To Trans-Atlantic Public Economics Seminar Economic Effects of Social Insurance and the Social Safety Net selection committee:

Please find attached for your consideration for inclusion in the upcoming Trans-Atlantic Public Economics Seminar. I am writing a short note to explain a somewhat unique feature of this submission. Our paper relies on administrative records held in the Federal Statistical Research Data Center (RDC). Any evidence produced in this environment requires review from Census Disclosure Officers. Unfortunately, due to the government shutdown, we were delayed in getting our results reviewed, although the exercises we discuss in general terms in the extended abstract have been completed.

Due to this constraint, we have submitted an extended abstract. We provide general details about the evidence we will produce and the way in which we will produce it. However, we are unable to present the actual evidence itself or discuss the implications of this evidence until the disclosure review is completed. We have provided placeholder tables and figures that mirror the structure (although not content) of the evidence that will be publicized in the coming weeks.

We anticipate having a full set of tables and figures disclosed and in the paper in the coming weeks. While we hope what we have provided is sufficient to evaluate the fit of the project, if there are any open questions, please do not hesitate to contact me.

We hope our study of the interaction between mass layoffs, the details of unemployment insurance design, and the criminal legal system will be a good fit, and we believe the project would benefit greatly from feedback from the seminar.

Thank you for your consideration,

Ben Pyle (the author who plans to attend the meeting as the presenter)

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Job Displacement, Crime, and the Value of Unemployment Insurance in the US*

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Abstract

This paper measures the impact of job loss and unemployment insurance on criminal behavior and social welfare. Comparing a sample of workers impacted by mass layoff events across the United States to those who were not laid off, we show that those who experience a lay off earned [EARNING RESULT] and were [OFFENDING RESULT]. We study how changes to unemployment compensation design by changing the replacement rate, duration of benefits, improving likelihood of successfully filing by working at an employer with higher successful UI filing can [MITIGATE/EXACERBATE] these results. Using a simulated instrument approach we show that those laid off who would receive a one-standard-deviation (X percentage point) higher replacement rate [EARNING RESULT] and offend [OFFENDING RESULT]. Altering the duration by 10 weeks [RESULTS]. Moving to an employer with a one-standard deviation higher rate of UI filing post layoff [RESULTS]. Interpreting these results through a model we consider the relative tradeoffs across a social planner considering altering the replacement rate, the duration, or filing success in the presence of an externality and [CONCLUSION].

Keywords: Unemployment Insurance, Mass Layoffs, Crime
JEL classification codes: J64 Unemployment: Models, Duration, Incidence, and Job Search; J65 Unemployment Insurance; Severance Pay; Plant Closings; K42 Illegal Behavior and the Enforcement of Law

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Work in progress, please do not circulate or cite without the authors' permissions. This extended abstract includes placeholders, but no results or discussion thereof, for results that may only be released pending Census disclosure review. Any opinions and conclusions expressed herein are those of the authors and do not reflect the views of the U.S. Census Bureau.

1 Introduction

Theoretical and empirical work over at least the last half-century has highlighted the important relationships between employment and criminal behavior. Those who face challenges in the formal employment work– those who are unemployed, working infrequently, or in particularly low-wage jobs are over-represented in the criminal legal system. The causal relationship between work and crime is likely complex and intertwined. There is significant evidence that a criminal record reduces future employment opportunities and fewer opportunities for stable, legal work leads to more criminal behavior. In this paper, we present new evidence that plausibly exogenous job loss causes [OFFENDING RESULT]. However, social insurance through unemployment compensation can [INSURANCE RESULT]. The fact that unemployment compensation [RESULT] is informative regarding what component of the job loss and crime relationship is driven by financial distress versus other disruptions; we show that is [RESULT].

This paper overcomes several barriers that have long made answering these questions challenging. Using administrative tax data, we are able to credibly identify [A LARGE NUMBER] of mass layoffs in our sample of 18 states. This tax data not only allows us to identify job losers in mass layoff events, but also their unemployment insurance filing. We merge this data with court and prison records to measure contact with the criminal legal system before and after job loss. Using well-established mass lay-offs designs (difference-in-differences), we can credibly identify the impact of job loss on offending. We are also able to present findings across a variety of populations (sex, marital status, race, and others) and outcomes (future earnings, UI filings, number and type of future crimes, future prison entry).

Given our rich data, we are able to analyze how unemployment insurance might mediate the job loss and crime relationship. Theory suggests that there may be competing effects of unemployment insurance in this context. By relieving financial strain, unemployment insurance may prevent criminal behavior. However, to the degree unemployment insurance extends the time job losers remain out of work, it may lead to additional criminal behavior that would have been prevented if the offender would have been incapacitated at their job.

To assess the impact of unemployment insurance on job-losers we consider 3 margins of unemployment compensation generosity: the replacement rate (how much of a persons wage is paid), the duration of payment (how many weeks of compensation are available to a claimant), and how likely they are to successfully file a claim (how likely they are to submit the paperwork and how likely that paperwork is to be challenged by other parties like the employer).

First, we show changes in work and offending behavior for people in the first years after layoff

in states that have enacted large changes in their unemployment insurance schemes in the past decades, compared to those that did not. This cross-state difference-in-difference evidence shows [XXX].

Next, we use a parallel design to the mass-layoffs literature comparing people at firms with mass layoffs who separate from their employer to those who stay, but add an additional interaction with various levers of unemployment compensation generosity at the time of layoff. To assess this relationship, we again use a difference-in-differences approach, but now interact job loss with our three measures of state policy generosity, relying on exogenous changes to state UI policies at the time of mass layoff or firm features, respectively. To measure changes in replacement rate, we use a simulated instrument approach as in Gruber (1997) and Kuka (2020). To measure duration, we use two approaches. First, we examine a similar simulated instrument approach, estimating how many weeks each state would offer in each year to a fixed sample of job losers. Next, we exploit a sharp 2013 change in UI federal benefit extension offerings previous explored in the literature. Finally, to measure firm impacts on claim filing, we use an AKM approach, in the spirit of Lachowska et al. (2025).

Each margin of UI generosity may face different trade-offs relating to the impact on future employment and criminal behavior. In order to make sense of the various trade-offs faced in the design of an optimal unemployment insurance system with various manipulable generosity margins and externalities, we develop a model that incorporates the social cost of crime.

This model and our empirical findings suggest that, [Policy Implications]

2 Data

We use rich administrative data linked through the Census Bureau data linkage infrastructure and accessed through the Federal Statistical Research Data Centers (FSRDCs) to observe individual socio-economic information as well as individual criminal and employment histories for the universe of workers across 18 states. This data allows to identify mass layoff events, unemployment insurance filing, criminal behavior, and a rich set of socio-economic characteristics across states with vastly different, and reforming, unemployment insurance systems.

To measure employment histories we primarily focus on worker W-2 Filings filed between 2005 and 2019. From these tax records we are able to observe an EIN (Employer Identification Number), which we use to track employers. We identify firms that experience mass layoffs as the EINs that have at least 25 employees in the year before layoff and experience at least a 33% reduction in workforce in a given year (that is having 33% or fewer unique W-2s filed in the year of layoff).

Criminal records are measured using the Criminal Justice Administrative Records System (CJARS), which compiles criminal justice records from many jurisdictions and agencies. (Finlay & Mueller-Smith, 2021). We restrict all of our analysis to states with sufficient coverage over our analysis period (between 2005 and 2019) to track the relevant outcomes relating to charges (from courts) or prison entry (typically from Correction Departments).

We also gather several demographic characteristics for our sample including information about race, age, sex (all from the numident), number of dependents, marital status, household income (from 1040 filings), and county and state of residence from (Finlay et al., 2023).

As documented in greater detal below, we characterize legal changes to the unemployment insurance using a simulated instrument generated by coding legal changes documented by the Department of Labor based on a fixed sample of workers in the Survey of Income and Program Participation (SIPP).

In Table 1, we show summary statistics for our core analysis sample, people working at firms with mass layoff events. As our analysis will compare workers who separate during these mass layoff and those who do not, column 1 provides details for job-separators and column 2 provides information for those who were not laid off.

3 State-Level Difference-in-Differences

During our analysis period several states have large declines in the generosity of their unemployment insurance systems. We focus on on 7 of these states: Missouri and South Carolina in 2011, Florida, Georgia in Michigan in 2012, North Carolina in 2013, and Kansas in 2014. To study these cuts in unemployment insurance, we compare separators after mass layoff events across states that reduced benefits to those that did not in a difference-in-differences and event study framework.

We restrict our analysis sample to workers who lost their job after working for their employer for at least 2 years (so they are very likely eligible for unemployment benefits), and focus on the year of job loss and the following year (the time period where workers might be receiving benefits).

