simulation constructs the target worker population, providing individual-level demographic, employment, and income characteristics as well as sampling weights that represent

the state workforce. Moreover, to ensure that the simulated population contains the full set of predictors needed for leave-taking prediction, the simulation utilizes CPS data to impute certain employment and eligibility-related variables which are not present in the ACS sample.

2. **Model Training:** To estimate the relationship between worker characteristics and leave-taking, a predictive model specified by the user (XGBoost) is trained using the Department of Labor’s FMLA Employee Survey micro-data incorporating features common to both FMLA and ACS datasets, including age, marital status, education, race, wages, family income, work hours, occupation, industry, union status, employer type, and household caregiving characteristics.
3. **Leave-Taking Status Simulation:** The trained predictive models are applied to the ACS population to simulate leave-taking status for each worker, generating predicted probabilities of leave need and participation and mapping behavioral relationships estimated from the FMLA survey to the broader state population represented in the ACS.
4. **Baseline Leave Length Simulation:** For each individual, the model simulates the length of leave that would be taken in the absence of a state-level paid leave program to represent the counterfactual leave behavior under existing conditions.
5. **Maximum Leave Length Simulation:** The simulation determines the maximum leave length that an individual would potentially require given their circumstances to represent latent leave demand and implicitly captures unmet leave needs that may be constrained by financial or institutional limitations in the absence of a paid program.
6. **Program-Induced Leave Length Determination:** The model determines the leave length taken in the presence of the state program by interpolating between the baseline leave length and the maximum leave need. This adjustment depends on the relative generosity of employer-provided benefits and state program wage replacement rates specified by the user, reflecting behavioral responses to increased income replacement during leave.
7. **Program Coverage Determination:** Using the user specified program eligibility rules and benefit parameters (e.g., wage replacement rate, weekly benefit cap, and maximum duration),

the model calculates the portion of leave covered by the state program to determine the duration of compensated leave and the level of benefits received.

8. **Participation and Take-up:** Program participation is assigned probabilistically using user-specified take-up rates (weights) for each of the six leave types by conducting random weighted draws among those who are predicted to have needed leave. This step may also be further adjusted using the α hyperparameter, which increases the likelihood of participation among workers with longer leave needs.
9. **Post-Simulation Output and Aggregation:** Finally, the pipeline produces a post-simulation ACS state sample containing individual-level outcomes, including leave lengths, program participation indicators, and benefits received. These results are aggregated using ACS sampling weights to estimate total program outlays, payroll tax revenues, leave usage, and subgroup-specific distributions for policy analysis.

3.2.3 Program Rules and Simulation Parameters

To conduct this analysis, we applied a specific policy framework—aligned with Economic Policy Institute (EPI) guidelines to the Worker PLUS baseline model. Given that 2020 represents the most recent comprehensive data year available for all variables, all simulation formulas utilize 2020 wage thresholds and cutoffs. The specific policy parameters are detailed below.

Leave Duration and Benefit Formula: The program provides up to 12 weeks of paid family and medical leave. The benefit structure follows a progressive wage replacement scale based on the State Average Weekly Wage (SAWW):

- **100% Replacement:** For workers earning up to 50% of the SAWW.
- **90% Replacement:** For workers earning between 51% and 80% of the SAWW.
- **80% Replacement:** For workers earning between 81% and 100% of the SAWW.

The maximum weekly benefit is capped at 100% of the state’s average weekly wage. Regardless of a worker’s prior earnings, the total weekly indemnity cannot exceed this threshold.

State-Specific Wage Benchmarks (2020): The simulation utilizes the following 2020 SAWW values to determine benefit eligibility and caps across the study region:

State	2020 SAWW	State	2020 SAWW
Alabama (AL)	\$931.23	Mississippi (MS)	\$791.07
Arkansas (AR)	\$880.00	North Carolina (NC)	\$1,102.00
Florida (FL)	\$971.00	Oklahoma (OK)	\$918.67
Georgia (GA)	\$1,023.71	South Carolina (SC)	\$916.30
Kentucky (KY)	\$944.60	Tennessee (TN)	\$1,027.00
Louisiana (LA)	\$918.00	Texas (TX)	\$970.71
Maryland (MD)	\$1,080.00	Virginia (VA)	\$1,137.00

Table 1: 2020 State Average Weekly Wage by Jurisdiction

Eligibility and Coverage: The program covers all full-time, part-time, and public-sector employees. To qualify, workers must have earned at least \$2,500 during the previous year and must be currently employed or have held employment within the last 12 weeks. Additionally, self-employed individuals are permitted to opt into the program.

Funding and Taxable Maximums: The program is funded via a quarterly employer payroll tax of 0.75% of total employee wages; there is no employee-side contribution. Taxable wages are subject to a cap consistent with the Social Security taxable maximum, which in 2020 was \$137,700.

Qualifying Leave Reasons: Benefits are available to both parents for the birth, adoption, or fostering of a child. Additionally, leave is granted for the serious illness or injury of the worker, or to care for a child, spouse, or parent.

Limitations

As described, it is evident the Worker PLUS simulation allows for considerable flexibility and contains a well thought out and detailed structure, but its framework relies on several simplifying assumptions that may affect the accuracy of predicted leave-taking behavior and program participation. More specifically, we outline three key mechanisms to improve — wage replacement, policy awareness, and job security — that are only partially captured in the current implementation.

Wage Replacement: A primary limitation of the Worker PLUS framework is its treatment of wage replacement as affecting leave outcomes only after leave-taking status has been predicted. More candidly, a worker’s expected wage replacement does not change their likelihood of taking leave; it only dictates the length of their leave and other parameters after the decision to take leave has already taken place.

This modeling structure implicitly assumes that wage replacement is independent of the demographic covariates used to predict leave-taking behavior. This assumption breaks if, for example, wage replacement varies systematically with occupation, employer characteristics, or income. In this case, the model may attribute variation in participation to demographic factors that actually reflects differences in expected wage replacement. As a result, the model may overestimate the causal influence of demographic variables on leave-taking decisions and misrepresent behavioral responses to changes in program generosity.

More broadly, the absence of wage replacement in the initial participation decision limits the model’s ability to capture the full incentive effects of paid leave policies, particularly for low-wage workers whose participation is highly sensitive to income replacement rates.

Job Security: Another important limitation concerns the role of job security in determining leave-taking behavior. Workers’ willingness to take leave depends not only on financial considerations but also on perceived employment risk. Counterintuitively, despite being granted paid leave, it is often possible for a worker to lose their job during said leave. Thus, “without job protection, workers will forgo needed leave” due to fear of dismissal or adverse career consequences. [6]

The current implementation of Worker PLUS does not explicitly model job security or layoff risk, but job security effects are implicitly captured through predictive models trained on observed leave-taking behavior in the FMLA data. Because the training data reflect realized worker choices — including instances in which workers needed leave but did not take it — the model learns behavioral patterns associated with observable characteristics that may correlate with job security. Thus, since the model uses variables such as occupation, industry, wages, work hours, and demographic characteristics as proxies for job security, these predictors may partially capture employment stability. But, since they do not directly measure workers’ perceived risk of job loss or employer responses to leave-taking, the model may fail to capture important variation in participation behavior driven

by institutional protections, workplace culture, or enforcement of job protection policies.

Policy Awareness: The Worker PLUS framework also does not explicitly model policy awareness, which may play a critical role in determining program participation, especially in the South where policy awareness may be lower. Workers must be aware of program availability, eligibility rules, and benefit generosity in order to respond to policy incentives.

In the current implementation, policy awareness is only implicitly incorporated through user-specified take-up rates, which determine the probability of program participation among eligible workers, but these are not endogenously determined by worker characteristics, information diffusion, or policy context, so the arbitrary participation probabilities may not reflect realistic variation in awareness across regions or populations.

This limitation is particularly important in contexts where awareness of paid leave programs is likely to be low, such as in regions without prior exposure to similar policies or with limited administrative outreach. For example, in settings with low baseline awareness, observed take-up may be substantially lower than predicted by the model. Conceptually, once job security and wage replacement constraints are addressed, participation decisions should depend strongly on whether workers are informed about the policy.

4 Data

The WorkerPLUS simulator is trained on data collected by the American Community Survey (ACS), the Current Population Survey (CPS), and the Department of Labor’s Family and Medical Leave Act (FMLA) Employee Survey. The ACS provides demographic data on state worker characteristics, including gender, income and disability. With data from the CPS, the model imputes variables predictive of leave-taking behavior but not available in the ACS. The FMLA Employee Survey contains variables about leave-taking behavior, such as leave duration and reasons for taking leave.

4.1 American Community Survey (ACS)

Conducted by the U.S. Census Bureau, the American Community Survey (ACS) provides detailed demographic and socioeconomic information on U.S. residents. For the sake of replicability, our implementation of the WorkerPLUS model follows the Department of Labor’s implementation, released in March 2021, in using the 2020 ACS as input data on worker characteristics. This iteration of the ACS has a sample size of about 3.5 million addresses in 3,220 counties.

4.2 Family and Medical Leave Act (FMLA) Employee Survey

The 2018 FMLA Employee Survey collected data in the time period from March 6, 2018 through February 24, 2019 at the individual and firm levels. It samples from adult workers across the United States through a combination of random digit dialing (RDD) survey and a web-based survey.

4.3 Current Population Survey (CPS)

The CPS is a nationwide survey containing detailed data on labor force participation which is missing in the ACS. Worker PLUS uses the CPS to complement the ACS by imputing these variables, which determine eligibility for leave, into the ACS-based population. The characteristics variables imputed from the CPS are listed in Table 2.