First, we show the raw data for key outcomes (wages earnings, employment, UI filing, criminal charges, and prison entry) in states that lowered their UI generosity and those that did not in Appendix Figure 8. As can be seen in the raw data [RESULTS DISCUSSION]

We estimate the regressions of the form

$$Y_{it} = \sum_k \beta_k 1[E_i = t - k] \times UI\ Reform_i + \sigma_i + \delta_t + \varepsilon_{it}$$

for individual i in year t. E_i are relative time indicators (k indexes relative time), σ and δ are state and year fixed. We also summarize the results $Y_{it} = \beta^{Post} + \sigma_i + \delta_t + \varepsilon_{it}$. This evidence shows that people who lose their jobs after large declines in the generosity of their states unemployment insurance systems [RESULTS]. Figure 1 displays event studies showing the evolution of replacement rates, unemployment insurance filing, wages, employment (filing any W2), the number of new court filings a worker receives, whether the worker received any new charge, the number of felony charges, whether the worker received any new felony charge, and whether the worker entered prison. DiD results are summarized in Table 2.

We find [RESULTS DISCUSSION].

Previous research has demonstrated difference across groups on the propensity and ability to successfully claim unemployment compensation. Additionally some groups may be differentially responsive to benefits based on how dependent upon there W2 wages they are or how they experience the stresses of losing their job. In Appendix Table 7 we display this result.

4 Examining Margins of the Unemployment Insurance System

In this section, we discuss how we use mass layoff events and variation in the unemployment insurance system across states to empirically evaluate how different margins of the UI system impact engagement with the criminal justice system. Throughout each of these exercises, we use a harmonized empirical specification and vary the differential margin of the UI system we consider. Across three complementary exercises, we examine variation in UI replacement rates, duration, and access.

4.1 Harmonized Empirical Strategy using Mass Layoff Events

The core of our empirical strategy leverages a series of mass layoff events to identify plausibly exogenous job loss events, following Jacobson et al. (1993). Relative to our empirical strategy in Section 3 which uses cross-cohort variation from job losers, we know leverage within-person variation in the timing of job loss and compare the evolution of their outcomes to stayer workers

who did not lose their jobs. Formally, we estimate general regressions of the following form:

$$Y_{it} = \sum_k \underbrace{\beta_k 1[E_i = t-k] \times Job\ Loss_i}_{\text{Dynamic effects of job loss}} + \sum_k \underbrace{\beta_k^Z 1[E_i = t-k] \times Job\ Loss_i \times Z_i}_{\text{Dynamic differential effect of UI system}} + \underbrace{\alpha_i + \delta_t}_{\substack{\text{Fixed} \\ \text{effects}}} + \sum_k \underbrace{\theta_k 1[E_i = t-k]}_{\substack{\text{Relative time} \\ \text{fixed effects}}} + \varepsilon_{it} \quad (1)$$

for individual i in year t. E_i are relative time indicators (k indexes relative time), $Job\ Loss_i$ is an indicator for losing a job during a mass layoff event, and Z_i is our measure of unemployment insurance generosity or access. In the below sections, we will adopt this general framework and examine the effects of different margins of the UI system by replacing Z_i with measures of generosity and access.

Additionally, we control for individual-level fixed effects α_i and year fixed effects δ_t, along with relative time indicators θ_k. Our coefficients of interest are β_k and β_k^Z, which respectively trace out the direct effects of job loss and the differential effects of the UI system. We normalize both sets of coefficients to two years before the job loss event ($k = -2$). Throughout we cluster our standard errors at the state-level and show robustness to inference techniques which are specifically designed to deal with few clusters.

The key identifying assumption behind Equation (1) is that the outcomes between job losers and job stayers would have continued to evolve in parallel absent the job loss event. Examining pre-period trends in β_k provide graphical evidence of this assumption. Additionally, to causally interpret β_k^Z, we require that absent differences in the UI system across state and layoff year, any remaining variation in treatment effects would not be systematically related to our measure of UI generosity (Olden & Møen, 2022).

Finally, we summarize the dynamic effects of Equation (1) through a semi-parametric version which summarizes the short-run (years 0-1) and long-run (years 2-4) impacts of job loss and the

differential impacts of the unemployment insurance system.

$$
\begin{aligned}
Y_{it} = \beta_0 + & \underbrace{\beta^{SR}[Job\ Loss_i \times Post_{it}^{SR}] + \beta^{LR}[Job\ Loss_i \times Post_{it}^{LR}]}_{\text{Direct job loss effects}} \\
& + \underbrace{\beta_Z^{SR}[Job\ Loss_i \times Post_{it}^{SR} \times Z_i] + \beta_Z^{LR}[Job\ Loss_i \times Post_{it}^{LR} \times Z_i]}_{\text{Differential effect of unemployment insurance system}} \\
& + \underbrace{\alpha_i + \delta_t}_{\substack{\text{Fixed} \\ \text{effects}}} + \sum_k \underbrace{\theta_k 1[E_i = t - k]}_{\substack{\text{Relative time} \\ \text{fixed effects}}} + \varepsilon_{it}
\end{aligned} \tag{2}
$$

We use the coefficients β_Z^{SR} and β_Z^{LR}, which report the average short- and long-run effects of the UI system, to quantify the welfare impacts of alternative UI designs in Section 6.

4.2 Variation in UI Replacement Rates

The first margin of the unemployment insurance system we examine is variation in the replacement rate. To measure the replacement rate, we update and replicate the simulated instrument design used in Kuka (2020), which builds on previous work from Gruber (1997). We first construct a fixed national sample from the SIPP consisting of all individuals observed in the first month of an unemployment spell between 2005 and 2019. Using this invariant sample, we combine each person's pre-unemployment earnings and number of children with contemporaneous state rules to determine UI eligibility and compute the implied weekly UI benefit in every state-year. We then form a simulated replacement rate by dividing each individual's weekly UI benefit by their weekly earnings and aggregate these simulated rates to year x state x children cells to obtain the average replacement rate RR_{cst}.[1] Together, this design isolates policy-driven variation rather than individual heterogeneity. We embed this policy-driven replacement rate variation, RR_{cst} into Equation (1) by setting $Z_i = RR_{cst}$.

4.2.1 Effects of UI Replacement Rate on Labor and Crime

We first examine the effect of job loss and our simulated replacement rate instrument on labor market outcomes and take-up of unemployment insurance. Figure 2 presents event-study results [RESULTS]. The instrument [RESULTS] Figure 3 presents the analogous results for criminal justice outcomes. Difference-in-Difference coefficients are summarized in Table 3. [RESULTS]

[1]This instrument captures two elements of program generosity: the amount of required pre-employment earnings and the amount of money a claimant receives based on those earnings.

Additional Results on Crime Types: Job loss and unemployment insurance may lead to differential offending across crime types. Understanding what types of crime change after layoff or receipt of additional insurance helps us understand if crimes are occurring to offset lost wages (property and especially theft crimes), or might be due to stressors from changed life circumstances. We show these findings in Appendix Table [RESULTS].

Heterogeneity in Effect of Replacement Rate: We again consider results across various groups that might have different experiences with UI policies. In particular we display treatment effects for a wide set of demographic and economic subgroups, including women, workers with differing levels of W-2 dependency, four adult age ranges (18-24, 25-34, 35-45, and older than 45), individuals with and without claimed dependents, and four racial and ethnic groups (White, Black, Hispanic, and Other). Appendix Figure **??** and Appendix Tables 8, 9, and 10 presents [RESULTS] across various groups.

4.3 Variation in UI Benefit Duration

The second margin of the unemployment insurance system we examine is benefit duration, which we quantify with two complementary exercises.

First, we examine a similar simulated instrument approach, estimating how many weeks each state would offer in each year to a fixed sample of job losers. To do so we perform a parallel exercise to our simulated instrument. Now, instead of simulating the replacement, we calculate the maximum duration available to our fixed sample of the unemployed, providing a simulated maximum duration measure. Using the same fixed national sample from the SIPP consisting of all individuals observed in the first month of an unemployment spell between 2005 and 2019, we combine each person's pre-unemployment earnings and number of children with contemporaneous state rules to determine UI duration and compute the implied UI benefit duration in every state-year. Together, this design isolates policy-driven variation rather than individual heterogeneity. We embed this policy-driven replacement rate variation, DUR_{cst} into Equation (1) by setting $Z_i = DUR_{cst}$.

4.3.1 Effects of UI Benefit Duration on Labor and Crime

We first examine the effect of job loss and our duration instrument on labor market outcomes and take-up of unemployment insurance. Figure 4 presents event-study results [RESULTS]. The instrument [RESULTS] Figure 5 presents the analogous results for criminal justice outcomes.