Table 2: CPS-only Variables Imputed into ACS

Variable	Concept	Reason for Imputation
<code>hourly</code>	Paid hourly indicator	Not observed in ACS
<code>oneemp</code>	Single employer indicator	Not observed in ACS
<code>weeks_worked</code>	Annual weeks worked	ACS variable is categorical
<code>empsize</code>	Employer size category	Not observed in ACS
<code>union</code>	Union membership indicator	Not observed in ACS
<code>fmla_eligible</code>	FMLA eligibility indicator	Requires <code>weeks_worked</code>

4.4 Other Data

Throughout the simulation pipeline, there will be other data used, including:

- Government data from RI, NJ and CA on claims filed by type of leave taken. The most

recent data (2023-24) is used and is divided by covered workforce to obtain the ground truth take-up rates.

- NIS-Child data to model vaccination rate improvements. NIS-Child is a dataset based on phone surveys used to monitor vaccination coverage among children. It includes vaccination data by state and income levels. The most recent data is from 2023.

4.5 Key Outcome Variables

The Worker PLUS simulation produces individual-level outcomes describing leave-taking behavior, program participation, and benefit receipt. The primary outcome variables used throughout this study are defined below.

Variable	Definition
Leave Need	Indicator for whether a worker requires leave for a qualifying reason (e.g., own illness, bonding, caregiving), predicted using FMLA-based behavioral models.
Leave Taken	Indicator for whether a worker takes leave after accounting for program eligibility, participation probabilities, and behavioral constraints.
Baseline Leave Length	Simulated duration of leave in the absence of a state paid leave program, representing counterfactual behavior under status quo conditions.
Program Leave Length	Leave duration taken under the policy scenario after accounting for wage replacement incentives and program rules.
Program Participation	Indicator for whether an eligible worker enrolls in and receives benefits from the program.
Benefit Eligibility	Indicator for whether a worker satisfies program rules for receiving paid leave benefits.
Annual Benefit Amount	Total monetary benefits received by a worker across all leave types during the simulation period.
Program Cost	Aggregate benefit payments across workers, computed using sampling weights.
Payroll Tax Revenue	Aggregate payroll tax contributions used to finance program benefits.

Table 3: Key simulation outcome variables.

5 Methodology

To improve the Worker PLUS microsimulation framework, we introduce three extensions to the baseline model: an incorporation of the policy-based wage replacement directly into the leave-

taking decision, an explicit measure of job security using predicted worker-level unemployment risk derived from longitudinal Current Population Survey (CPS) data, and a model of policy awareness using empirical awareness measures and administrative data from existing paid leave programs.

5.1 Incorporating Wage Replacement into WorkerPLUS

5.1.1 Treatment of wage replacement in the original model

In the original implementation, the take-up decision is estimated as

$$\Pr(\text{take}_{it} = 1 \mid X_i) = f(X_i),$$

where X_i includes demographics, earnings, and job characteristics, but does *not* include any measure of wage replacement. In the FMLA data, however, observed leave-taking behavior is partly driven by employer-provided replacement rates. Workers with low or zero replacement may not take leave because of liquidity constraints. Omitting replacement from the take equation induces an omitted-variable problem: the estimated coefficients on income and related covariates absorb the effect of replacement. When the policy counterfactually raises the replacement rate (e.g., to 60%, 80%, or 100%), the original model still predicts take using

$$\hat{p}_{it}^{\text{orig}} = f(X_i),$$

so behavioral responses to policy generosity are suppressed. As a result, the model tends to under-predict leave-taking under more generous PFML parametrizations.

5.1.2 Modifications

We modified the take equation to incorporate a pay variable:

$$\Pr(\text{take}_{it} = 1 \mid X_i, \text{pay}_i) = f(X_i, \text{pay}_i).$$

The model is still trained on FMLA data, where pay_i reflects observed employer replacement (conditional on taking leave). In the simulation step, however, we replace this with a policy-based

replacement rate computed from program parameters:

$$\text{pay}_i^{\text{policy}} = g(\text{wage}_i; \text{policy schedule}),$$

including flat or progressive replacement rules and any dependency allowances. This allows the predicted take probability to respond directly to policy generosity. We continue to impute status quo employer replacement in the ACS for two reasons: first, employer pay enters the length extension formulas (e.g., via interactions between employer and state replacement in the counterfactual leave length *cfl*); second, it is necessary for modeling dual receivers and crowd-out. Thus, employer replacement is still simulated for structural length mechanics, while policy replacement drives behavioral take-up decisions.

5.1.3 Remaining limitations.

A key limitation remains in the identification of the pay effect. In FMLA, employer replacement is only observed for workers who take leave, so the training sample effectively estimates replacement conditional on taking leave. We do not observe counterfactual replacement for non-takers, nor do we observe how they would respond to higher replacement. Thus, when we simulate

$$\hat{p}_{it}^{\text{policy}} = f(X_i, \text{pay}_i^{\text{policy}}),$$

we are extrapolating from cross-sectional variation in employer replacement to policy-driven variation. The model assumes that the behavioral elasticity with respect to employer pay equals that with respect to policy pay. While this improves upon the original omitted-variable specification, it remains a reduced-form approximation rather than a fully identified structural estimate of causal responses to counterfactual replacement rates.

5.2 Job Security

To address the limitation that Worker PLUS does not explicitly model job security or layoff risk, we extend the simulation framework by incorporating an externally estimated measure of worker-level unemployment risk. Our implementation follows recent work by Brendan Chapuis

and John Coglianesse at the Federal Reserve on measuring individual unemployment risk using large administrative and survey data. [7] They further show that these individual unemployment probabilities can be predicted using demographic and employment characteristics such as industry, occupation, education, and wage levels.

Thus, our central idea is that workers facing higher unemployment risk experience weaker job security and are therefore less likely to take leave due to fear of job loss. By incorporating this measure into the participation decision, the simulation more directly models behavioral responses to employment risk rather than relying solely on demographic proxies.

5.2.1 Unemployment Risk Estimation via Gradient Boosting

To explicitly model job security, we first construct a longitudinal dataset using the Current Population Survey (CPS). Unlike the baseline Worker PLUS implementation, which relies on cross-sectional demographic proxies, our approach estimates worker-level unemployment risk using panel variation in employment outcomes over time.

We use CPS microdata from 2014–2020 and construct a one-year-ahead panel by matching individuals across survey waves using the personal identifier `peridnum` together with demographic characteristics. For each year t , individuals observed in year t are matched to their records in year $t + 1$, and the final longitudinal dataset is created by merging consecutive CPS files and retaining individuals observed in both periods. This construction allows the model to estimate forward-looking unemployment risk rather than relying on contemporaneous employment status. The resulting dataset contains worker characteristics at time t and realized unemployment outcomes at time $t + 1$, enabling prediction of individual unemployment risk.

Once we create the dataset, we estimate individual unemployment risk using a Light Gradient Boosting Machine (LightGBM) classifier (see `train_unemployment_risk.py`). Gradient boosting machines (GBMs) are ensemble learning methods that construct a sequence of decision trees, with each tree correcting the prediction errors of the previous trees iteratively, allowing the model to capture complex nonlinear relationships and interactions among predictors. More specifically, LightGBM is particularly well suited for this application since it handles high-dimensional categorical data efficiently, uses a leaf-wise tree growth strategy to strengthen its detection of rare events such as unemployment, and works in a computationally efficient and scalable manner.

The model is trained using weighted observations with CPS sampling weights and tuned via cross-validation to minimize the weighted Brier score (root mean squared prediction error). The final model produces predicted unemployment probabilities

$$r_i = \Pr(U_{i,t+1} = 1 \mid X_{i,t}),$$

where $\Pr(U_{i,t+1})$ is the probability individual i is employed at year $t+1$ and $X_{i,t}$ is the set of features of individual i .

We convert predicted unemployment risk into a job security measure

$$s_i = 1 - r_i,$$

so that higher values correspond to greater employment stability. The trained model is saved and loaded during simulation to generate worker-level job security scores for the target population.

5.2.2 Integration into the Worker PLUS Simulation

We incorporate the job security score into the program participation stage of the simulation. In the baseline Worker PLUS framework, program participation is determined probabilistically using user-specified take-up rates for each leave type. Our modification adjusts these probabilities using worker-specific job security weights.

When the simulation determines whether an individual takes leave, the participation probability is reweighted using the job security score:

$$p_i^{\text{adj}} = p_i \cdot s_i,$$

where p_i is the baseline take-up probability and s_i is the job security score. This adjustment reduces participation among workers facing high unemployment risk and increases participation among workers with greater job security.

5.2.3 Code Modifications

Implementation required modifications to the simulation pipeline (see `_5_simulation.py`). All changes are marked in the source code with the comment `(neww)`. The implementation introduces worker-specific job security weights derived from predicted unemployment risk and integrates these weights into the program participation stage of the simulation.

To improve transparency and reproducibility, we present the core code modifications below.

Importing Risk Model Dependencies: We first introduce dependencies required for loading the trained unemployment risk model.

```
import joblib # (neww)
import lightgbm as lgb
```

The `joblib` library is used for efficient model serialization, while `LightGBM` provides the gradient boosting framework used to estimate unemployment risk.