Difference-in-Difference coefficients are summarized in Table 4. [RESULTS]

Heterogeneity in Effect of Replacement Rate: We again consider results across various groups that might have different experiences with UI policies. In particular we display treatment effects for a wide set of demographic and economic subgroups, including women, workers with differing levels of W-2 dependency, four adult age ranges (18-24, 25-34, 35-45, and older than 45), individuals with and without claimed dependents, and four racial and ethnic groups (White, Black, Hispanic, and Other). Appendix Figure **??** and Appendix Tables 11, 12, and 13 presents [RESULTS] across various groups.

Additional Results on Crime Types: While replacement rates may have a particular impact on the types of crimes, extending the benefits over a longer period, rather than paying more each month, may have differing impacts. We show Appendix Table [RESULTS]

4.4 Variation in UI Access Across Employers

The final margin of unemployment insurance generosity we consider is variation in access across employers. When workers are displaced from a firm and claim UI, firms have an opportunity to contest the validity of that claim. To the extent firms vary in the degree to which they contest these claims, this behavior generates variation in ease of access to UI across firms (Lachowska et al., 2025).

Following Lachowska et al. (2025), we quantify the variation in this extensive margin access to UI through estimation of an AKM model (Abowd et al., 1999), where we relate the probability of claiming UI to a vector of firm and individual fixed effects and a series of time-varying controls. Formally, we estimate models of the following form:

$$y_{ijt} = \underbrace{\alpha_i}_{\substack{\text{Worker} \\ \text{effects}}} + \underbrace{\psi_{j(i,t)}}_{\substack{\text{Firm} \\ \text{effects}}} + X'_{it}\beta + \varepsilon_{ijt} \tag{3}$$

for individual i, separating from firm j, in year t.[2] Using a sample of twice-separating workers, we collect the $\psi_{j(i,t)}$ fixed effects from estimation of Equation (3), which represent time-invariant firm-specific variation in access to UI. Firms effects may be larger if for example they are less likely to contest separating workers' UI claims. Below, we use these firm effects to quantify the effects of

[2]In the vector X'_{it} we include a series of year fixed effects and a cubic in age. Following Card et al. (2013) we normalize the cubic to be zero at age 40 and omit the linear term to permit identification of the year fixed effects.

access to UI on labor market outcomes and criminal justice system involvement.

A key concern with using firm-effects as a regressor is that they contain both true differences between firms and a substantial degree of measurement error (Kline, 2024). We combat this measurement error through use of a split-sample IV (SSIV) approach, where we split our sample of separating workers into two balanced sets and estimate the firm-effects in each subsample, using one set of firm effects to instrument for the other. While our SSIV approach comes with the caveat that our estimation sample is slightly reduced since the firm effects are only identified within each connected subset, the marginal firms that are only in one subset or the other tend to have very few separators and are noisily estimated even in the full sample.

Appendix Figure **??** describes the distribution of the firm effects. We report the distribution of firm effects for each component of the split-sample IV and the bias-corrected variance, along with the pooled set of firm effects. [DISCUSSION OF RESULTS AND MAGNITUDES RELATIVE TO (Lachowska et al., 2025)]

For the firm effects, $\psi_{j(i,t)}$ to be interpreted as causal objects, we require the standard exogenous mobility assumption, that is, workers do not sort to firms based on the error term, ε_{ijt}. Such an assumption could be violated if workers sort to (and then separate from) firms where they are more likely to be able to claim unemployment insurance, above and beyond what would be predicted by the employer effect alone. Put differently, if there are match effects on claiming between worker i and firm j, this assumption will be violated. Our use of mass layoffs to identify exogenously separating workers limits the potential for this type of sorting to occur.

We provide two empirical exercises that support the validity of the exogenous mobility assumption, following (Lachowska et al., 2025). First, Panel A of Appendix Figure **??** presents a binscatter of the relationship between changes in firm claiming rates and changes in worker claiming rates. [RESULT] Panel B replaces the change in firm claiming rates with changes in firm effects, finding [RESULT]

Having established the validity of the estimated firm effects, we embed this heterogeneity into our dynamic difference-in-differences model from Section 4.1, replacing $Z_i = \psi_{j(i,t)}$.

4.4.1 Effects of UI Access on Labor and Crime

We first examine the effect of job loss and our simulated replacement rate instrument on labor market outcomes and take-up of unemployment insurance. Figure 6 presents event-study results [RESULTS]. The instrument [RESULTS] Figure 7 presents the analogous results for criminal justice outcomes. Difference-in-Difference coefficients are summarized in Table 5. [RESULTS]
Additional Results on Crime Types: Appendix Table [RESULTS]

4.5 Summary Discussion of Results

Finally, we present results simultaneously considering all three margins and their interactions. While we are likely underpowered in this specification, we find [RESULTS].

Taken as a whole these results suggest that the impact of increasing the replacement rate by 5 p.p. is [RESULTS], increasing the duration rate by one week is [RESULTS], and moving workers to a firm with a one-standard deviation higher successful claim filing rate is [RESULT].

5 Model

Model Setup. We use a canonical model of optimal unemployment insurance (Chetty 2008) adjusted to our setting. We consider an unemployed individual who engages in job search (s) and compensating activities, specifically crime (a). We normalize s to equal the probability of finding a job, denoting the search effort cost by $\phi(s)$; and we normalize a to be the "reward" from the activity, denoting the crime effort cost by $\mu(a)$.

If search is unsuccessful, the agent receives unemployment benefits b. If search is successful, the agent begins working for wage w and pays tax τ used to finance unemployment benefits. Engaging in crime increases consumption in either state of the world, but at a cost of lower earnings if employed by p ("penalty").

With this setup, consumption when unemployed is $c_u = b + a$, and consumption when employed is $c_e = w - \tau + a - p$. The agent's value function is then:

$$J(b) \equiv \max_{s,a} \left[(1-s)\, u(c_u) + s\, u(c_e) - \phi(s) - \mu(a) \right] \tag{4}$$

Planner's Problem. The planner chooses the unemployment benefit system that maximizes the agent's expected utility. The planner policy choices include benefit generosity, b, and a tax rate to fund benefits, τ.

The traditional budget constraint, so that expected taxes collected must be at least as high as expected benefits paid, is captured by: $(1-s)b - s\tau \leq 0$. Importantly, our findings emphasize the need for broader budget considerations since benefits reduce crime. The budgetary gains from reduced crime are threefold. First, they include direct costs, such as damages and policing ($ amount). Second, they include spillovers to other agents, such as crime externalities. We model these two component jointly as a having a cost of θ per unit of crime. Third, they include indirect costs vie the reduction in earnings if employed (affecting tax revenue).

The planner therefore solves:

$$W(b) \equiv \max_{b,\tau} J(b) \quad \text{subject to} \quad (1-s)b - s\tau \leq 0. \tag{5}$$

We assume that search effort s is fixed in order to focus on the implications of our findings for for the optimal design of unemployment insurance (as the results for s are well-established in the literature).

Welfare Gains from More Generous UI. Welfare change from an increase in b is given by:

$$\frac{dW}{db} = (1-s)u' - sv'\frac{d\tau(b)}{db} \tag{6}$$

where

$$\frac{d\tau(b)}{db} = \frac{1-s}{s} + \frac{1}{s}(sp+\theta)\frac{da^*(b)}{db}.$$

It follows that:

$$\frac{dW}{db} = (1-s)(u'-v') - (sp+\theta)\frac{da^*(b)}{db}.$$

The first term is the traditional insurance value term. The second term is the novel portion of the fiscal externality that we estimate, which stems from the effects of crime reduction from more generous benefits.

6 Optimal Program Design With Measured Externalities

To assess the relative efficiency of the three policy levers studied (replacement rate, benefit duration, and claim accessibility) we conduct a budget-neutral exercise from the perspective of a constrained social planner. In this framework, the planner has a fixed budget to allocate toward unemployment compensation and seeks to maximize welfare by identifying which margin delivers the highest return on the marginal dollar spent. Unlike traditional optimal UI calculations that focus primarily on the trade-off between consumption smoothing and moral hazard (reduced search effort), our calculation explicitly incorporates the fiscal externality of crime prevention. As derived in Equation 6, the welfare gain from increased generosity includes a correction term, $(sp+\theta)\frac{da^*(b)}{db}$, which accounts for the reduction in direct costs of crime (damages and policing) and the preservation of future tax revenue by avoiding incarceration-driven earnings penalties.