Adding Worker-Level Unemployment Risk: We introduce a new function that assigns unemployment risk and job security scores to each worker in the ACS population. The function loads a trained LightGBM model and generates predicted unemployment probabilities.

```
def add_unemployment_risk(self, acs, model_fp=None, min_prob=1e-6):
    """
    Adds predicted unemployment risk + job security columns to ACS dataframe.
    Looks for a LightGBM sklearn model saved via joblib.
    """

    if ('unemp_risk_12m' in acs.columns) and ('job_security' in acs.columns):
        return acs

    if model_fp is None:
        base_dir = os.path.dirname(os.path.abspath(__file__))
        model_fp = os.path.join(
            base_dir, "data", "cps", "risk_model_output",
```

```

        "unemployment_risk_lgbm.joblib"
    )

    if (not os.path.exists(model_fp)):
        acs['unemp_risk_12m'] = np.nan
        acs['job_security'] = np.nan
        return acs

    model = lgb.Booster(model_file=model_fp.replace(".joblib", ".txt"))

    feature_cols = model.feature_name()
    X = acs[feature_cols]

    risk_pred = model.predict(X)
    risk_pred = np.clip(risk_pred, min_prob, 1.0)

    acs['unemp_risk_12m'] = risk_pred
    acs['job_security'] = 1.0 - risk_pred

    return acs

```

This function generates a worker-level unemployment risk score r_i and converts it to a job security score $s_i = 1 - r_i$. The job security measure is subsequently used to adjust participation probabilities.

The simulation pipeline calls this function immediately after loading the ACS microdata:

```

# add predicted unemployment risk/job security (neww)
acs = self.add_unemployment_risk(acs)

```

Job-Security Adjusted Participation: The most important modification occurs in the leave take-up simulation stage. The baseline Worker PLUS model assigns participation using weighted random draws based on leave length and user-specified take-up rates. We extend this procedure by incorporating job security weights that bias participation toward workers with lower unemployment

risk.

```
# --- Job-security adjusted take-up draw (neww) ---
sub = acs[acs['cpl_%s' % t] >= min_takeup_cpl]

sec_w = None

if 'job_security' in sub.columns:
    sec_w = sub['job_security'].clip(lower=0.01, upper=1.0).fillna(1.0)
elif 'unemp_risk_12m' in sub.columns:
    sec_w = (1.0 - sub['unemp_risk_12m']).clip(lower=0.01, upper=1.0).fillna(1.0)

if alpha > 0:
    len_w = (sub['cpl_%s' % t] ** alpha)
    shuffle_w = (len_w * sec_w) if (sec_w is not None) else len_w
elif alpha == 0:
    shuffle_w = sec_w
else:
    shuffle_w = None

draws = get_weighted_draws(
    sub[col_w],
    p_draw,
    self.random_state,
    shuffle_weights=shuffle_w
)

acs.loc[acs['cpl_%s' % t] >= min_takeup_cpl, 'takeup_%s' % t] = draws
```

This modification reweights participation probabilities using worker-specific job security. Workers with higher job security receive greater weight in the stochastic draw, reflecting a lower perceived risk of job loss when taking leave. The adjustment interacts multiplicatively with the original leave-length weighting mechanism, preserving the structure of the baseline simulation.

5.2.4 Modification Visualizations: Texas Case Study

We evaluate the impact of the job-security adjustment by comparing simulation outcomes for Texas under the baseline and modified models.

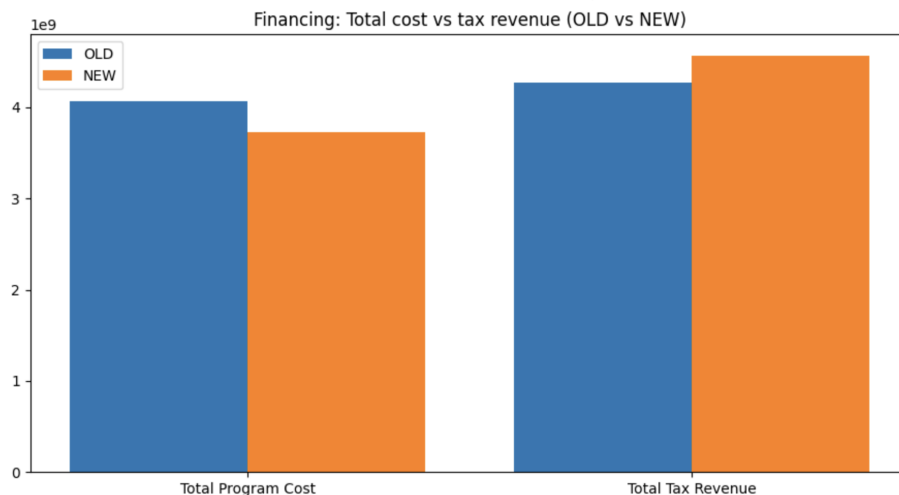


Figure 1: Comparison of total program costs and tax revenue under the baseline and job-security-adjusted simulations.

Figure 1 shows that incorporating job security reduces total program costs while increasing tax revenue. The reduction in costs reflects lower participation among workers facing high unemployment risk, while increased revenue results from changes in program participation composition.

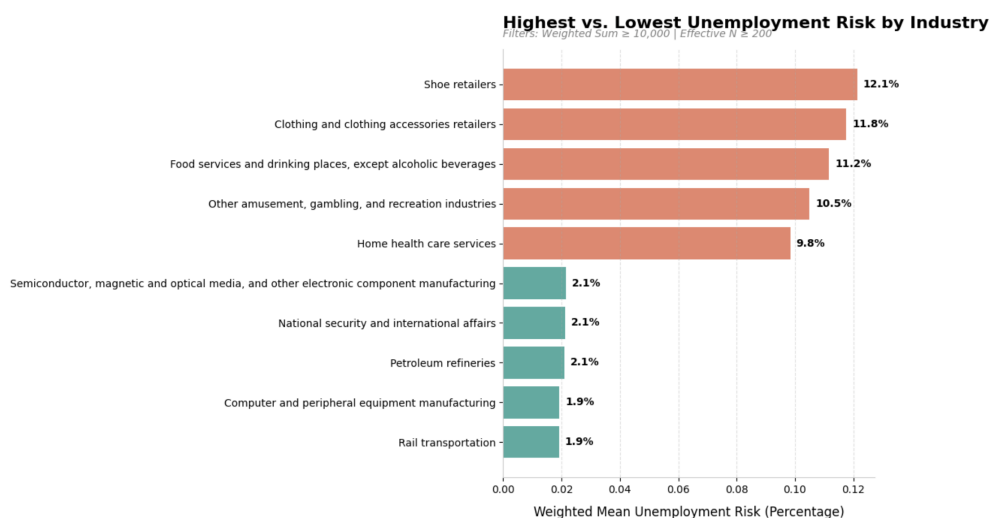


Figure 2: Highest and lowest unemployment risk industries predicted by the gradient boosting model.

Figure 2 reports predicted unemployment risk by industry. The model identifies retail, food services, and entertainment industries as having the highest unemployment risk, while manufac-

turing and transportation sectors exhibit lower risk. These results align with known differences in employment stability across sectors and validate the model’s predictive structure.

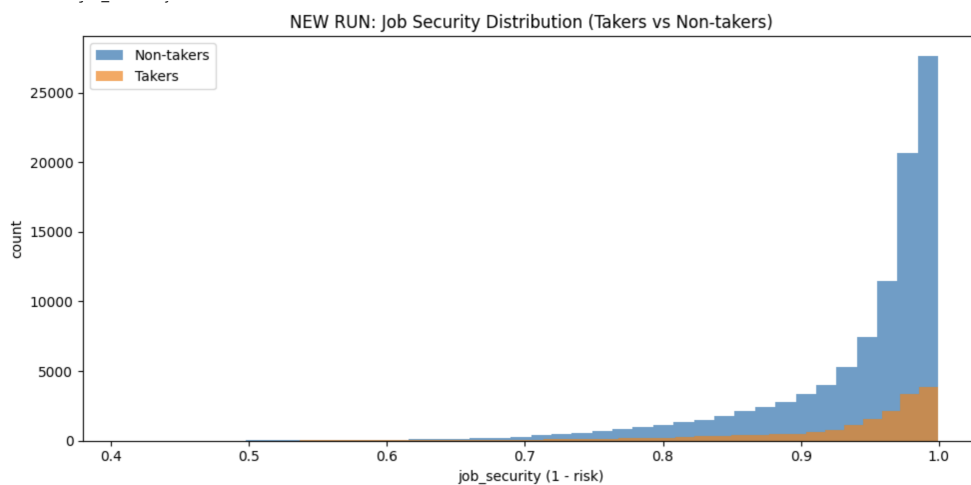


Figure 3: Distribution of job security scores for leave takers and non-takers.

Figure 3 shows that participation increases with job security. Workers with higher job security scores are substantially more likely to take leave, confirming that the adjustment introduces the intended behavioral mechanism.

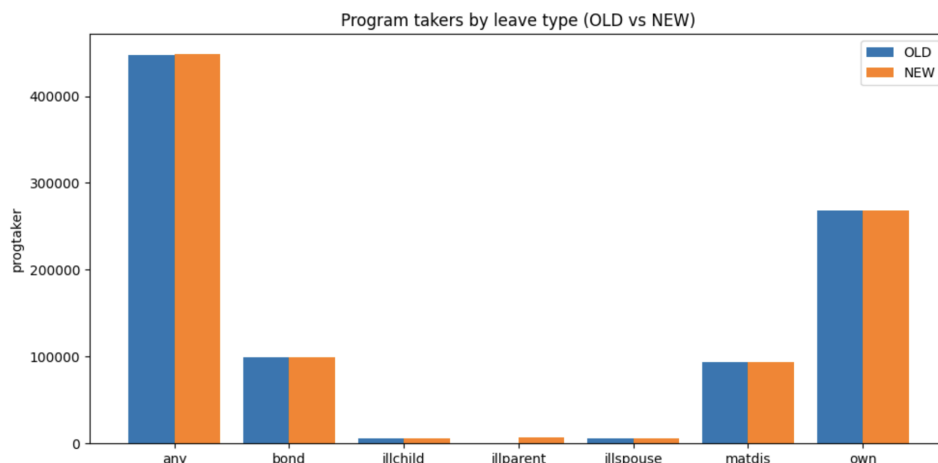


Figure 4: Program participation by leave type under baseline and modified simulations.