We operationalize this by comparing the "net cost" of an equivalent expenditure across the three distinct margins: increasing the replacement rate, extending the potential duration of benefits, or increasing the likelihood of successful filing (access). We utilize our empirical estimates of

β_Z^{SR} and β_Z^{LR} from Equation 2 to quantify the causal impact of each margin on labor supply and criminal offending. For instance, while extending duration may provide liquidity, it risks mechanically increasing the time out of work, potentially leading to adverse long-run effects if idleness complements criminal activity. Conversely, increasing the replacement rate or reducing administrative friction (access) may alleviate the immediate financial strain that drives offending without necessarily inducing the same magnitude of prolonged unemployment. By weighing the consumption smoothing benefits against the net fiscal cost—adjusted for the savings generated by the estimated reduction in criminal charges and prison entry—we determine which policy lever minimizes the "fiscal leakage" of the UI system while maximizing social welfare.

7 Conclusion

References

Abowd, J. A., Kramarz, F., & Margolis, D. N. (1999). High wage workers and high wage firms. *Econometrica*, *67*(2), 251–333.

Card, D., Heining, J., & Kline, P. (2013). Workplace heterogeneity and the rise of west german wage inequality. *The Quarterly Journal of Economics*, *67*(2), 251–333.

Finlay, K., & Mueller-Smith, M. (2021). Criminal justice administrative records system (cjars) [dataset].

Finlay, K., Mueller-Smith, M. G., & Street, B. (2023). Children's indirect exposure to the u.s. justice system: Evidence from longitudinal links between survey and administrative data. *The Quarterly Journal of Economics*, *138*(4), 2181–2224. https://doi.org/10.1093/qje/qjad021

Gruber, J. (1997). The consumption smoothing benefits of unemployment insurance. *American Economic Review*, *87*(1), 192–205.

Jacobson, L. S., LaLonde, R. J., & Sullivan, D. G. (1993). Earnings Losses of Displaced Workers. *American Economic Review*, *83*(4), 685–709.

Kline, P. (2024). Firm wage effects. *Handbook of Labor Economics*, *5*, 115–181.

Kuka, E. (2020). Quantifying the benefits of social insurance: Unemployment insurance and health. *Review of Economics and Statistics*, *102*(3), 490–505.

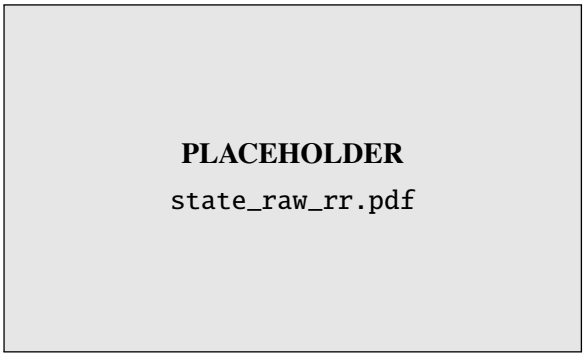
Lachowska, M., Sorkin, I., & Woodbury, S. A. (2025). Employers and unemployment insurance take-up. *American Economic Review*, *115*(8), 2529–2573.

Olden, A., & Møen, J. (2022). The Triple Difference Estimator. *The Econometrics Journal*, *25*(3), 531–553.

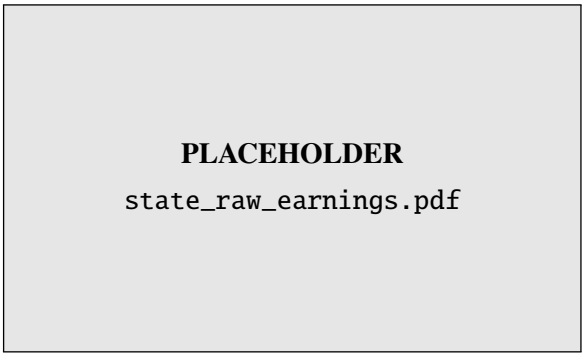
8 Figures

Figure 1: Event studies around state UI policy reforms

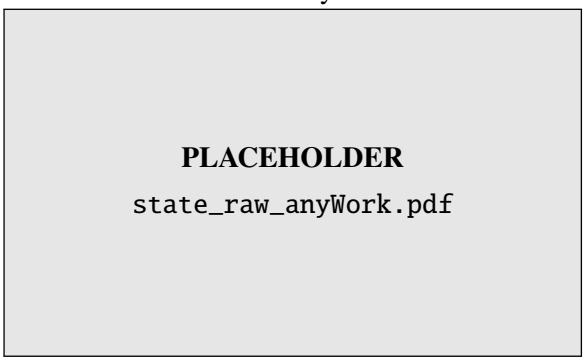
Panel A: UI Replacement Rates



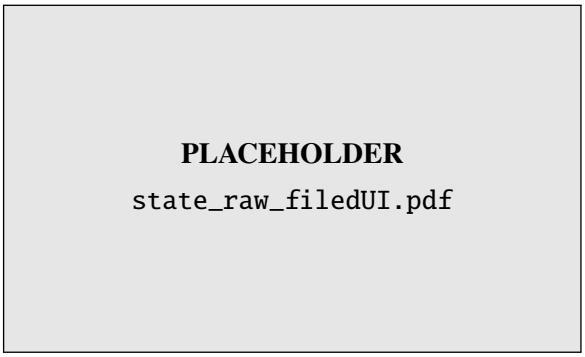
Panel B: W2 Earnings



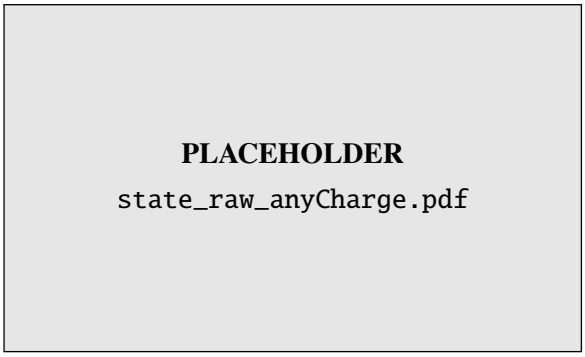
Panel C: Any Work



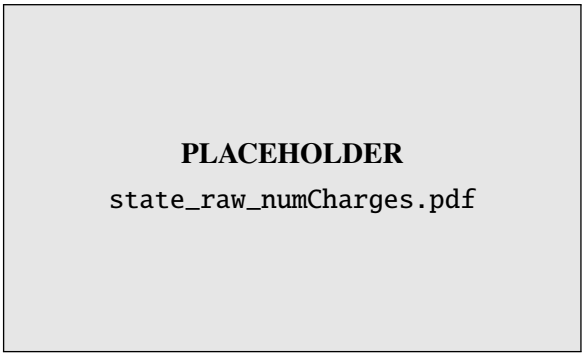
Panel D: Filed UI



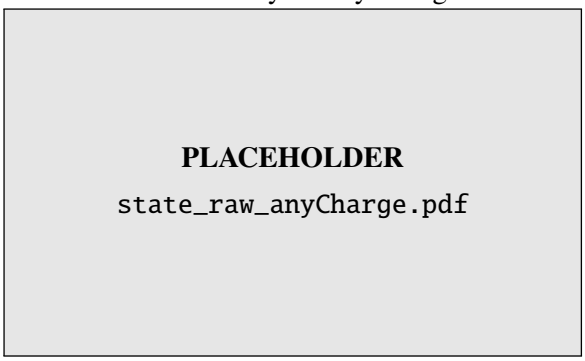
Panel E: Any Charge



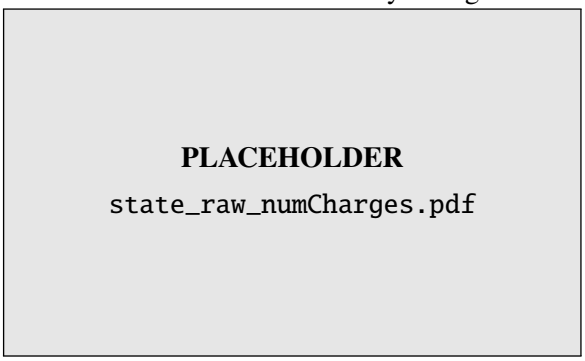
Panel F: Number of Charges



Panel G: Any Felony Charge



Panel H: Number of Felony Charges



Panel I: Prison Entry

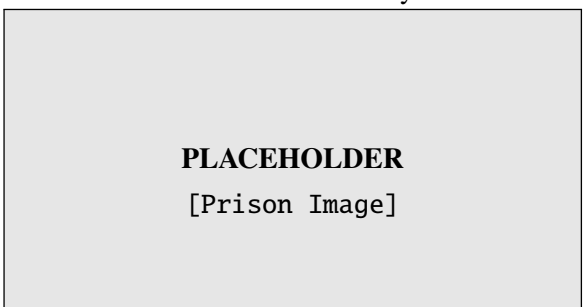


Figure 2: Event Studies: Labor Market Outcomes, Direct Effects & Replacement Rate Instrument



Notes: Each outcome is presented with its own header, followed by the two columns of event study estimates: the main effect of job loss (left) and the interaction with the simulated replacement rate (right).