Figure 4 compares participation patterns by leave type. Overall take-up patterns remain largely unchanged across specifications. The only observed difference arises from a configuration discrepancy in which parental illness was not included as an allowable leave reason in the baseline simulation parameters. After correcting this specification, participation patterns are otherwise

identical, indicating that the job-security adjustment primarily affects participation levels rather than the composition of leave types.

5.2.5 Limitations of the Job Security Extension

While the introduction of a job security measure improves the behavioral realism of the Worker PLUS simulation, several limitations remain.

First, the unemployment risk model relies on observational CPS data and therefore captures correlations rather than causal relationships between worker characteristics and employment outcomes. The predicted unemployment probabilities reflect historical patterns in the data, but may not fully represent how workers perceive job security or how employers respond to leave-taking under a new policy environment. As a result, the estimated job security measure should be interpreted as a proxy for perceived employment risk rather than a direct measure of job protection.

Moreover, the longitudinal CPS panel is constructed by matching individuals across survey waves using identifiers and demographic characteristics. Although this matching procedure allows for forward-looking prediction of unemployment risk, there were many individuals who were unable to be matched, which may introduce measurement error in the estimated outcomes. The model also relies on the very strong assumption that predicted unemployment risk directly influences leave-taking behavior through a simple reweighting of participation probabilities. This is surely an oversimplification of the true decision-making process when leave-taking, and therefore our model does not explicitly model employer responses, workplace retaliation risk, or formal job protection mechanisms. Consequently, the specification may oversimplify the complex institutional and behavioral channels through which job security affects leave decisions.

Finally, the unemployment risk model is trained on historical labor market conditions and therefore assumes that future employment dynamics resemble past patterns. Structural changes in labor markets, policy environments, or regional economic conditions could alter the relationship between worker characteristics and unemployment risk, limiting the external validity of the estimates.

Despite these limitations, incorporating an explicit measure of employment risk provides a tractable way to account for job security concerns within the simulation and represents an improvement over relying solely on demographic proxies. Overall, the proposed extension introduces

an explicit measure of employment risk into the participation decision while preserving the structure of the Worker PLUS framework. The results demonstrate that accounting for job security can meaningfully affect predicted program utilization and costs, suggesting that employment risk is an important behavioral determinant of leave-taking.

5.3 Awareness

The Worker PLUS also has a critical issue with the input take-up rates that it requires as parameters. The take-up rates provided as a default are arbitrary, meaning that the simulation results are only rough estimates based on the arbitrary take-up rates inputted. Therefore, we seek a better proxy to make the take-up rates less arbitrary for more accurate results.

Awareness of the FMLA and leave policies in general serve as a good proxy for take-up, because this was not yet accounted for in the Worker PLUS model or our model anywhere. Yet, awareness of a policy is a necessary condition to utilize it, and in the South especially policy awareness is generally lower. A higher awareness will imply higher take-up, *ceteris paribus*. Therefore, we use awareness of the FMLA to proxy take-up rates as it has a direct influence on take-up.

5.3.1 Data Compilation

The Awareness variable used throughout our model is derived from Question E2 of the FMLA 2018 Employee Survey: *“Have you ever heard of the federal Family and Medical Leave Act?”*

We code the answer of Yes as 100% awareness and the answer of No as 0% awareness. We compute the average awareness of the states with unpaid leave and the average awareness of the states with paid leave by 2018 (due to data limitations, state-level breakdowns are not available).

In addition, we use administrative data to compile the empirical take-up rates of the states which have implemented paid leave, separated by type. The following table represents the empirical data. Due to lack of granular data by type of leave for some types of leave in CA and RI, merged data was split using the granular ratios observed in the New Jersey dataset.

Leave Category	California		New Jersey		Rhode Island	
	Claims	Take-Up	Claims	Take-Up	Claims	Take-Up
Own serious illness	469,685	2.510%	39,196	0.950%	28,563	5.100%
Bonding	280,707	1.500%	45,107	1.090%	7,395	1.320%
Maternity	208,936	1.120%	17,436	0.422%	3,833	0.684%
Parent’s health	17,814	0.095%	3,911	0.095%	948	0.169%
Spouse’s health	11,000	0.059%	2,415	0.059%	586	0.105%
Child’s health	8,677	0.046%	1,905	0.046%	462	0.083%

5.3.2 Linear Regression to Predict Awareness

A linear regression with an intercept was then performed, weighted by workforce size. The model predicts take-up percentage based on the interaction between leave category and awareness.

$$TakeUp_i = \beta_0 + \sum_k \beta_k \mathbb{1}\{\text{reason} = k\} \cdot \text{Awareness} + \epsilon_i$$

We obtain the following results for our regression. The own illness, bonding and maternity awareness all yield statistically significant results, while the caring for other’s health yields insignificant results, likely due to the relatively low rates relative to the first three types of leave.

Interaction Term	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	0.060	0.231	0.26	0.8002
Own serious illness : Awareness	2.671	0.390	6.84	1.8×10^{-5} *
Bonding : Awareness	1.677	0.402	4.17	0.0013 *
Maternity : Awareness	1.294	0.458	2.83	0.0153 *
Parent’s health : Awareness	0.057	0.504	0.11	0.9116
Spouse’s health : Awareness	0.032	0.464	0.10	0.9283
Child’s health : Awareness	-0.014	0.374	-0.04	0.9698

Using this regression, we predict the take-up for the South as a whole. The following values are the final projected take-up rates (% of covered workforce) for currently unpaid states.

Reason for Leave	Predicted Take-Up Rate (%)
Own serious illness	2.24%
Bonding	1.44%
Maternity	1.03%
Parent’s health	0.11%
Spouse’s health	0.06%
Child’s health	0.05%

The main limitation to this approach is the lack of state-level results. This means that there is less precision with our simulation than what would have been possible. We considered adding ACS data for more proxies, including median income, education level and female employment rate in each state. However, given that there are only 3 paid leave states while we need to predict over a dozen Southern states, and considering Southern states are demographically very different to the paid leave states, adding any type of demographic proxy like those in the ACS would lead to extrapolation and serious overfitting, regardless of the regression or machine learning model used. Therefore, to preserve robustness of the model, we opt to use only awareness.

5.3.3 Limitations of predicting leave take-up using CPS-MORG 2024 data

In one attempt in estimating specific leave take-up rates and variation for each Southern state, we used data from the Current Population Survey Merged Outgoing Rotation Groups (CPS MORG) 2024 release. Because the CPS does not directly measure awareness of leave policies such as the Family and Medical Leave Act (FMLA), we construct behavioral proxies for leave-taking and evaluate whether worker characteristics can serve as proxies for awareness.

We constructed two binary indicators capturing leave-taking at the weekly level. These measures capture extensive-margin leave-taking in the CPS reference week and serve as proxies for formal leave usage.

1. **Medical leave take-up:** equal to one if an individual reports being absent due to their own illness or injury while remaining employed.

2. **Parental leave take-up:** equal to one if an individual reports maternity or paternity-related absence while still attached to their job.

To approximate awareness and access to formal leave systems, we considered several potential proxies:

- Union membership (institutional awareness and enforcement)
- Government employment (structured employer policies)
- Education (informational awareness)
- Age (lifecycle control)

We estimated linear probability models (LPMs) of leave take-up using CPS sampling weights and heteroskedasticity-robust standard errors.

$$Takeup_i^{(k)} = \beta_0^{(k)} + \beta_1^{(k)} \cdot UnionMember_i + \varepsilon_i^{(k)}, \quad k \in \{\text{medical, parental}\} \quad (2)$$

where $Takeup_i$ is a binary indicator for leave-taking and $UnionMember_i$ indicates union membership. The model is estimated as a linear probability model using CPS sampling weights and heteroskedasticity-robust standard errors.

5.3.4 Regression Evidence

Initial specifications including all candidate proxies reveal that not all variables meaningfully predict leave-taking. Government employment is not statistically significant in either medical or parental leave models, and postgraduate education does not consistently predict outcomes. While education and age are statistically significant, they primarily capture occupational structure and lifecycle effects rather than awareness.

Given these results, we focused our attention to union membership, which emerges as the only consistent and conceptually valid proxy for institutional awareness.

Table 4 presents the results from models including only union membership.

Table 4: Union Membership and Leave Take-Up (Linear Probability Models)

	Medical Leave Take-Up	Parental Leave Take-Up
Union Member	0.0028*** (0.001)	0.0011* (0.001)
Constant	0.0090*** (0.000)	0.0027*** (0.000)
Observations	123,117	123,117
R^2	0.000	0.000

Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Union membership is positively associated with leave-taking in both models. For medical leave, unionized workers are approximately 0.28 percentage points more likely to take leave, relative to a baseline rate of about 0.9 percent. For parental leave, the effect is smaller (0.11 percentage points) and only marginally statistically significant.

Despite statistical significance, the models exhibit very low explanatory power ($R^2 \approx 0.000$), indicating that union membership explains little of the variation in individual leave-taking behavior.

5.3.5 State-level Analysis

To assess whether institutional awareness explains geographic variation, I aggregate the data to the state level and compute (1) weighted union membership rates (2) observed leave take-up rates (3) predicted take-up rates based on the union-only model.

Table 4 compares predicted and observed take-up across Southern states.

Table 5: Predicted vs Observed Leave Take-Up in Southern States

State	Union Share	Predicted Medical	Observed Medical	Predicted Parental	Observed Parental
Alabama	0.081	0.00920	0.00941	0.00280	0.00201
Arkansas	0.049	0.00911	0.01045	0.00276	0.00224
Delaware	0.102	0.00926	0.01312	0.00282	0.00308
District of Columbia	0.082	0.00920	0.00588	0.00280	0.00241
Florida	0.066	0.00916	0.00882	0.00278	0.00353
Georgia	0.048	0.00911	0.01003	0.00276	0.00239
Kentucky	0.077	0.00919	0.01314	0.00279	0.00155
Louisiana	0.059	0.00914	0.01136	0.00277	0.00154
Maryland	0.136	0.00936	0.00785	0.00285	0.00412
Mississippi	0.073	0.00918	0.01319	0.00279	0.00180
North Carolina	0.032	0.00907	0.00650	0.00275	0.00389
Oklahoma	0.061	0.00914	0.00939	0.00278	0.00205
South Carolina	0.030	0.00906	0.01086	0.00274	0.00057
Tennessee	0.045	0.00910	0.01123	0.00276	0.00080
Texas	0.050	0.00911	0.00816	0.00276	0.00230
Virginia	0.047	0.00910	0.00363	0.00276	0.00438
West Virginia	0.110	0.00928	0.01211	0.00283	0.00191

Predicted values are based on union-only linear probability models.

A key pattern emerges from this comparison. First, predicted take-up rates are nearly constant across states. Medical leave predictions cluster tightly around 0.009, while parental leave predictions remain near 0.0027. This reflects both the small magnitude of the union coefficient and limited variation in unionization rates across states.

In contrast, observed take-up rates vary substantially across states. Medical leave ranges from approximately 0.005 to 0.013, and parental leave ranges from near zero to over 0.004. These differences are an order of magnitude larger than the variation captured by the model.

The contrast between predicted and observed values highlights a central finding of this analysis: While union membership is statistically associated with leave-taking at the individual level, it explains very little of the cross-state variation in take-up.

This suggests that institutional awareness, as proxied by union membership, is not the primary driver of geographic differences in leave usage. Instead, other factors like differences in state-level

policy environments, variation in job characteristics and workplace flexibility, and informal norms or constraints affecting leave-taking behavior play a larger role; factors which are immeasurable or cannot be proxied through CPS-MORG.

6 Results

This section summarizes simulation outputs for Southern states under the proposed policy design.

6.1 Eligibility Expansion

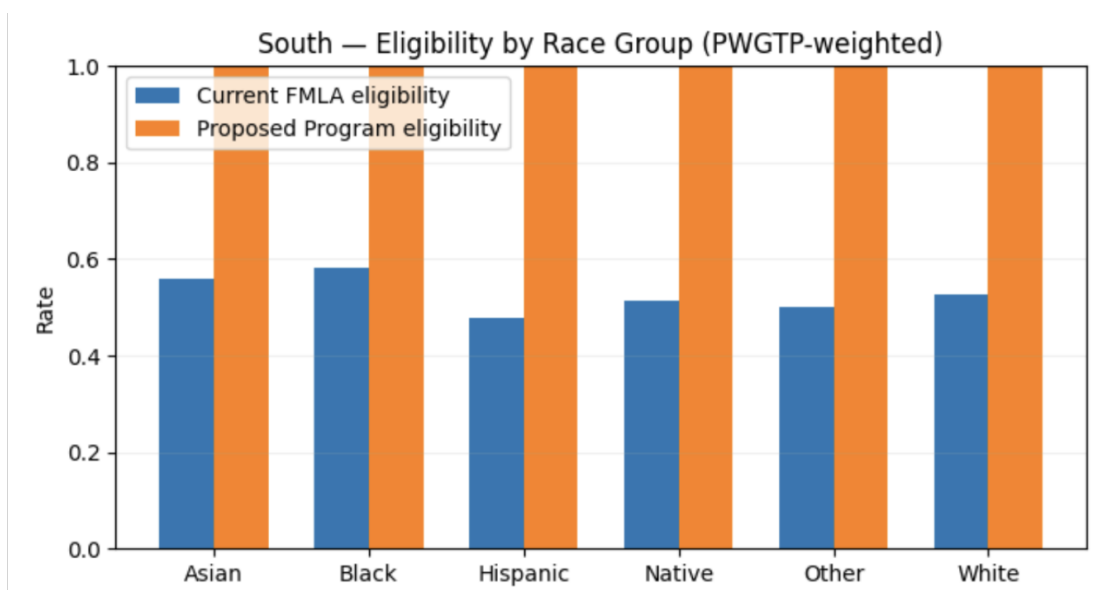


Figure 5: By race group: proposed program eligibility minus current FMLA eligibility. Because proposed eligibility is universal (rate = 1), larger values indicate lower baseline FMLA coverage.

Universal eligibility under the proposed program and cross-state expansion relative to current FMLA. Figure 5 plots the difference between proposed program eligibility and current FMLA eligibility by state. Under the EPI policy outline used here, proposed eligibility is effectively universal (eligibility rate of 1) across leave types. Therefore, the cross-state differences in Figure 5 primarily reflect variation in *baseline* coverage under current FMLA rules: states with lower current coverage mechanically show larger expansions when moving to a universal policy.

The largest expansions are observed for Florida, Kentucky, and Texas. Notably, these are historically conservative/“red” states; however, the figure alone does not establish a causal political

mechanism. The most direct interpretation is simply that these states have comparatively lower baseline FMLA eligibility in the current system, so the move to universal eligibility produces the largest measured increase.

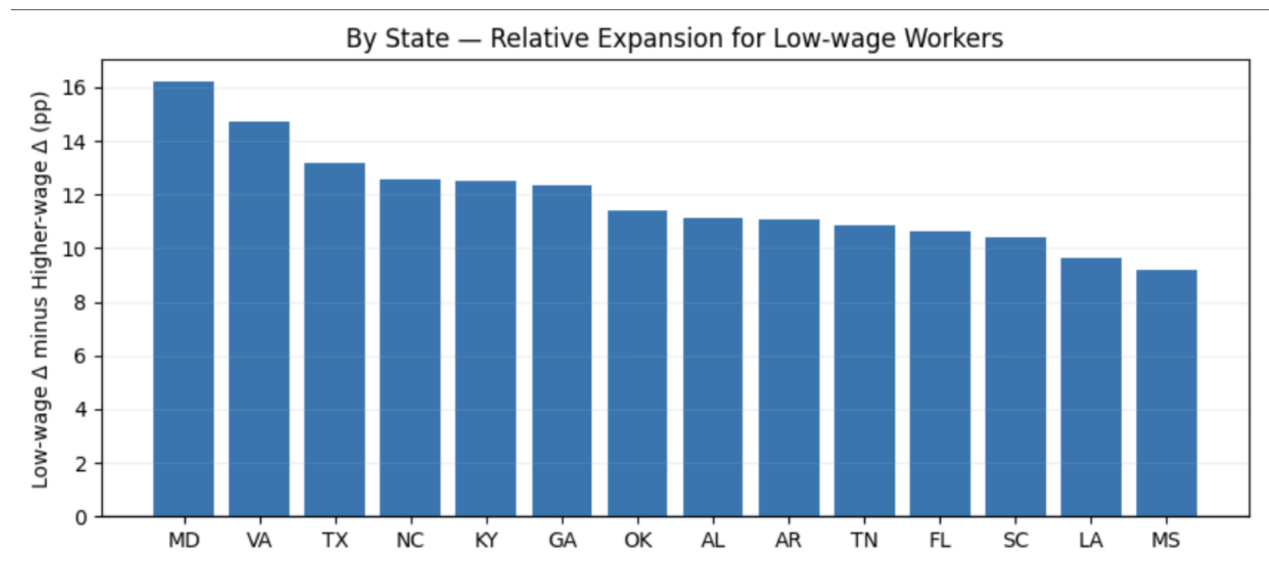


Figure 6: By state: relative eligibility expansion for low-wage workers (low-wage Δ minus higher-wage Δ). Larger values indicate a bigger narrowing of wage-based eligibility gaps under universal eligibility.

Relative eligibility expansion for low-wage workers. Figure 6 compares the eligibility expansion for low-wage workers to that for higher-wage workers (low-wage Δ minus higher-wage Δ) by state. The largest relative expansions for low-wage workers occur in Maryland and Virginia, which are generally more socially liberal states. This pattern *may* be suggestive of meaningful baseline differences in how low-wage workers are covered under current rules across states, but it is not conclusive evidence of any political or institutional mechanism on its own. The figure should be interpreted primarily as a descriptive ranking of where universal eligibility narrows wage-based eligibility gaps the most.

6.2 Take-up Patterns

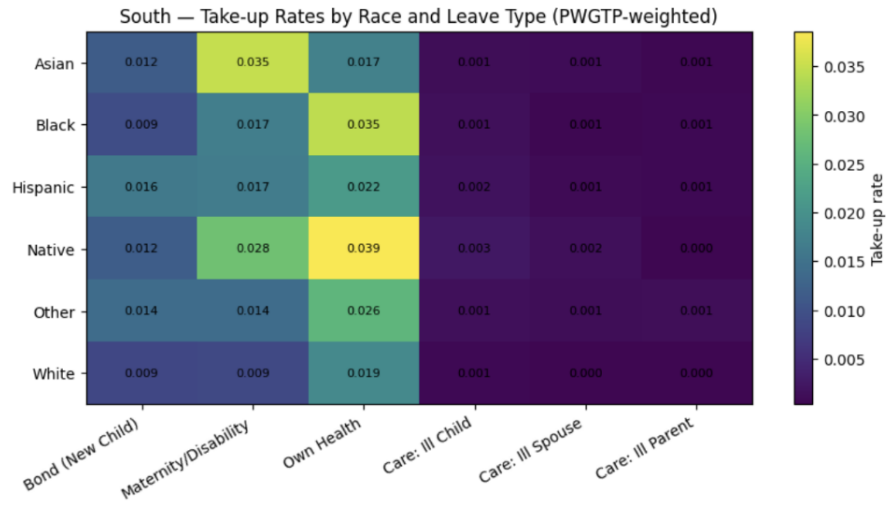


Figure 7: Take-up rates by leave type and state (all vs. private-only), and PWGTP-weighted heatmap of take-up rates by race and leave type, with eligibility by race.