Figure 3: Event Studies: Crime Outcomes, Direct Effects & Replacement Rate Instrument



Notes: Each outcome is presented with its own header, followed by the two columns of event study estimates: the main effect of job loss (left) and the interaction with the simulated replacement rate (right).

Figure 4: Event Studies: Labor Market Outcomes, Direct Effects & Max Duration Instrument



Notes: Each outcome is presented with its own header, followed by the two columns of event study estimates: the main effect of job loss (left) and the interaction with the simulated maximum duration (right).

Figure 5: Event Studies: Crime Outcomes, Direct Effects & Max Duration Instrument

Num. of Charges

Job Loss	Job Loss x Repl. Rate
PLACEHOLDER NumCharges_JobLoss_Main.pdf	PLACEHOLDER NumCharges_JobLoss_x_DUR.pdf

Any Charge

Job Loss	Job Loss x Repl. Rate
PLACEHOLDER AnyCharge_JobLoss_Main.pdf	PLACEHOLDER AnyCharge_JobLoss_x_DUR.pdf

Num. Felony Charges

Job Loss	Job Loss x Repl. Rate
PLACEHOLDER NumFelony_JobLoss_Main.pdf	PLACEHOLDER NumFelony_JobLoss_x_DUR.pdf

Prison Entry

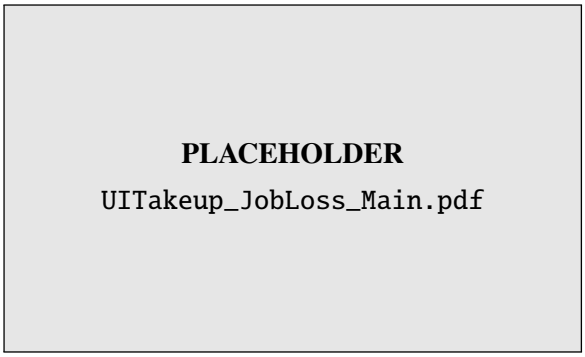
Job Loss	Job Loss x Repl. Rate
PLACEHOLDER PrisonEntry_JobLoss_Main.pdf	PLACEHOLDER PrisonEntry_JobLoss_x_DUR.pdf

Notes: Each outcome is presented with its own header, followed by the two columns of event study estimates: the main effect of job loss (left) and the interaction with the simulated maximum duration (right).

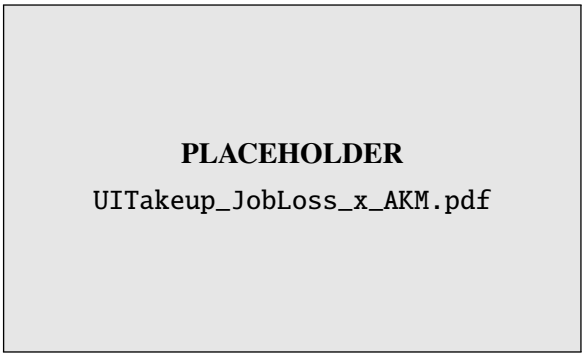
Figure 6: Event Studies: Labor Market Outcomes, Direct Effects & AKM Take-up Instrument

UI Takeup

Job Loss

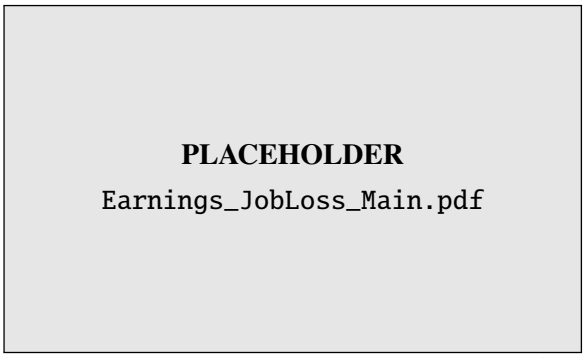


Job Loss x Repl. Rate

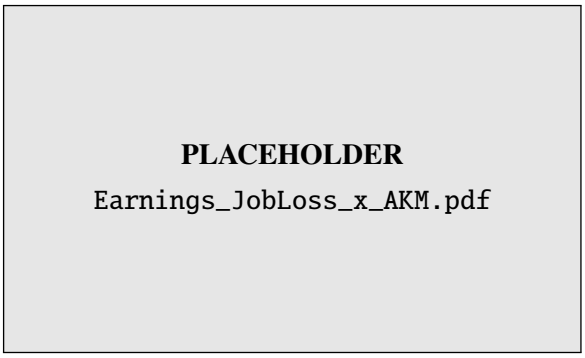


W2 Earnings

Job Loss

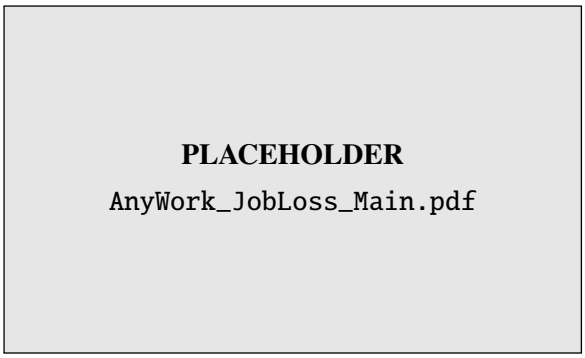


Job Loss x Repl. Rate

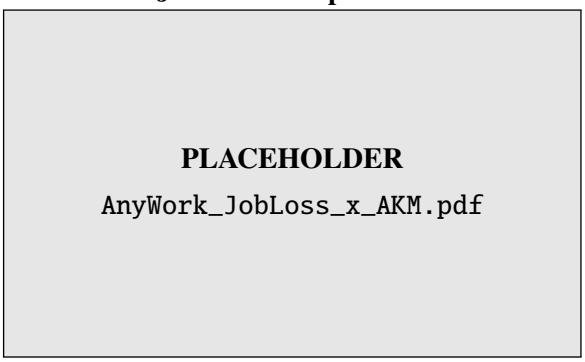


Any Work

Job Loss

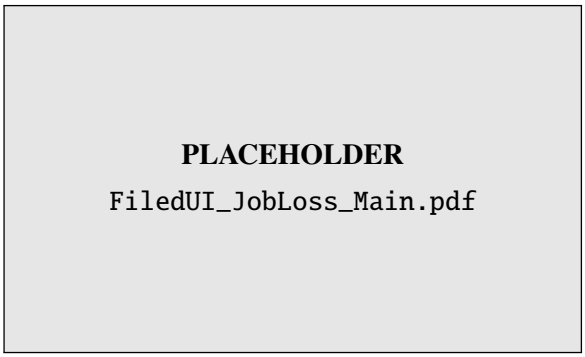


Job Loss x Repl. Rate

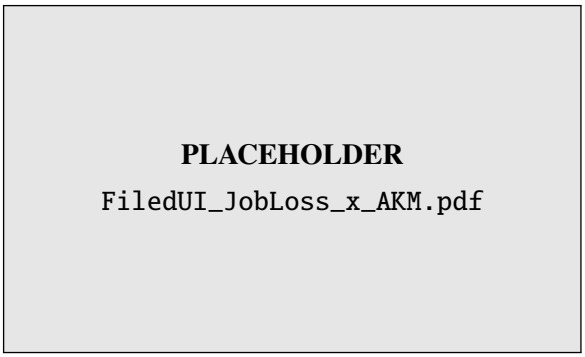


Filed UI

Job Loss



Job Loss x Repl. Rate

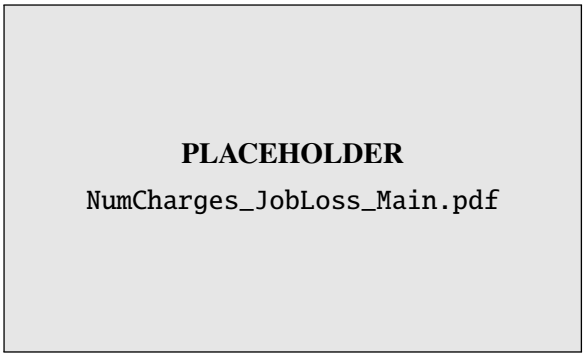


Notes: Each outcome is presented with its own header, followed by the two columns of event study estimates: the main effect of job loss (left) and the interaction with the AKM instrument (right).