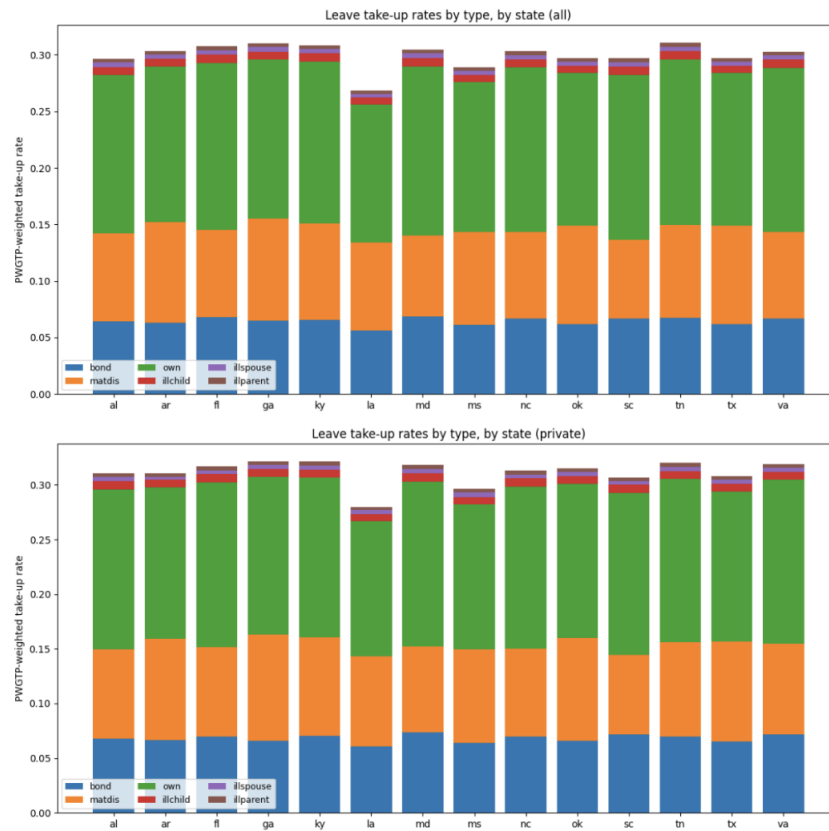


Figure 8: Take-up rates by leave type and state (all vs. private-only), and PWGTP-weighted heatmap of take-up rates by race and leave type, with eligibility by race.

Take-up patterns by leave type, race, and state. Figure 7 and 8 provide (i) stacked bars of take-up rates by leave type across states (all workers and private-only), and (ii) a heatmap of take-up rates by race and leave type (PWGTP-weighted), alongside eligibility-by-race bars. A few direct visual observations stand out:

- Across states, overall take-up levels appear similar in magnitude, with the composition of take-up dominated by a small number of leave types (visually, the largest stacked components are consistent across states).
- In the heatmap, Native workers exhibit comparatively higher take-up rates in multiple leave categories relative to other groups (the Native row contains some of the largest annotated values).
- Caregiving-related leave categories appear low across groups (darker colors and small printed values), while non-care categories show larger values and more variation.
- The eligibility-by-race plot reflects the policy design: proposed program eligibility is at (or near) 1 for all groups, whereas current FMLA eligibility varies and is noticeably lower.

These plots are descriptive, but together they suggest that universal eligibility substantially raises eligibility levels across all groups, while participation behavior (who takes leave, and for what reasons) still varies by group and leave type.

6.3 Distributional Benefits

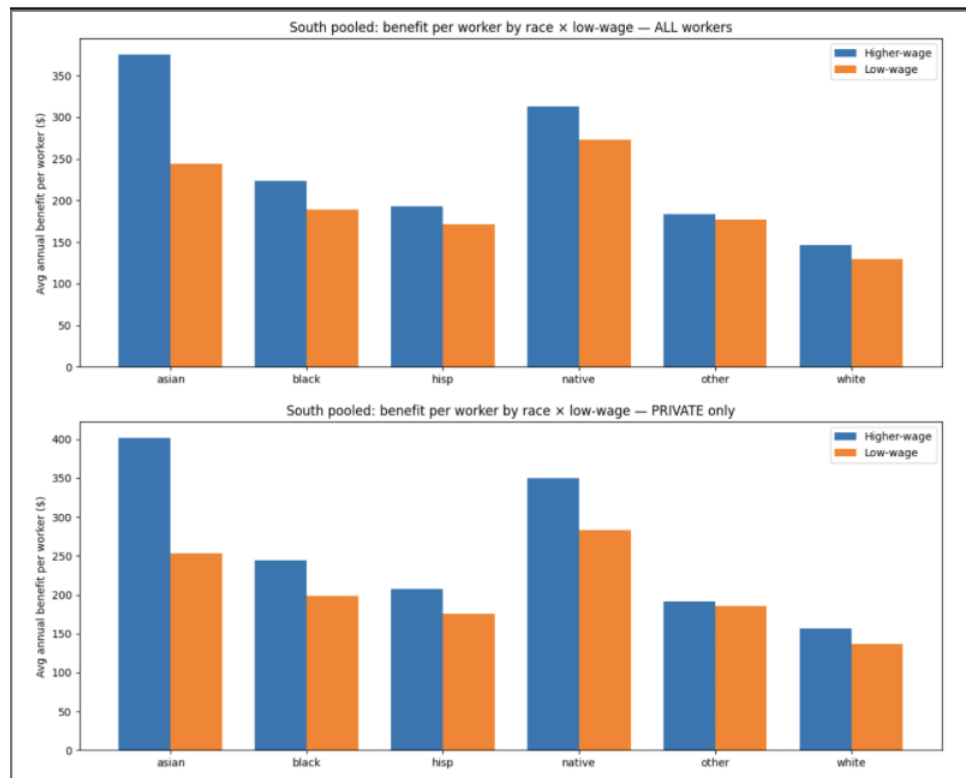


Figure 9: Average annual benefit per worker by race and wage category (all workers vs. private-sector workers).

Benefits by race and wage status. Figure 9 shows average annual benefits per worker by race group and wage category (higher-wage vs. low-wage), for both the full population and the private-sector subsample. Two basic patterns are clear. First, within every race category, higher-wage workers receive higher average benefits than low-wage workers, indicating a persistent benefit gap by wage group. Second, across race categories, Native workers exhibit comparatively high benefits in both wage strata. Asian workers also appear relatively high compared to other groups, while White workers appear lower on average. These patterns are visually consistent in both the “all workers” and “private only” panels, suggesting that the overall distributional patterns are not driven solely by including public-sector workers.