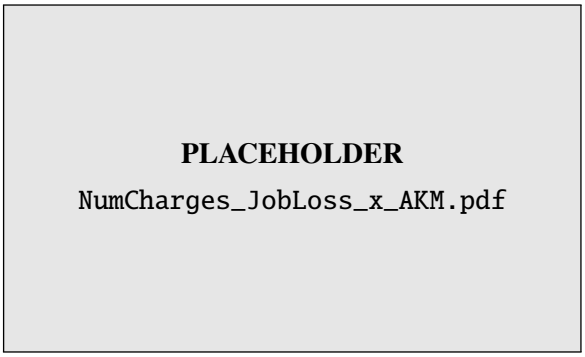
Figure 7: Event Studies: Crime Outcomes, Direct Effects & AKM Take-up Instrument

Num. of Charges

Job Loss

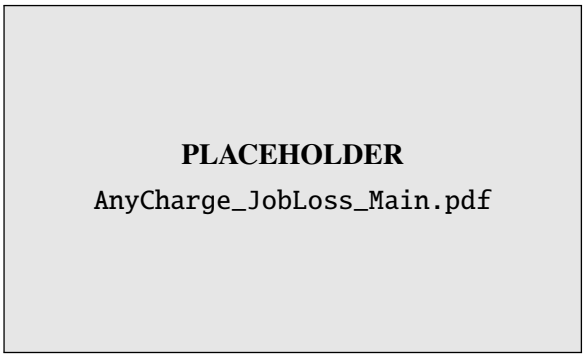


Job Loss x Repl. Rate

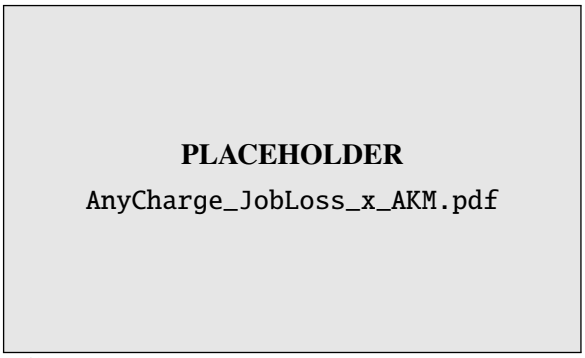


Any Charge

Job Loss

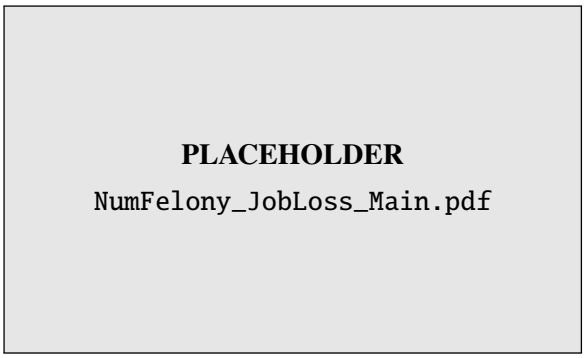


Job Loss x Repl. Rate

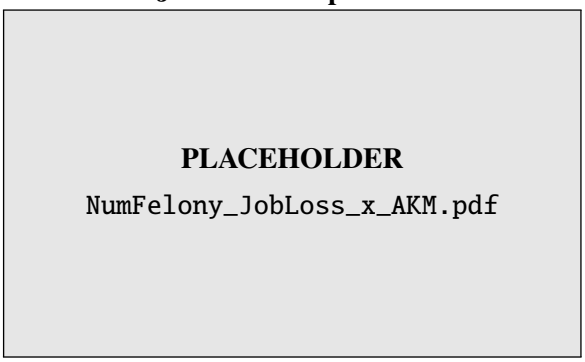


Num. Felony Charges

Job Loss

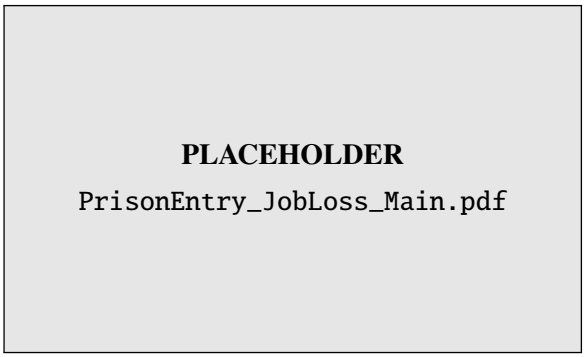


Job Loss x Repl. Rate



Prison Entry

Job Loss



Job Loss x Repl. Rate



Notes: Each outcome is presented with its own header, followed by the two columns of event study estimates: the main effect of job loss (left) and the interaction with the AKM instrument (right).

Table 1: Summary Statistics

	Job-loss status	
	(1) Firm Separators	(2) Firm Stayers
Pre-period Earnings	To be disclosed	To be disclosed
W-2 Dependency Earnings	To be disclosed	To be disclosed
Age	To be disclosed	To be disclosed
Claimed Dependents	To be disclosed	To be disclosed
White	To be disclosed	To be disclosed
Black	To be disclosed	To be disclosed
Hispanic	To be disclosed	To be disclosed
Other Race	To be disclosed	To be disclosed

Notes: This table displays summary statistics split by job separators and those who remained at firms with mass layoffs.

Table 2: State DiD Design

	Outcome:								
	(1) RR	(2) UI Takeup	(3) Wages	(4) Employment	(5) # Charges	(6) Any Charge	(7) # Felony Charges	(8) Any Felony Charge	(9) Prison Entry
β^{Post}	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
Pre-Period Mean	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
N	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD

Notes: This table displays estimates (β^{Post}) from $Y_{it} = \beta^{Post} + \sigma_i + \delta_t + \varepsilon_{it}$. Each column represents the results from a separate regression. HAC standard errors are clustered at the state level. *** $p < .01$, ** $p < .05$, * $p < .10$

Table 3: Individual Job Loss - Replacement Rate Instrument

	Outcome:							
	(1) UI Takeup	(2) Wages	(3) Employment	(4) # Charges	(5) Any Charge	(6) # Felony Charges	(7) Any Felony Charge	(8) Prison Entry
$\beta^{SR}[Job\ Loss_i \times Post_{it}^{SR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta^{LR}[Job\ Loss_i \times Post_{it}^{LR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{SR}[Job\ Loss_i \times Post_{it}^{SR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{LR}[Job\ Loss_i \times Post_{it}^{LR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
Pre-Period Mean	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
N	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD

Notes: This table displays estimates from Equation 2. Each column represents the results from a separate regression. HAC standard errors are clustered at the state level. *** $p < .01$, ** $p < .05$, * $p < .10$

Table 4: Individual Job Loss - Maximum Duration Instrument

	Outcome:							
	(1) UI Takeup	(2) Wages	(3) Employment	(4) # Charges	(5) Any Charge	(6) # Felony Charges	(7) Any Felony Charge	(8) Prison Entry
$\beta^{SR}[Job\ Loss_i \times Post_{it}^{SR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta^{LR}[Job\ Loss_i \times Post_{it}^{LR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{SR}[Job\ Loss_i \times Post_{it}^{SR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{LR}[Job\ Loss_i \times Post_{it}^{LR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
Pre-Period Mean	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
N	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD

Notes: This table displays estimates from Equation 2. Each column represents the results from a separate regression. HAC standard errors are clustered at the state level. *** $p < .01$, ** $p < .05$, * $p < .10$

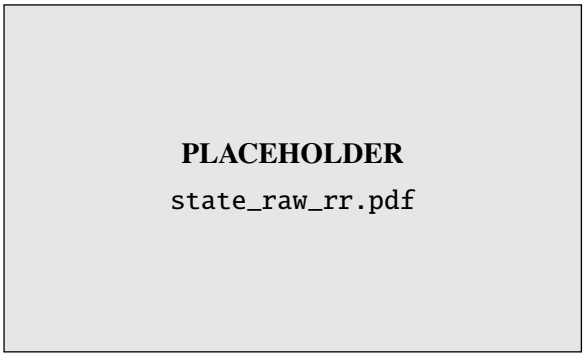
Table 5: Individual Job Loss - Firm Uptake AKM Instrument

	Outcome:							
	(1) UI Takeup	(2) Wages	(3) Employment	(4) # Charges	(5) Any Charge	(6) # Felony Charges	(7) Any Felony Charge	(8) Prison Entry
$\beta^{SR}[Job\ Loss_i \times Post_{it}^{SR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta^{LR}[Job\ Loss_i \times Post_{it}^{LR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{SR}[Job\ Loss_i \times Post_{it}^{SR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{LR}[Job\ Loss_i \times Post_{it}^{LR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
Pre-Period Mean	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
N	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD

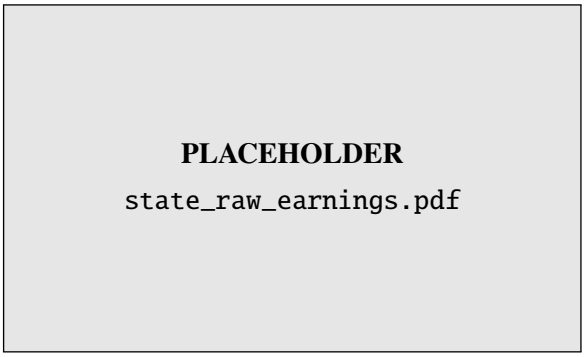
Notes: This table displays estimates from Equation 2. Each column represents the results from a separate regression. HAC standard errors are clustered at the state level. *** $p < .01$, ** $p < .05$, * $p < .10$

Figure 8: Raw data around state UI policy reforms

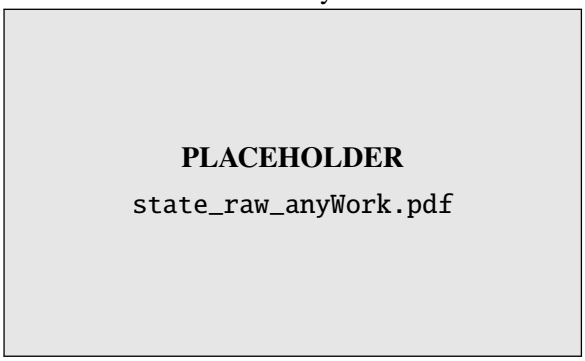
Panel A: UI Replacement Rates



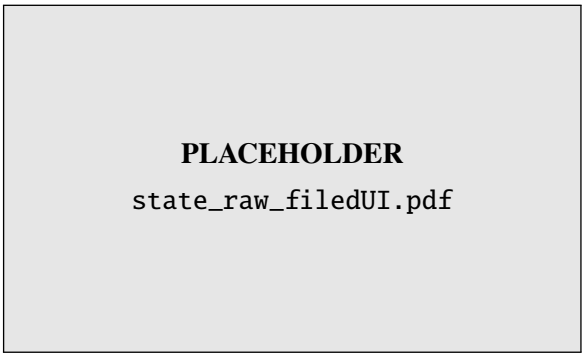
Panel B: W2 Earnings



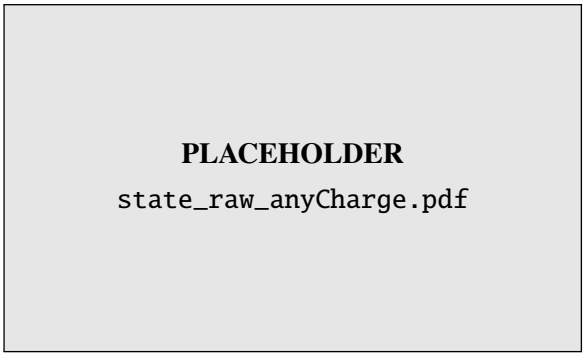
Panel C: Any Work



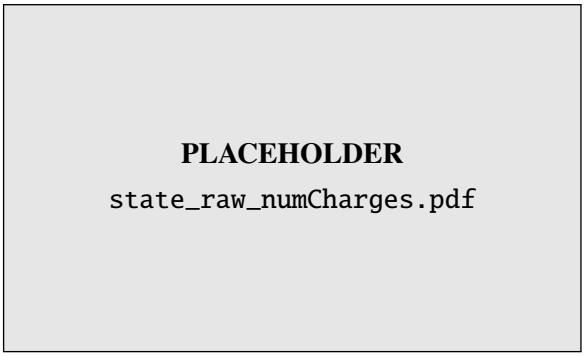
Panel D: Filed UI



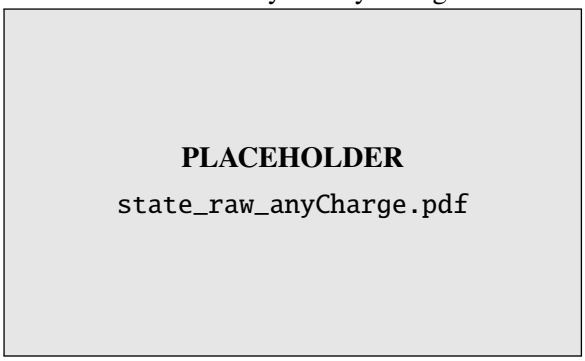
Panel E: Any Charge



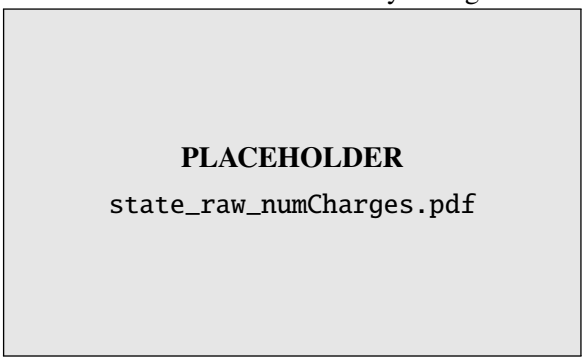
Panel F: Number of Charges



Panel G: Any Felony Charge



Panel H: Number of Felony Charges



Panel G: Prison Entry

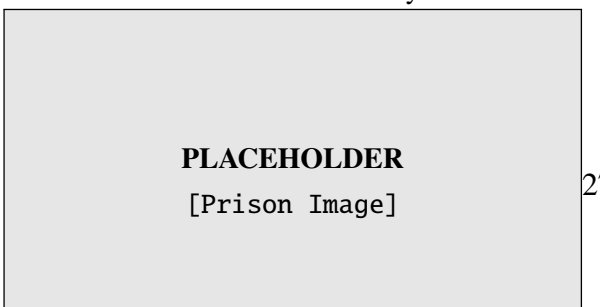


Table 6: State DiD - Heterogeneity

	Outcome:								
	(1) RR	(2) UI Takeup	(3) Wages	(4) Employment	(5) # Charges	(6) Any Charge	(7) # Felony Charges	(8) Any Felony Charge	(9) Prison Entry
Women	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
W-2 Dependency Earnings	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
Age 18-24	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
Age 25-34	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
Age 35-45	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
Age 45+	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
No Claimed Dependents	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
Claimed Dependents	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
White	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
Black	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
Hispanic	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
Other Race	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)

Notes: This table displays estimates (β^{Post}) from $Y_{it} = \beta^{Post} + \sigma_i + \delta_t + \varepsilon_{it}$. Each cell represents the results from a separate regression. Pre-period group means are shown in brackets. HAC standard errors are clustered at the state level. *** $p < .01$, ** $p < .05$, * $p < .10$

Table 7: State DiD - Specific Crime Types

	Any Charge:					
	(1) Murder	(2) Assault	(3) ...	(4) ...	(5) ...	(6) Criminal Traffic
Post Layoff	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
Post Layoff x Instrument	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
Instrument	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
Pre-Period Mean	TBD	TBD	TBD	TBD	TBD	TBD
N	TBD	TBD	TBD	TBD	TBD	TBD

Notes: This table displays estimates (β^{Post}) from $Y_{it} = \beta^{Post} + \sigma_i + \delta_t + \varepsilon_{it}$. Each cell represents the results from a separate regression. Pre-period group means are shown in brackets. HAC standard errors are clustered at the state level. *** $p < .01$, ** $p < .05$, * $p < .10$

Table 8: Replacement Rate DiD - Heterogeneity

	Outcome:							
	(1) UI Takeup	(2) Wages	(3) Employment	(4) # Charges	(5) Any Charge	(6) # Felony Charges	(7) Any Felony Charge	(8) Prison Entry
Women								
$\beta^{SR}[Job\ Loss_i \times Post_{it}^{SR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta^{LR}[Job\ Loss_i \times Post_{it}^{LR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{SR}[Job\ Loss_i \times Post_{it}^{SR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{LR}[Job\ Loss_i \times Post_{it}^{LR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
N	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
W-2 Earnings Dependency								
$\beta^{SR}[Job\ Loss_i \times Post_{it}^{SR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta^{LR}[Job\ Loss_i \times Post_{it}^{LR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{SR}[Job\ Loss_i \times Post_{it}^{SR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{LR}[Job\ Loss_i \times Post_{it}^{LR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
N	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
No Claimed Dependents								
$\beta^{SR}[Job\ Loss_i \times Post_{it}^{SR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta^{LR}[Job\ Loss_i \times Post_{it}^{LR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{SR}[Job\ Loss_i \times Post_{it}^{SR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{LR}[Job\ Loss_i \times Post_{it}^{LR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
N	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
Claimed Dependents								
$\beta^{SR}[Job\ Loss_i \times Post_{it}^{SR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta^{LR}[Job\ Loss_i \times Post_{it}^{LR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{SR}[Job\ Loss_i \times Post_{it}^{SR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{LR}[Job\ Loss_i \times Post_{it}^{LR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
N	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD

Notes: This table represents estimates from Equation 2 for each subgroup. HAC standard errors are clustered at the state level. *** $p < .01$, ** $p < .05$, * $p < .10$