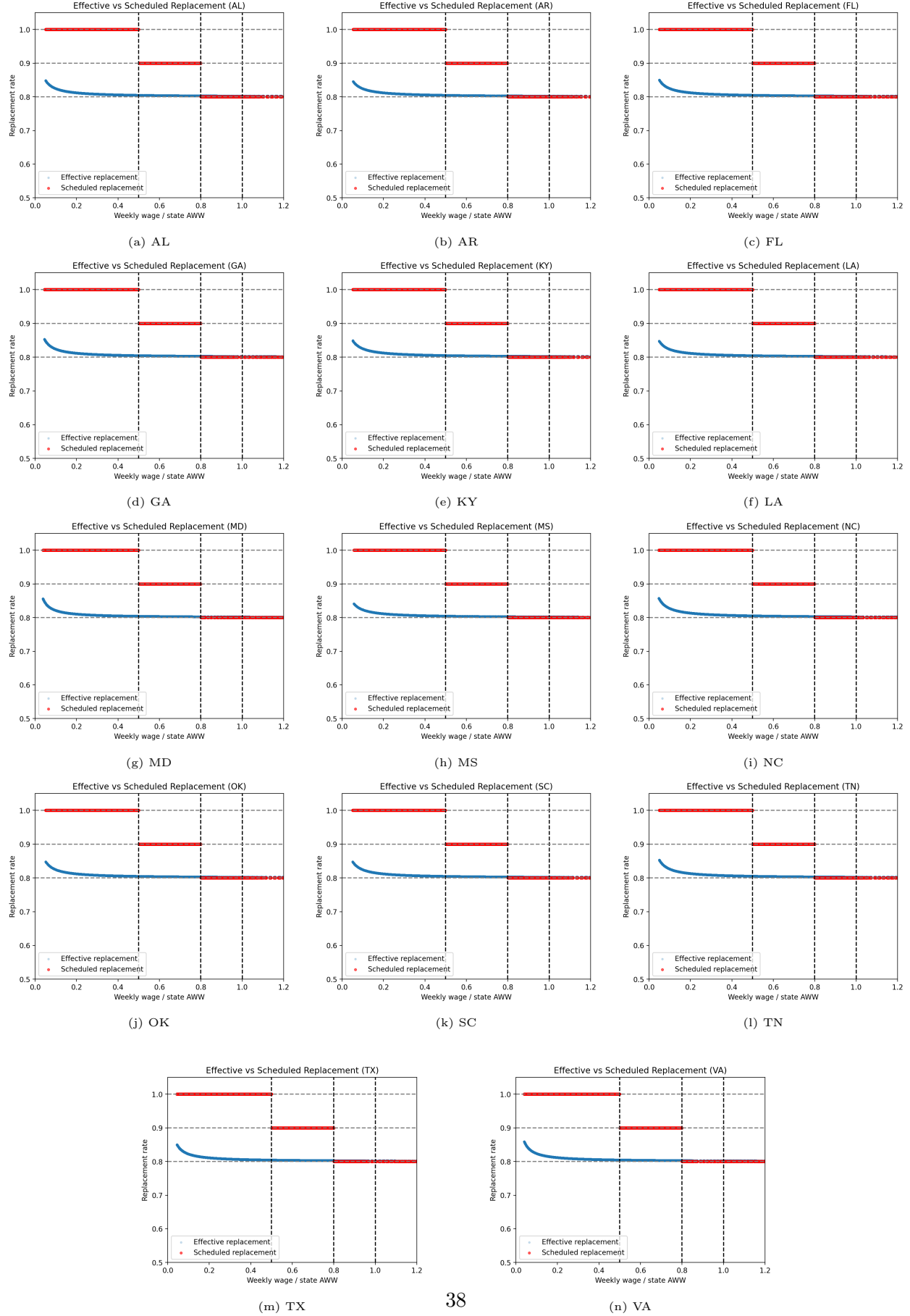


Figure 10: Effective versus scheduled replacement rates by state.

6.4 Policy Mechanics: Graduated Wage Replacement

Graduated wage replacement rate by state. Figure 10 shows a systematic divergence between the scheduled statutory replacement rate (red step function) and the effective replacement rate produced by the simulation (blue curve). The scheduled rate reflects a bracket-based policy description, with flat segments at 1.0, 0.9, and 0.8 corresponding to wage intervals defined as percentages of the state average weekly wage (AWW). In contrast, the effective replacement rate declines smoothly as wages increase, even within intervals where the statutory marginal rate is constant. Rather than forming horizontal bands at 1.0 or 0.9, the effective rate slopes downward and gradually converges toward 0.8 at higher wage levels. This pattern indicates that the model implements the schedule as a marginal progressive system and then reports an average replacement rate, rather than assigning a flat bracket-specific rate to total earnings.

The effective replacement rate and the scheduled statutory rate do not coincide for several structural reasons:

- The function `get_average_rrp` applies replacement rates marginally to wage slices and then computes an average over total wages. For example, suppose the schedule is 100% up to \$50,000 and 90% on earnings above \$50,000 up to the next cutoff. A worker earning \$70,000 does not receive 90% of their entire wage. Instead, the first \$50,000 is replaced at 100% and the remaining \$20,000 at 90%. Total replaced earnings are

$$50,000 \cdot 1.0 + 20,000 \cdot 0.9 = 68,000,$$

so the reported replacement rate is

$$\frac{68,000}{70,000} = 0.971,$$

which is strictly below 1.0 and not equal to 0.9. In general, if wage is w and the first cutoff is c , then within the second bracket the average replacement rate equals

$$\frac{c \cdot 1.0 + (w - c) \cdot 0.9}{w} = 0.9 + \frac{0.1c}{w},$$

which declines smoothly in w . Thus the reported effective rate is an *average* over marginal slices, not the bracket's marginal rate itself.

- As wages increase within a given bracket, a larger share of earnings is replaced at lower marginal rates from earlier slices. This mechanically reduces the average replacement rate even before the worker crosses the next statutory cutoff.
- Additional features such as dependency allowances and caps, which are applied before the averaging step, can further modify the effective rate relative to the simple step-function schedule.

6.5 Sector and Gender Breakdowns

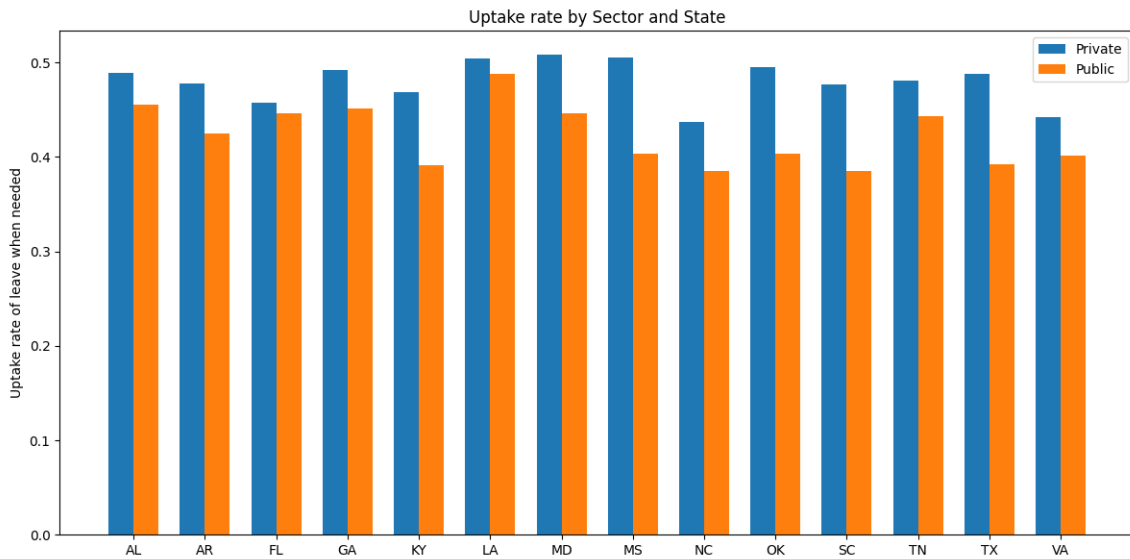


Figure 11: Comparison of take-up rates of private and public sectors

Take-up patterns by sector and state. Figure 11 provides a comparison of take-up rates between public sector and private sector employees as a rate of leave taken when needed. We observe that the private sector has a higher take-up rate of leave when needed across all Southern states.

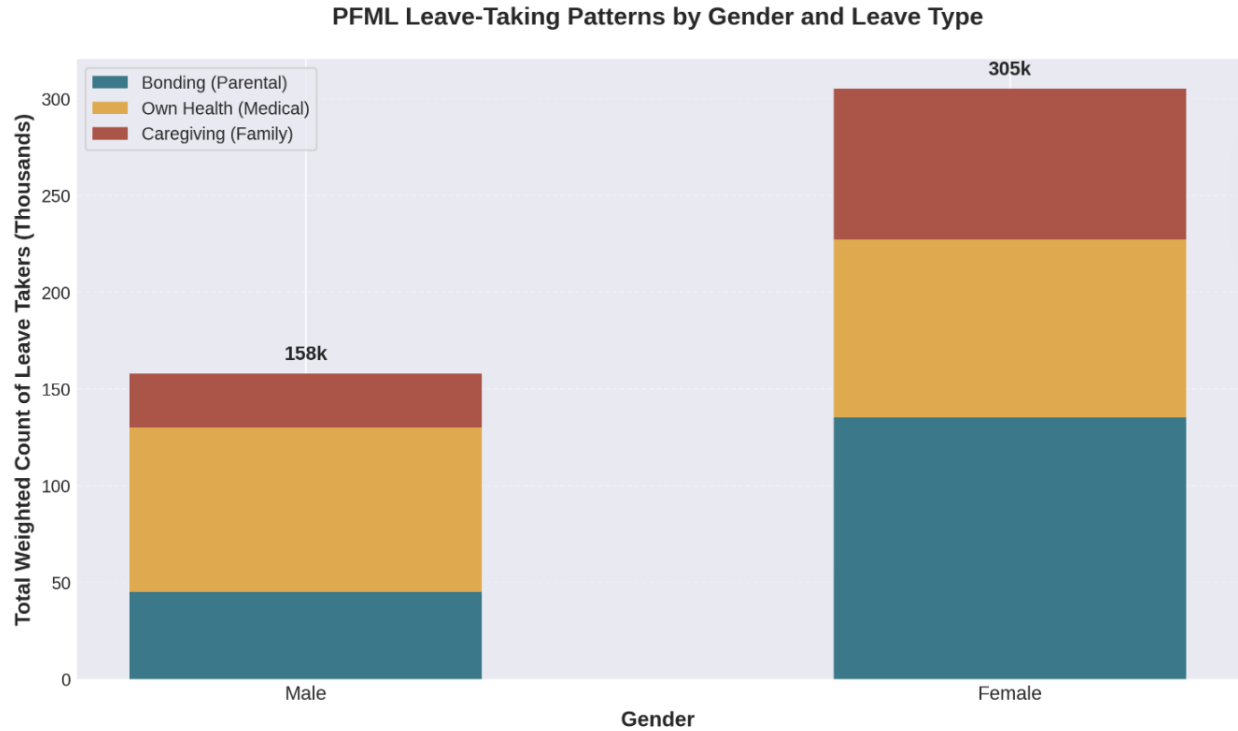


Figure 12: Identifying the Difference between Male and Female Usage Patterns

Usage Patterns by Leave Type and Gender Figure 12 reveals persistent gender disparities in PFML leave-taking patterns that reflect deeply entrenched caregiving norms, even under a universal paid leave policy. Women take nearly twice as much leave overall compared to men, and the composition of their leave differs dramatically. Women’s leave is distributed across bonding, own health, and caregiving responsibilities, demonstrating that they shoulder the majority of both parental responsibilities and family caregiving duties. In contrast, men’s leave usage is heavily concentrated in their own health needs, with comparatively lower rates of bonding leave and minimal caregiving leave. This suggests that despite the availability of gender-neutral paid leave benefits, traditional gender roles persist in how families allocate care responsibilities. The fact that women take three times as much bonding leave as men, and nearly three times as much caregiving leave, indicates that universal PFML policies alone do not eliminate gendered divisions of labor. Additional interventions such as paternity leave incentives, workplace culture changes, and targeted outreach may be necessary to encourage more equitable sharing of family care responsibilities between genders.

6.6 Fiscal Outcomes

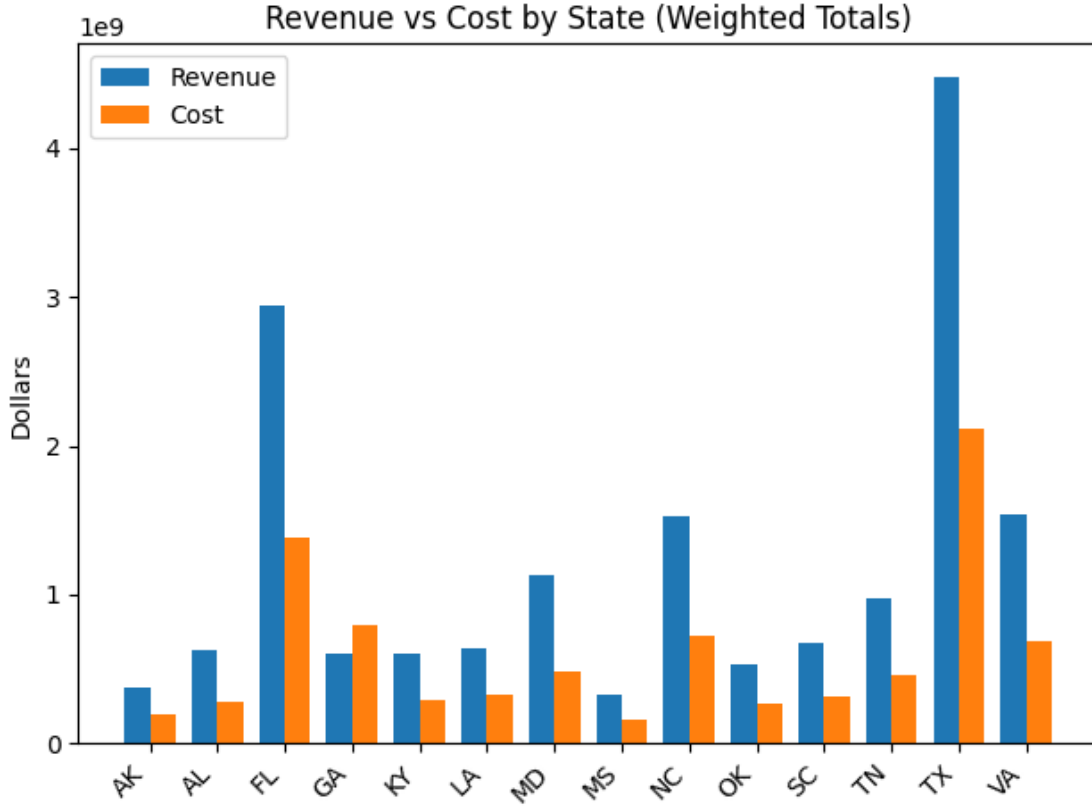


Figure 13: Projected payroll tax revenue and benefit costs by state (weighted totals).

Revenue and Cost by State: Figure 13 compares projected payroll tax revenue with simulated benefit expenditures across states. Revenue is computed as the weighted sum of individual-level tax contributions,

$$\sum_i \text{ptax_rev_final}_i \cdot \text{PWGTP}_i,$$

while costs are calculated as the weighted sum of simulated annual benefits across all leave types,

$$\sum_i \left(\sum_k \text{annual_benefit}_{ik} \right) \cdot \text{PWGTP}_i.$$

Across all states, projected revenue exceeds projected costs, indicating that the program is fiscally sustainable under the baseline Worker PLUS parameterization. The magnitude of both revenue and cost varies substantially across states, reflecting differences in wage distributions, labor force size, and simulated leave-taking behavior. Larger states, such as Texas and Florida,

generate significantly higher revenues due to a broader taxable wage base, while also exhibiting higher benefit payouts.

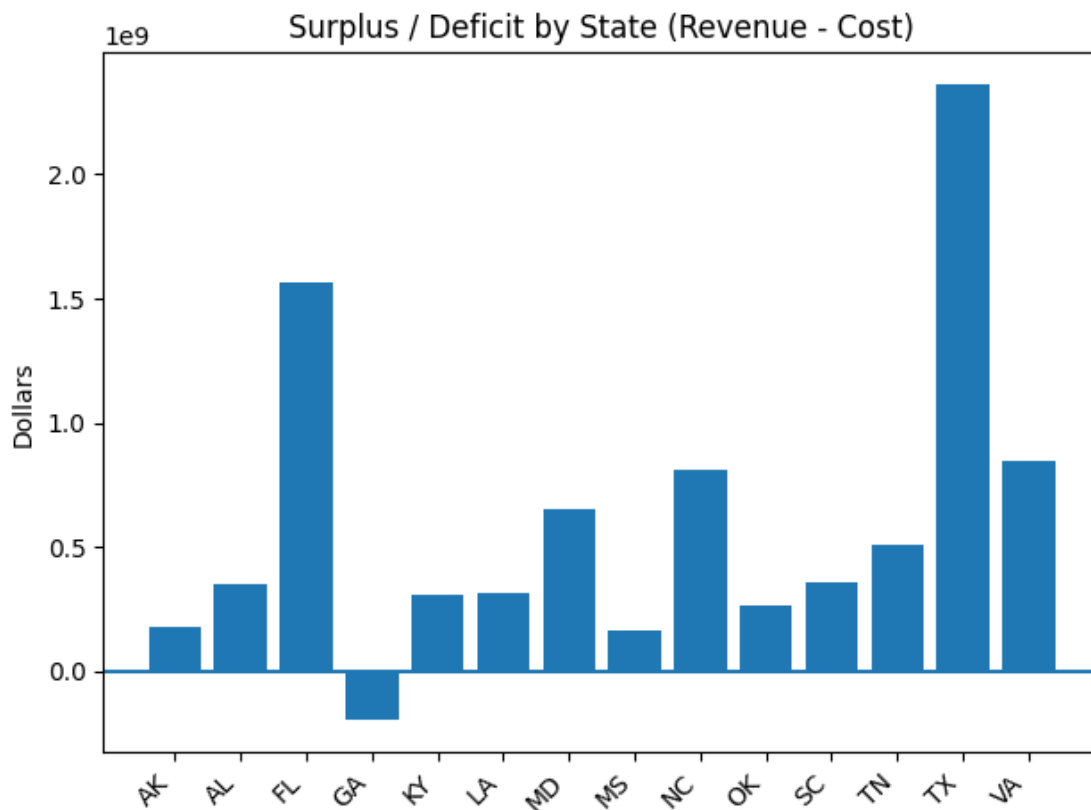


Figure 14: Net fiscal balance (revenue minus cost) by state.

Net Fiscal Balance: To more directly assess solvency, Figure 14 plots the net fiscal balance for each state. Positive values indicate that payroll tax revenues exceed benefit payouts. All states exhibit a positive balance, reinforcing the conclusion that the program is solvent under the modeled assumptions.

However, there is notable heterogeneity in surplus magnitude. States with larger labor markets and higher aggregate wages generate larger surpluses in absolute terms, while smaller states exhibit more modest margins. This variation highlights that fiscal sustainability within the model is driven not only by policy parameters (such as tax rates and replacement schedules), but also by underlying labor market characteristics and behavioral responses embedded in the simulation.

The Worker Plus model improves upon standard simulations by explicitly linking worker-level benefit eligibility and take-up (from ACS microdata) with payroll-based financing (from ABF). As

a result, the observed surpluses reflect a consistent equilibrium between:

- the distribution of earnings (tax base),
- the distribution of leave-taking needs and durations (benefit demand), and
- policy parameters governing eligibility and replacement rates.

Taken together, these results suggest that, under current assumptions, the proposed paid leave program is financially viable across states. At the same time, the variation in surplus margins indicates that program sustainability is sensitive to both state-level economic conditions and the behavioral assumptions embedded in the Worker Plus simulation.

7 Conclusion

7.1 Conclusion

Through our model, implementing the 12-week PFML program in the Southern US states would greatly expand current coverage and would reduce gaps in coverage. This expansion was especially strong for low-wage workers, who had the largest relative coverage gains across the states. The progressive wage replacement structure supports lower-income workers. Policy take-up patterns vary by sector and gender, with higher female participation and stronger bonding/parental leave usage. Our projected take-up rates lead to measurable public health gains. The model projected approximately 6,170 additional child vaccinations, with nearly 4,200 from low-income families. Overall, the PFML policy functions as both an economic stabilization policy and an increased equity initiative in the South. Some limitations of our project included the lack of state-level awareness data, requiring us to use combined prediction methods, and this could have limited model precision. The model also assumed that the behavior and responses under the new Southern PFML policy mirror patterns from existing implementations, which may not actually be the case.

7.2 Next Steps

Future work and steps could incorporate state-specific awareness measures and improved data on job protection and wage replacement responsiveness. Further analysis of sector and gender

differences could also create more detailed equity projections. Modeling additional outcomes, such as maternal health, long-term labor force attachment, and employer turnover effects could provide a more complete analysis of cost and benefit of this policy. Further testing and refining of alternative replacement brackets, payroll tax rates, and eligibility thresholds could further impact optimal policy design for the Southern states.

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8 Appendix

[Public Github Repo with all Code](#)