Table 9: Replacement Rate DiD - Heterogeneity (Race)

	Outcome:							
	(1) UI Takeup	(2) Wages	(3) Employment	(4) # Charges	(5) Any Charge	(6) # Felony Charges	(7) Any Felony Charge	(8) Prison Entry
White								
$\beta^{SR}[Job\ Loss_i \times Post_{it}^{SR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta^{LR}[Job\ Loss_i \times Post_{it}^{LR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{SR}[Job\ Loss_i \times Post_{it}^{SR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{LR}[Job\ Loss_i \times Post_{it}^{LR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
N	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
Black								
$\beta^{SR}[Job\ Loss_i \times Post_{it}^{SR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta^{LR}[Job\ Loss_i \times Post_{it}^{LR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{SR}[Job\ Loss_i \times Post_{it}^{SR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{LR}[Job\ Loss_i \times Post_{it}^{LR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
N	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
Hispanic								
$\beta^{SR}[Job\ Loss_i \times Post_{it}^{SR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta^{LR}[Job\ Loss_i \times Post_{it}^{LR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{SR}[Job\ Loss_i \times Post_{it}^{SR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{LR}[Job\ Loss_i \times Post_{it}^{LR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
N	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
Other Race								
$\beta^{SR}[Job\ Loss_i \times Post_{it}^{SR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta^{LR}[Job\ Loss_i \times Post_{it}^{LR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{SR}[Job\ Loss_i \times Post_{it}^{SR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{LR}[Job\ Loss_i \times Post_{it}^{LR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
N	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD

Notes: This table represents estimates from Equation 2 for each subgroup. HAC standard errors are clustered at the state level. *** $p < .01$, ** $p < .05$, * $p < .10$

Table 10: Replacement Rate DiD - Heterogeneity (Age)

	Outcome:							
	(1) UI Takeup	(2) Wages	(3) Employment	(4) # Charges	(5) Any Charge	(6) # Felony Charges	(7) Any Felony Charge	(8) Prison Entry
Age 18–24								
$\beta^{SR}[Job\ Loss_i \times Post_{it}^{SR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta^{LR}[Job\ Loss_i \times Post_{it}^{LR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{SR}[Job\ Loss_i \times Post_{it}^{SR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{LR}[Job\ Loss_i \times Post_{it}^{LR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
N	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
Age 25–34								
$\beta^{SR}[Job\ Loss_i \times Post_{it}^{SR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta^{LR}[Job\ Loss_i \times Post_{it}^{LR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{SR}[Job\ Loss_i \times Post_{it}^{SR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{LR}[Job\ Loss_i \times Post_{it}^{LR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
N	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
Age 35–45								
$\beta^{SR}[Job\ Loss_i \times Post_{it}^{SR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta^{LR}[Job\ Loss_i \times Post_{it}^{LR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{SR}[Job\ Loss_i \times Post_{it}^{SR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{LR}[Job\ Loss_i \times Post_{it}^{LR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
N	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
Age 45+								
$\beta^{SR}[Job\ Loss_i \times Post_{it}^{SR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta^{LR}[Job\ Loss_i \times Post_{it}^{LR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{SR}[Job\ Loss_i \times Post_{it}^{SR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{LR}[Job\ Loss_i \times Post_{it}^{LR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
N	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD

Notes: This table represents estimates from Equation 2 for each subgroup. HAC standard errors are clustered at the state level. *** $p < .01$, ** $p < .05$, * $p < .10$

Table 11: Benefit Duration DiD - Heterogeneity

	Outcome:							
	(1) UI Takeup	(2) Wages	(3) Employment	(4) # Charges	(5) Any Charge	(6) # Felony Charges	(7) Any Felony Charge	(8) Prison Entry
Women								
$\beta^{SR}[Job\ Loss_i \times Post_{it}^{SR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta^{LR}[Job\ Loss_i \times Post_{it}^{LR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{SR}[Job\ Loss_i \times Post_{it}^{SR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{LR}[Job\ Loss_i \times Post_{it}^{LR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
N	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
W-2 Earnings Dependency								
$\beta^{SR}[Job\ Loss_i \times Post_{it}^{SR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta^{LR}[Job\ Loss_i \times Post_{it}^{LR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{SR}[Job\ Loss_i \times Post_{it}^{SR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{LR}[Job\ Loss_i \times Post_{it}^{LR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
N	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
No Claimed Dependents								
$\beta^{SR}[Job\ Loss_i \times Post_{it}^{SR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta^{LR}[Job\ Loss_i \times Post_{it}^{LR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{SR}[Job\ Loss_i \times Post_{it}^{SR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{LR}[Job\ Loss_i \times Post_{it}^{LR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
N	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
Claimed Dependents								
$\beta^{SR}[Job\ Loss_i \times Post_{it}^{SR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta^{LR}[Job\ Loss_i \times Post_{it}^{LR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{SR}[Job\ Loss_i \times Post_{it}^{SR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{LR}[Job\ Loss_i \times Post_{it}^{LR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
N	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD

Notes: This table represents estimates from Equation 2 for each subgroup. HAC standard errors are clustered at the state level. *** $p < .01$, ** $p < .05$, * $p < .10$

Table 12: Benefit Duration DiD - Heterogeneity (Race)

	Outcome:							
	(1) UI Takeup	(2) Wages	(3) Employment	(4) # Charges	(5) Any Charge	(6) # Felony Charges	(7) Any Felony Charge	(8) Prison Entry
White								
$\beta^{SR}[Job\ Loss_i \times Post_{it}^{SR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta^{LR}[Job\ Loss_i \times Post_{it}^{LR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{SR}[Job\ Loss_i \times Post_{it}^{SR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{LR}[Job\ Loss_i \times Post_{it}^{LR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
N	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
Black								
$\beta^{SR}[Job\ Loss_i \times Post_{it}^{SR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta^{LR}[Job\ Loss_i \times Post_{it}^{LR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{SR}[Job\ Loss_i \times Post_{it}^{SR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{LR}[Job\ Loss_i \times Post_{it}^{LR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
N	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
Hispanic								
$\beta^{SR}[Job\ Loss_i \times Post_{it}^{SR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta^{LR}[Job\ Loss_i \times Post_{it}^{LR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{SR}[Job\ Loss_i \times Post_{it}^{SR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{LR}[Job\ Loss_i \times Post_{it}^{LR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
N	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
Other Race								
$\beta^{SR}[Job\ Loss_i \times Post_{it}^{SR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta^{LR}[Job\ Loss_i \times Post_{it}^{LR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{SR}[Job\ Loss_i \times Post_{it}^{SR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{LR}[Job\ Loss_i \times Post_{it}^{LR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
N	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD

Notes: This table represents estimates from Equation 2 for each subgroup. HAC standard errors are clustered at the state level. *** $p < .01$, ** $p < .05$, * $p < .10$

Table 13: Benefit Duration DiD - Heterogeneity (Age)

	Outcome:							
	(1) UI Takeup	(2) Wages	(3) Employment	(4) # Charges	(5) Any Charge	(6) # Felony Charges	(7) Any Felony Charge	(8) Prison Entry
Age 18–24								
$\beta^{SR}[Job\ Loss_i \times Post_{it}^{SR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta^{LR}[Job\ Loss_i \times Post_{it}^{LR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{SR}[Job\ Loss_i \times Post_{it}^{SR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{LR}[Job\ Loss_i \times Post_{it}^{LR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
N	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
Age 25–34								
$\beta^{SR}[Job\ Loss_i \times Post_{it}^{SR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta^{LR}[Job\ Loss_i \times Post_{it}^{LR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{SR}[Job\ Loss_i \times Post_{it}^{SR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{LR}[Job\ Loss_i \times Post_{it}^{LR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
N	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
Age 35–45								
$\beta^{SR}[Job\ Loss_i \times Post_{it}^{SR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta^{LR}[Job\ Loss_i \times Post_{it}^{LR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{SR}[Job\ Loss_i \times Post_{it}^{SR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{LR}[Job\ Loss_i \times Post_{it}^{LR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
N	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
Age 45+								
$\beta^{SR}[Job\ Loss_i \times Post_{it}^{SR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta^{LR}[Job\ Loss_i \times Post_{it}^{LR}]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{SR}[Job\ Loss_i \times Post_{it}^{SR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
$\beta_Z^{LR}[Job\ Loss_i \times Post_{it}^{LR} \times Z_i]$	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD
	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)	(TBD)
N	TBD	TBD	TBD	TBD	TBD	TBD	TBD	TBD

Notes: This table represents estimates from Equation 2 for each subgroup. HAC standard errors are clustered at the state level. *** $p < .01$, ** $p < .05$, * $p < .10$